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Title of the thesis:

**NOVEL IMAGE-BASED DIETARY
ASSESSMENT TOOLS: THE ROLE OF THE
MACHINE LEARNING APPROACHES FOR
FOOD RECOGNITION AND NUTRITIONAL
EVALUATION IN EPIDEMIOLOGICAL
STUDIES**

PhD Candidate
Dr. Rachele Bianco

Supervisor
Prof. Maria Parpinel

Co-supervisor
Prof. Miriam Isola

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LIST OF ABBREVIATIONS

A

AI, Artificial Intelligence; ALA, Alpha-Linolenic Acid; ANN(s), Artificial Neural Network(s); ANOVA, analysis of variance; ASA24, Automated Self-Administered 24-hour Dietary Assessment; ASL, Asymmetric Loss; AUC-ROC, Area Under the Receiver Operating Characteristic Curve; AUFA, Animal Unsaturated Fatty Acids

B

BCM, Body Cell Mass; BDA, Banca Dati di Composizione degli Alimenti per Studi Epidemiologici in Italia; BIA, Bioelectrical Impedance Analysis; BMI, Body Mass Index

C

CA, Cluster Analysis; CART, Classification and Regression Tree; CC, Congruence Coefficient; CI, Confidence Interval; CNF, Canadian Nutrient File; CREA-AN, Consiglio per la Ricerca in Agricoltura e l'analisi dell'Economia Agraria – Alimenti e Nutrizione; CRP, C-Reactive Protein; CVD, Cardiovascular Diseases; CVDPoRT, Cardiovascular Disease Population Risk Tool

D

DAFNE, Data Food Networking; DAS28-CRP, Disease Activity Score in 28 Joints – C-Reactive Protein; DBP, Diastolic Blood Pressure; DCNN(s), Deep Convolutional Neural Network(s); DIETSCAN, Dietary Patterns and Cancer; DHA, Docosahexaenoic Acid; DL, Deep Learning; DP(s), Dietary Pattern(s); DPA, Docosapentaenoic Acid; DQI, Dietary Quality Index; DT(s), Decision Tree(s)

E

ECW, Extracellular Water; EFA, Exploratory Factor Analysis; EPA, Eicosapentaenoic Acid; EPIC, European Prospective Investigation into Cancer and Nutrition; EuroFIR AISBL, European Food Information Resource Association Internationale Sans But Lucratif

F

FAO, Food and Agriculture Organization; FCDB(s), Food Composition Database(s); FFM, Fat-Free Mass; FFQ, Food Frequency Questionnaire; FM, Fat Mass; FN, False Negatives; FP, False Positives; FSIQ, Full-Scale Intelligence Quotient

G

GIFt, Gestational Intake of Food toward Healthy Outcomes; GPU, Graphics Processing Unit

H

HDL, High-Density Lipoprotein; HEI, Healthy Eating Index; HER2, Human Epidermal Growth Factor Receptor 2; HR, Hazard Ratio; hrHPV, High-Risk Human Papillomavirus

I

ICW, Intracellular Water; IDEFICS, Identification and Prevention of Dietary- and Lifestyle-Induced Health Effects in Children and Infants; IncV3, InceptionV3; INDACO, Incorporating Nonadditivity and Nonlinearity within the Dietary Patterns and Cancer Risk Association; INFOODS, International Network of Food Data Systems; INN, Istituto Nazionale della Nutrizione; IQR, Interquartile Range

K

k-NN(s), k-Nearest Neighbor(s)

L

LA, Linoleic Acid; LARN, Livelli di Assunzione di Riferimento di Nutrienti ed Energia per la Popolazione Italiana; LASSO, Least Absolute Shrinkage and Selection Operator; LDL, Low-Density Lipoprotein; LIME, Local Interpretable Model-Agnostic Explanations; LINE-1, Long Interspersed Nuclear Element-1

M

MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MDS, Mediterranean Diet Score; ML, Machine Learning; MLP, Multi-Layer Perceptron; MMSE, Mini-Mental State Examination; MPoRT, Mortality Population Risk Tool; MSE, Mean Squared Error; MUFA(s), Monounsaturated Fatty Acid(s);

N

NaN, Not a Number; NEHO, Neonatal Environment and Health Outcomes; NHLBI, National Heart, Lung, and Blood Institute; NIH, National Institutes of Health

O

OR, Odds Ratio; ORDET, Ormoni e Dieta nell'Eziologia del Tumore della Mammella

P

PC, Principal Component; PCA, Principal Component Analysis; PCFA, Principal Component Factor Analysis; PLS, Partial Least Squares; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; PROSPERO, Prospective Register of Systematic Reviews; PUFA(s), Polyunsaturated Fatty Acid(s); PWV, Pulse Wave Velocity

R

R50, ResNet-50; R101, ResNet-101; RAE, Retinol Activity Equivalent; ReLU, Rectified Linear Unit; RGB, Red-Green-Blue; RMSE, Root Mean Squared Error; ROCAV, Risk of Cardiovascular Diseases and Abdominal Aortic Aneurysm in Varese; RR, Relative Risk; RRR, Reduced Rank Regression

S

SBP, Systolic Blood Pressure; SDAI, Simplified Disease Activity Index; SES, Socioeconomic Status; SFA(s), Saturated Fatty Acid(s); SHAP, SHapley Additive exPlanations; SMOTE, Synthetic Minority Over-sampling Technique; SVM(s), Support Vector Machine(s)

T

TBW, Total Body Water; TG(s), Triglyceride(s); TN, True Negatives; TP, True Positives

U

USDA, United States Department of Agriculture

V

ViT-B-16, Vision Transformer Base-16; VUFA, Vegetable Unsaturated Fatty Acids

W

WALNUT-BDA, Web App Linked to the BDA; WB-BMD, Whole-Body Bone Mineral Density; WCRF, World Cancer Research Fund; WHO, World Health Organization; WP(s), Work Package(s).

ABSTRACT

Diet is a multidimensional exposure, and quantifying its contribution to chronic disease risk remains challenging in nutritional epidemiology. Traditional dietary assessment methods (e.g., diet records, 24-hour recalls, and food frequency questionnaires–FFQs) suffer from recall and reporting bias, and feasibility constraints, particularly in large-scale studies. In parallel, recent deep learning (DL) advances have enabled image-based approaches that may support automated dietary assessment, although their transferability across food cultures and database standards remains limited.

This doctoral thesis investigates how harmonized food composition databases (FCDBs), DL models, and web-based dietary assessment workflows can jointly improve dietary exposure measurement. The work is organized into six research projects spanning evidence synthesis, cross-country data harmonization, model development, and epidemiological implementation.

First, two systematic reviews examined *a posteriori* dietary patterns (DPs) identified in Italian free-living populations (2001–2022), focusing on methodological consistency and cross-study reproducibility. Across studies, substantial heterogeneity in preprocessing, factor extraction, and labeling limited comparability. Nevertheless, 186 dietary patterns were consolidated into 11 reproducible groups. While evidence for dietary pattern–outcome associations was heterogeneous and often underpowered, vegetable-based and starchy patterns showed consistent and opposing links with gastric cancer.

Second, the U.S.-based Nutrition5k dataset was adapted to the Italian context through ingredient-level harmonization with the Italian Banca Dati di Composizione degli Alimenti per Studi Epidemiologici in Italia (BDA). This process highlighted methodological gaps between FCDBs (ingredient definitions, missing values, and portion standardization) but confirmed the feasibility of generating an Italian-harmonized dataset suitable for model training.

Third, several DL architectures (ResNet, Inception, and Vision Transformer) were trained on Nutrition5k images to predict dish mass, energy, macronutrients, and ingredients. Targeted dataset curation, frame filtering, and ingredient–mass correction improved prediction performance, with Vision Transformer models providing the most consistent results across tasks and scenarios.

Finally, this work resulted in the development of two resources to support future Italian applications: (1) a pilot multimodal dataset of Italian composite recipes with RGB-Depth

imaging and ingredient/nutrient annotation, and (2) a privacy-compliant web platform linking a validated FFQ to the Italian FCDB for automated intake estimation, implemented during recruitment within the INDACO study.

Overall, this thesis provides evidence, datasets, and tools to support scalable, culturally adaptable image-based dietary assessment for epidemiology and public health research.

1. INTRODUCTION

1.1 NUTRITIONAL EPIDEMIOLOGY

Nutritional epidemiology has developed from the interest that diet may influence human disease (1). This area of research has expanded substantially in recent decades, but the first epidemiologic methods date back more than two hundred years when researchers began to identify essential nutrients. Initially focused on nutrient deficiency syndromes (e.g., scurvy, rickets), the field has progressively shifted toward major non-communicable diseases, including cancer, cardiovascular disease, obesity, and other metabolic disorders (1–3).

Compared with nutritional deficiency syndromes, non-communicable diseases often have multifactorial etiology, including dietary, genetic, occupational, psychological, behavioral, socio-economic and infectious factors, that may act independently or in synergy. Additionally, these conditions show long latency periods, with disease onset typically resulting from prolonged cumulative exposure. Consequently, relatively few incident cases are observed over short follow-up periods, despite a high lifetime burden, which complicates the identification of specific dietary determinants. For instance, overweight and obesity affect over one third of the global population, and projections estimate that by 2030 approximately 38% of adults will be overweight and 20% obese. Moreover, non-communicable diseases are often not readily reversible and may result from either excessive or insufficient intake of dietary components (1–3).

The primary objectives of nutritional epidemiology include monitoring dietary intake and nutritional status at the population level, generating and testing hypotheses on diet–disease relationships, and quantifying the strength of these associations to inform prevention strategies. However, investigating the influence of diet on disease etiology remains challenging due to the complex and multifactorial nature of both diet and disease. Diet is multidimensional: food components are highly correlated, bioactive compounds may interact, and intake varies within individuals over time and across populations. Dietary behaviors are further shaped by socio-economic, cultural, and psychological factors. As a result, dietary exposure is typically assessed indirectly through self-reported instruments and, when available, biomarkers (1,3).

Disease complexity adds further challenges, as many diet–disease associations are modest and require large samples to detect reliably. Therefore, developing scalable, valid, and cost-effective dietary assessment methods remains a major priority. Despite progress over the past

three decades, evidence on the role of diet in major chronic diseases remains incomplete, supporting continued methodological innovation in dietary assessment and epidemiologic analysis (1).

1.1.1 Representing diet in nutritional epidemiology: from nutrients to dietary patterns

Traditional approaches

Diet is often described by its chemical composition. Nutrient-based approaches are useful to link intake to biological mechanisms and to test hypotheses on total nutrient exposure, particularly when many foods contribute small amounts of a compound. This approach is most robust when the compound is chemically well defined and can be accurately measured (1). On the other hand, describing diets in terms of foods or food groups has several advantages for disease associations, especially in exploratory analyses where the causal nutrient is unknown (4). They are also more directly translatable to dietary recommendations, as individuals change nutrient intake mainly through food choices. Moreover, nutrient-level evidence alone may be insufficient, because foods contain complex mixtures of compounds that interact and influence absorption and metabolism (1).

Traditional nutritional epidemiology has largely focused on single nutrients or foods (5). While this facilitates interpretation and comparison across populations, it has important limitations. Diet is consumed as meals and dietary patterns, not as isolated nutrients. In addition, many nutrients are highly correlated, complicating the estimation of independent effects. Finally, nutrient-based models may misattribute risk to a single component and may fail to capture food-specific effects beyond nutrient composition (e.g., different physiological effects of milk and yogurt, despite their similar nutritional composition) (1,5).

Given the complexity of diet, single-nutrient approaches may be insufficient to account for interactions among foods and nutrients; therefore, integrative methods are often needed to reduce the risk of missing relevant associations (6).

Dietary patterns

To overcome the limitations of single-nutrient or single-food analyses, several authors have more recently proposed to study overall dietary patterns, considering how foods and nutrients are consumed together (7–9). A dietary pattern refers to a combination of dietary components that aim to summarize either the total diet or key aspects of a population's diet. Dietary patterns

can be created using food groups or nutrients and are often expressed as a percentage of total energy intake.

Considering dietary patterns aligns more closely with real-world eating behaviors, in which nutrients and foods are typically consumed in combination. This approach captures variation in overall dietary intake and allows researchers to investigate the joint effects of foods and nutrients on human health. However, this methodology has its own limitations, including subjective decisions, unresolved methodological challenges in pattern identification, and concerns regarding the validity and reproducibility of derived patterns (10,11).

In nutritional research, statistical methods for dietary pattern analysis serve three primary purposes: (1) descriptive analysis of food and nutrient intake relationships; (2) data reduction to generate variables for further hypothesis testing, and (3) support in the development of dietary questionnaires (7).

Dietary patterns are commonly classified into three broad categories: *a priori* (investigator-defined), *a posteriori* (data-driven), and mixed-type (data-driven, response-dependent) (7–9).

A priori dietary patterns measure the individual adherence to dietary guidelines based on scientific evidence linking food and nutrient intake to health outcomes. Researchers assign a score to each component and combine component scores into an overall index (e.g., Mediterranean Diet Score, MDS; Healthy Eating Index, HEI; or Dietary Quality Index, DQI) reflecting these relationships. While these indexes are easy to construct and facilitate cross-population comparisons, they rely on current knowledge and may not capture the complexity or cultural specificity of dietary habits.

A posteriori dietary patterns are derived empirically from dietary data collected with tools like FFQs, 24-hour recalls, or dietary records. Commonly identified through techniques like factor analysis, principal component analysis (PCA), or cluster analysis, these patterns reflect actual dietary behaviors observed within a population. Although not based on predefined hypotheses or linked directly to health outcomes, they offer valuable insights into prevailing eating habits. However, the lack of standardization in variable selection, data preprocessing, and labeling introduces a degree of subjectivity, which can compromise the reproducibility and comparability of findings across studies. Despite these limitations, data-driven approaches remain useful for characterizing population-level dietary trends and informing public health strategies aimed at improving diet quality.

Mixed-type dietary patterns are increasingly used to bridge this gap. These approaches, such as reduced rank regression (RRR), partial least squares (PLS), and classification and regression trees (CART), incorporate disease-related response variables directly into the pattern derivation process. This allows the identification of dietary patterns that are not only empirically grounded but also potentially predictive of health outcomes.

Recent methodological advances, particularly in the analysis of a posteriori and mixed-type dietary patterns, have led to the development of more flexible and interpretable tools. These include Bayesian factor analysis with sparsity priors, finite mixture models, and treelet transform, all designed to improve pattern reproducibility, comparability across studies, and biological interpretability (12). While these advanced methods offer significant potential, they require careful tuning and are most appropriate when study objectives justify their added complexity. The main methods used for dietary pattern analysis are summarized in **Table 1.1**, which outlines their classification, key characteristics, strengths, and limitations. This overview is adapted from (12) and is intended to assist in selecting the most appropriate approach depending on study objectives, data availability, and whether health outcomes are incorporated.

Table 1.1. Overview of main methods for dietary pattern analysis in nutritional epidemiology

Method	Approach Type	Description	Strengths	Limitations	Common Tools
A priori scores	Investigator-defined	Scoring based on dietary guidelines or reference diets	Simple to compute; linked to health outcomes; comparable across studies	Subjective design; may not reflect actual intake; limited diet complexity	HEI, MDS, DQI
PCA / EFA	A posteriori (data-driven)	Reduces dietary data into patterns based on correlations among food/nutrient groups	Empirically driven; identifies real intake patterns	Subjective preprocessing; limited reproducibility across populations	SPSS, SAS, R (factanal, psych)
CA	A posteriori (data-driven)	Groups individuals based on similar dietary profiles	Intuitive interpretation; useful for public health messaging	Sensitive to input selection and outliers; no standard criteria for choosing cluster number	R (kmeans, hclust), SAS
RRR	Mixed-type (response-dependent)	Identifies patterns that explain variation in disease-related variables	Links diet to intermediate health markers; combines a priori and a posteriori logic	Requires strong selection of response variables; limited generalizability	SAS, R (rrcov, caret)
PLS	Mixed-type (response-dependent)	Maximizes covariance between dietary predictors and health-related responses	Balances prediction and interpretation; flexible	Complex interpretation; less commonly used	R (pls), Python (scikit-learn)

Treelet Transform	A posteriori (sparse data-driven)	Combines PCA and hierarchical clustering to derive sparse, interpretable patterns	Better interpretability; suited for small/sparse datasets	Subjective cut-level selection; limited validation in large-scale epidemiology	R (treelet)
Finite Mixture Models	A posteriori (model-based)	Probabilistic clustering with estimation of group membership	Handles heterogeneity; accounts for uncertainty in classification	Computationally intensive; sensitive to initial values and distributional assumptions	R (mclust), LatentGO LD
CART / Decision Trees	Mixed-type	Non-parametric model to identify intake patterns linked to a health outcome	Easy to interpret; identifies specific dietary subgroups	Instability of trees; overfitting risk; usually needs large sample sizes	R (rpart), Python (scikit-learn)

Abbreviations: CA, Cluster Analysis; CART, Classification and Regression Tree; DQI, Dietary Quality Index; EFA, Exploratory Factor Analysis; FFQ, Food Frequency Questionnaire; HEI, Healthy Eating Index; MDS, Mediterranean Diet Score; PCA, Principal Component Analysis; PLS, Partial Least Squares; RRR, Reduced Rank Regression.

In conclusion, there is no universally optimal way to define dietary patterns in epidemiological research. The best approach depends on the research question, the quality and granularity of the dietary data, and the availability of outcome-related variables. In general, a multilevel analysis (considering nutrients, foods, food groups, and overall dietary patterns) is recommended to gain the most comprehensive insights into the diet–health relationship (1,8,12).

1.1.2 Assessing habitual dietary intake: variability and methodological challenges

Assessing dietary habits is essential for estimating exposure to energy, nutrients, anti-nutrients, and other bioactive components in clinical and epidemiological contexts. In clinical practice, dietary assessment supports the evaluation of nutritional status, the detection of under- and overnutrition, and the monitoring of adherence to dietary prescriptions. In nutritional epidemiology, dietary habits are commonly measured through food consumption surveys (13), which underpin surveillance studies aimed at identifying dietary determinants of disease risk (10,11).

Diet is a complex, time-varying exposure composed of multiple interacting components consumed in variable amounts and combinations. Beyond inter-individual differences, dietary habits and food composition change over time due to cultural, ecological, and infrastructural factors (12). For this reason, understanding the temporal variability of dietary intake is essential when selecting appropriate dietary assessment tools and when interpreting results. Short-term intake is characterized by within-person variability driven by day-to-day fluctuations, weekday/weekend patterns, and seasonality. In settings with limited food preservation and

distribution, seasonal availability may strongly affect nutrient intake (e.g., vitamin A from specific fruits and vegetables) (1,14). Given this variability, a single-day dietary assessment is insufficient to accurately capture habitual intake. Measurement error in dietary assessment includes both random components (e.g., day-to-day variation) and systematic components (e.g., underreporting, reporting bias linked to social desirability, or individual characteristics). If intake is collected for only one or few days, an individual's long-term diet may be misclassified, attenuating associations with health outcomes and reducing statistical power. Notably, national surveys have often relied on a single 24-hour recall per participant (15). The consequence of this intra-individual variability is a general attenuation of the associations between dietary exposure and health outcomes, making it more difficult to detect or quantify robust links between diet and disease risk. This limitation can be partly mitigated by collecting multiple days of dietary records or 24-hour recalls, averaging out day-to-day variability, and allowing for more accurate estimation of usual intake. The number of days required depends on the nutrient or food group of interest and the level of precision needed for the analysis. Yet, in large-scale epidemiological studies, this approach is frequently impractical due to logistical and financial constraints. Alternative methods such as food frequency questionnaires (FFQs) and diet histories are designed to capture habitual intake over longer time frames and can help reduce the impact of short-term variability. In this context, FFQs and diet histories remain the most feasible options, despite their inherent limitations. In validation studies, objective biomarkers (e.g., doubly labeled water for energy intake or urinary nitrogen for protein) have been used to evaluate and correct dietary assessment tools, but their use is limited by cost, logistics, and the lack of sensitive biomarkers for many nutrients.

Another critical issue is the accuracy of food composition databases (FCDBs) used to convert reported food intake into nutrient intake. These databases may be incomplete or outdated, and nutrient content can vary by region, season, agricultural practices, processing, and cooking methods. Therefore, continuously updated and country-specific food composition tables are essential to ensure accurate estimation of nutrient exposure (12).

In conclusion, the choice of dietary assessment method must balance measurement accuracy, feasibility, and cost. The optimal approach depends on study design, target dietary components, available resources, and the acceptable level of exposure misclassification. A clear understanding of these methodological implications is essential to ensure the validity and generalizability of findings (16).

1.2 TRADITIONAL DIETARY ASSESSMENT TOOLS

Dietary assessment tools can be classified as prospective (direct) or retrospective (indirect, memory-based) methods. Prospective methods involve real-time recording of food and beverage intake over a defined period, often with weighed portions. When appropriately implemented, they provide detailed information on current diet but require substantial participant engagement and may be affected by misreporting and reactivity. Underreporting is common, particularly in individuals with overweight or obesity, and prospective tools are therefore often used in clinical contexts where monitoring is a key objective (16). Retrospective methods collect intake information through recall, either over the short term (e.g., 24–48 h) or over longer reference periods (e.g., one month to one year). They are generally less burdensome and less costly, and can capture habitual dietary patterns, although they remain susceptible to recall bias and other systematic errors. Tool selection should reflect the study aims, available resources, population characteristics, and the required accuracy, while accounting for random and systematic error and the precision–feasibility trade-off in large-scale studies (1,12).

1.2.1 *Dietary Record*

Dietary records are prospective, open-ended methods that document all foods, beverages, and supplements consumed over a defined period (typically 1–7 days). Intake is recorded during or shortly after consumption, reducing reliance on memory. Following an in-depth training session with trained personnel, participants are guided in accurately describing the type and quantity of each food item consumed, along with relevant contextual information such as the time and place of consumption, preparation method, recipe details (for composite dishes), product brand (for packaged items), and, when applicable, physiological (e.g., hunger) or emotional states (e.g., stress, joy, boredom) that may have influenced eating behavior (17).

Diet records may be weighed or estimated. Weighed records use kitchen scales to quantify portions and provide high precision, often serving as a reference in validation studies. Estimated records rely on household measures and portion-size aids. While the weighed method offers greater precision and is often considered the reference standard in validation studies, the estimated version is more feasible in population-based research where participant burden must be minimized.

To improve data quality, participants should be instructed to report key details (e.g., edible part, fat content, raw vs cooked weight) and records should be reviewed with trained personnel to identify omissions and resolve ambiguities. Eating outside the home poses additional

limitations due to incomplete information on recipes and preparation; participants may therefore be encouraged to collect ingredient and cooking details when possible (1).

Portion estimation can be supported using scales, standardized utensils, and conversion charts. If portion sizes are missing, standard reference values may be applied during coding. In Italy, these can be derived from the “Livelli di Assunzione di Riferimento di Nutrienti ed Energia per la Popolazione Italiana – LARN,” (18) or from validated photographic atlases (19,20), or food label information on commercial products.

Dietary records are not affected by recall bias and their open format captures a wide range of foods and preparation methods, supporting detailed food classification and portion estimation (1). When collected over multiple days, this method also allows estimation of an individual’s usual dietary intake and is therefore applicable in both clinical and epidemiological settings (17).

However, dietary records are resource-intensive and may induce behavioral changes (reactivity), potentially reducing representativeness. Underreporting remains a common limitation, especially among individuals with overweight or obesity.

To reduce burden and improve feasibility, paper diaries have increasingly been complemented or replaced by digital tools and mobile applications enabling real-time logging, automated coding, integration with FCDBs, and image-based portion estimation. These tools may improve completeness and reduce transcription errors, particularly in younger or tech-literate groups, although validation across populations and settings remains necessary (21–23).

1.2.2 24-hour Recall

The 24-hour recall is a retrospective dietary assessment method based on an interview in which participants report all foods, beverages, and supplements consumed in the previous 24 hours. It collects detailed information on food items, preparation methods, ingredients, brand names, and consumption context. Portion sizes are commonly estimated using household measures or photographic atlases (19,20). Traditionally conducted face-to-face by trained interviewers, the 24-hour recall is increasingly administered by telephone or through computer-assisted systems that guide portion reporting and automate food coding and nutrient calculations, reducing transcription errors and standardizing data processing. More recently, web-based platforms (e.g., ASA24 in the USA, myfood24 in the UK, and GloboDiet in Europe) have integrated food

images, automated prompts, and nutrient databases to support scalable and standardized data collection (24–26).

Key strengths of the 24HR include low participant burden and good acceptability. It has limited influence on eating behavior and, due to its open format, can capture all consumed items without restricting dietary scope. When repeated across non-consecutive days and seasons, it enables estimation of usual intake and seasonal variability (1).

However, the 24HR relies on memory and accurate portion-size reporting, which may vary by age, education, and other individual factors. A single recall is insufficient to estimate habitual intake; repeated administrations are required to capture long-term dietary exposure (1,16).

1.2.3 Food Frequency Questionnaire

The FFQ is the primary tool used in nutritional epidemiology to estimate an individual's usual dietary intake over extended periods, typically ranging from several weeks to years. Unlike 24-hour recalls or food diaries, FFQs provide a cost-effective approach for assessing long-term dietary exposure in large populations and are therefore commonly used in cohort studies, case-control studies, and surveillance surveys (1). FFQs include a predefined list of foods selected according to study aims (e.g., energy, macronutrients, specific foods, or dietary patterns) and adapted to the target population. Participants report intake frequency over a reference period (typically the previous month or year), with interviewer-administered or self-administered formats. Depending on the inclusion of portion size information, FFQs may be non-quantitative, semi-quantitative, or quantitative (17). Newly developed FFQs require validation and reproducibility testing, typically against diet records or repeated 24HRs, with or without biomarker calibration (1,27).

FFQs are practical for large-scale studies due to their low burden, standardized structure, and feasibility in settings where repeated 24HRs or records are not possible. However, they depend on memory and subjective reporting of frequency and portion size, and are prone to recall and social desirability bias. Errors may be larger for episodically consumed foods, mixed dishes, and seasonal items. Long food lists (e.g., over 100 items) can also increase fatigue and reduce response accuracy.

To address these limitations, FFQs are increasingly implemented as web- or app-based tools incorporating automated skip patterns, integrated nutrient databases, interactive interfaces, and visual aids for portion-size reporting. These digital solutions can reduce data entry errors and

improve standardization, supporting broader adoption in North America and Europe, particularly among younger and technology-literate populations (28–31).

1.3 FOOD COMPOSITION DATABASES

1.3.1 Food composition databases: an overview

Dietary assessment tools provide information on current or habitual consumption, which are translated into energy and nutrient intakes using FCDBs, which are the basis for nutritional analyses in both clinical and epidemiological contexts (1).

Over time, the focus on nutrient data has grown significantly, driven by increasing evidence of the role of diet in the onset and progression of chronic diseases. This has led to the development of national and international dietary guidelines, which rely on high-quality food composition data from validated sources. In this context, national FCDBs play a critical role in ensuring the reliability of intake estimates and supporting nutrition policy and research. The regulatory importance of FCDBs highlights the need for rigorous standards regarding sample representativeness, analytical accuracy, and documentation practices. Initially compiled in printed tables, these data have increasingly transitioned to digital formats, allowing for improved storage, efficient data retrieval, and more flexible applications, especially in large-scale nutritional epidemiology (32).

However, the comparability of findings across countries depends on the compatibility of national databases. This has spurred international initiatives aimed at harmonizing data structures and compilation methodologies. In particular, the INFOODS program (International Network of Food Data Systems) (33), launched in 1984 under the auspices of the Food and Agriculture Organization (FAO) (34), works to improve the global availability, quality, and consistency of food composition data. In Europe, the European Food Information Resource (EuroFIR AISBL) provides a technical and quality framework for national compilers and facilitates access to harmonized datasets (35), including FoodEXplorer, which integrates data from 26 European countries and international partners (36). Together, INFOODS and EuroFIR support standardization of food composition data for improved comparability in nutrition and public health research.

1.3.2 *Compiling requirements and limitations of use of food composition databases*

In nutrition research, the terms *compilation* or *compiling* refer to the systematic processes of data collection, selection, evaluation, and management within a FCDB. These processes are involved in building and maintaining a FCDB. These processes are guided by internationally recognized methodologies and quality criteria which aim to ensure that the resulting data are reliable, consistent, well-documented, and fit for purpose (37–39).

Despite significant progress in recent decades, several limitations remain in the use of FCDBs, particularly when applied in clinical and epidemiological research (32):

1. **Variability in food composition:** nutrient content can fluctuate due to numerous factors, including agricultural practices (e.g., soil type, fertilization, animal feed), seasonal variation, storage conditions, processing techniques, and cooking methods. As a result, the values reported in databases may not precisely represent the actual composition of individual food items consumed, and some data may become outdated;
2. **Implications for clinical and regulatory use:** in clinical practice, the nutrient values reported in dietary assessments are only estimates, not exact measurements. From a regulatory standpoint, inaccuracies in the quantification of certain nutrients (e.g., labile components like vitamin C, folate, and fat-soluble vitamins) can affect nutritional labelling, dietary guidelines, and policy development;
3. **Cross-country inconsistencies:** discrepancies in data compilation methods, food coding systems, and nutrient definitions between countries hinder international comparability. Even with harmonization efforts, aligning data from different national databases remains a challenge for cross-national research and meta-analyses;
4. **Underrepresentation of modern food products:** the growing consumption of ultra-processed foods, fortified products, and dietary supplements has significantly influenced nutrient exposure in many populations. However, these items are often poorly represented or entirely absent in many national food composition tables, creating a gap between recorded and actual nutrient intake.

Overall, while FCDBs are an indispensable resource for converting food consumption into nutrient intake estimates, their proper use requires an understanding of the compilation process, data limitations, and contextual assumptions embedded in each dataset.

1.3.3 Methods of compiling food composition databases

Early FCDBs relied primarily on laboratory analyses. Over time, compilation increasingly incorporated existing analytical evidence, leading to two main approaches: direct and indirect methods (32). Data quality depends on how values are generated and documented (32).

The direct method relies on original analytical values generated under standardized laboratory conditions. This approach allows for strict control over sampling, analytical techniques, and quality assurance procedures, thus producing highly reliable data. However, it is also time-consuming, resource-intensive, and expensive, and it may not always be feasible in countries with limited analytical infrastructure.

By contrast, the indirect method uses data extracted from secondary sources such as scientific publications, unpublished laboratory reports, or existing food composition tables. This data may include: (1) estimated values (i.e., derived from analytical values, or extrapolated from incomplete or partial analyses of food items); (2) calculated values (i.e., derived from recipe formulations or from the nutrient contents of individual ingredients, adjusted by preparation factors); (3) borrowed values (i.e., taken from other databases or tables, if provided that adequate reference to the original source is available), and (4) presumed values (i.e., assigned based on assumptions or threshold regulations—e.g., set to zero when below detectable levels). Since these data types are typically less controlled and may vary in quality, careful evaluation is necessary before their inclusion in a database. The indirect method is particularly useful when analytical resources are scarce, or when food supplies heavily depend on imported or pre-packaged items for which compositional data already exist. Although this method requires fewer analytical resources than the direct method, it can still be time-consuming and costly due to the extensive examination required.

Most FCDBs currently adopt a hybrid strategy, combining direct analytical data for frequently consumed foods with indirect sources for less common items. To preserve validity and comparability, standardized evaluation criteria should be applied (32,37–39), and the use of imputed or presumed values should be minimized where possible. Transparent documentation and harmonized compilation procedures remain essential for the reliability of FCDB-based dietary assessment and policy applications.

1.3.4 Italian food composition databases

Italy has two main FCDBs currently in use:

- 1) the CREA FCDB, curated by the Consiglio per la Ricerca in Agricoltura e l'analisi dell'Economia Agraria – Alimenti e Nutrizione (CREA-AN) (40), and
- 2) the FCDB for Epidemiological Studies in Italy, developed for research purposes (41).

While both aim to provide reliable nutrient composition data for foods consumed in Italy, they differ in origin, structure, compilation methods, and intended use. The following sections describe the historical background, structure, and methodology of each database.

CREA Food Composition Database

The CREA FCDB originates from the Istituto Nazionale della Nutrizione (INN), founded in 1936 and reorganized into CREA-AN in 2015. Since 1958, the institution has compiled and updated Italian national food composition tables, which represent a key reference for nutrition research and practice. CREA-AN is among the few Italian public institutions generating original analytical food composition data using internationally validated protocols.

The current database contains detailed nutritional information for more than 1100 foods, including raw ingredients, processed items, and composite dishes, based on both original analytical data and bibliographic sources. Compilation follows international standards for sampling, chemical analysis, food description/classification, and data documentation. The database is part of the EuroFIR network and contributed to the CEN/TC 387 Project Committee on Food Composition Data (2008–2013), supporting harmonization and comparability across European datasets. Data are available through the AlimentiNutrizione.it portal (42), which provides nutrient values per 100 g and per standard portion, together with metadata (e.g., analytical methods, sampling details, and bibliographic references). The latest update (2019) included new analytical and bibliographic data, revised nutrient values, and improvements to the user interface (42). The portal also includes complementary resources (e.g., food consumption data, labelling information, and dietary guidelines).

Despite its central role, CREA-AN activities have been affected by discontinuous funding and structural constraints, leading to irregular updates. Recent initiatives have aimed to strengthen the long-term governance and sustainability of data production.

Food Composition Database for Epidemiological Studies in Italy

The Banca Dati di Composizione degli Alimenti per Studi Epidemiologici in Italia (BDA) was developed specifically for Italian epidemiological studies (43). In contrast to national food

composition tables based on direct laboratory analyses, the BDA was compiled from pre-existing data sources. The first edition was released in 1998 (44) followed by updates in 2008, 2015, and most recently in 2022 (17). Since 2012, the compilation and management processes have been reviewed and certified by EuroFIR AISBL. Alignment with EuroFIR standards and standardized operating procedures improves transparency and reduces the risk of systematic errors.

The development of the BDA followed a structured, multi-step process, summarized in an ad hoc flow chart presented in **Figure 1.1** and detailed in the bullet points below.

1. Selection of foods and components: The first edition (44) included only foods commonly consumed by participants in the epidemiological studies (43). Over time, to broaden coverage and improve completeness, the list was expanded through consultation of other databases and through evaluations of emerging products in the Italian market. The most recent edition (17) includes 1,109 foods, up from 788 in 1998, and reports values for 86 components per food item, covering: energy (2 variables), water, 17 macronutrients, 13 minerals, 15 vitamins (of which 9 water-soluble and 6 fat-soluble), 21 fatty acids, 18 amino acids, and alcohol. Sources used to compile these data include: (1) FCDBs from both Italian (42,45) and international sources (46–50); (2) nutrition labels (possible after EU Regulation 1169/2011 (51), which mandates nutrition labelling for most food products on the market); (3) scientific articles, books, and journals, with preference for Italian publications or studies on Italian-origin foods; (4) legislative documents and production specifications (e.g., DOP, IGP, STG); (5) laboratory reports, and (6) reconstructed recipes, in which nutrient content is estimated by combining known ingredients and adjusting for preparation factors (52).

2. Data collection, evaluation, and integration of food composition data: Once potential sources are identified, their suitability is assessed based on the origin of the food item, the definition of each component, and the analytical methods used. Only data compatible with BDA definitions are retained. When integrating values from multiple sources for a single food item, care is taken to assess comparability in terms of food description and macronutrient composition (53). Where sufficient comparability exists, data are merged using standardized procedures to reduce missing values and maintain internal consistency.

3. Coding system of food composition data: The coding system consists of two distinct levels. The first level involves food coding, where each food item is assigned a unique internal BDA code, as well as a code corresponding to the specific edition. This internal code is also linked to an international identification code. The second level involves the encoding of each food

component in accordance with EuroFIR criteria. Each individual data point is associated with a series of metadata, which provides a comprehensive description of the data's type, its origin (e.g., recipe, calculation), its integrity (e.g., original or modified data), and its bibliographic source.

4. Definition of aggregated data: Some entries in the BDA are derived from aggregated data. These may be calculated as simple averages or weighted means based on regional or national consumption data. In other cases (e.g., composite or novel foods) nutritional content is estimated by constructing recipes using foods with complete nutrient profiles.

5. Data storage and controls: Finalized data are stored electronically and validated using automated procedures. Checks are performed on the full nutritional profile of each food item, as well as on individual nutrient values, to ensure internal coherence and data quality.

1.3.5 Transitioning to advanced methodologies in dietary assessment

Given the epidemiological nature of the INDACO project (Incorporating Nonadditivity and nonlinearity within the Dietary patterns And Cancer risk association) (see **Paragraph 1.5**), the BDA was selected as the primary FCDB. Its long-standing use in Italian epidemiological research, adherence to international compilation standards, and detailed coverage of foods relevant to the Italian population make it particularly well-suited to the study's objectives.

Although dietary intake is still often collected through traditional methods, such as paper-based food diaries or smartphone applications that allow participants to transmit data to trained coders (25,26,28–31,54), emerging tools are exploring real-time data acquisition. For example, new image-based methods enable users to photograph their meals at the moment of consumption, enhancing accuracy and reducing participant burden (55). These technological advancements are laying the groundwork for a new generation of dietary assessment tools. Once nutrient data have been derived through standard FCDBs, the application of artificial intelligence, particularly machine learning, offers new opportunities to model dietary exposures more flexibly and precisely. By overcoming limitations of conventional tools such as recall bias, respondent fatigue, and linear assumptions in statistical models, machine learning enables the identification of complex, nonadditive, and nonlinear patterns in dietary data. This is especially critical in the context of INDACO, which aims to develop innovative, data-driven models of cancer risk prediction based on real-world dietary behaviors.



1.4 ARTIFICIAL INTELLIGENCE IN NUTRITIONAL RESEARCH

The growing volume and level of detail of dietary data, together with the limitations of traditional dietary assessment tools and FCDBs, have accelerated the use of advanced computational methods in recent years. Among these, artificial intelligence (AI) has gained growing attention for its potential to process large datasets, identify complex patterns, and support decision-making with limited human intervention. In nutritional research, AI techniques are being applied to improve the accuracy of dietary assessments, automate food recognition, and support predictive modeling in epidemiological studies. The following sections provide an overview of AI and its subfields, particularly machine learning and deep learning, as a basis for examining their potential applications in dietary assessment and nutrition-related epidemiological research.

1.4.1 What is Artificial Intelligence and why does it matter in nutrition

Artificial Intelligence refers to the ability of computer systems to perform tasks that typically require human intelligence, such as learning from data, recognizing patterns, solving problems, and making decisions. In the context of nutrition science and public health, AI offers promising solutions to longstanding challenges in data collection, analysis, and interpretation (56).

By automating complex tasks and extracting insights from large and heterogeneous datasets, AI can enhance the accuracy, scalability, and personalization of nutritional assessments and interventions. For example, AI can:

- 1) Detect dietary patterns from large-scale data with greater nuance than traditional statistical methods (57,58)
- 2) Predict health outcomes based on individual dietary habits, lifestyle, and genetic profiles (59,60)
- 3) Automate dietary assessment through tools that analyze food images, voice inputs, or text entries in real time (55,61)
- 4) Personalize nutritional advice by integrating multiple data sources (e.g., dietary intake, biomarkers, behavior tracking) (62)

A practical example is the development of mobile applications that use AI to estimate the nutrient content of meals from photographs taken by users. These tools combine image recognition, portion size estimation, and food composition data to provide immediate feedback on dietary intake, reducing reliance on manual food logging and improving user compliance.

Building on this example, the growing availability of food-related data from mobile apps, sensors, and digital health records has further expanded the opportunities for AI applications in nutrition. As the field moves toward precision nutrition and population-wide strategies for diet-related disease prevention, AI provides the methodological backbone to support scalable, data-driven, and adaptive approaches. To better understand how these systems work and how they can be applied in the nutritional domain, the following sections explore two key subfields of AI: machine learning (ML) and deep learning (DL).

1.4.2 Machine Learning: concepts and methods

Machine Learning is a subfield of Artificial Intelligence that focuses on developing algorithms capable of learning from data and making predictions or decisions without being explicitly programmed for each specific task. Unlike Deep Learning, which relies on complex neural network architectures, ML encompasses a broader range of statistical and algorithmic approaches that can be applied to both structured and unstructured data. In nutritional epidemiology, ML offers powerful tools for identifying complex relationships between dietary exposures and health outcomes, handling high-dimensional datasets, and building predictive or classification models tailored to specific research objectives (63).

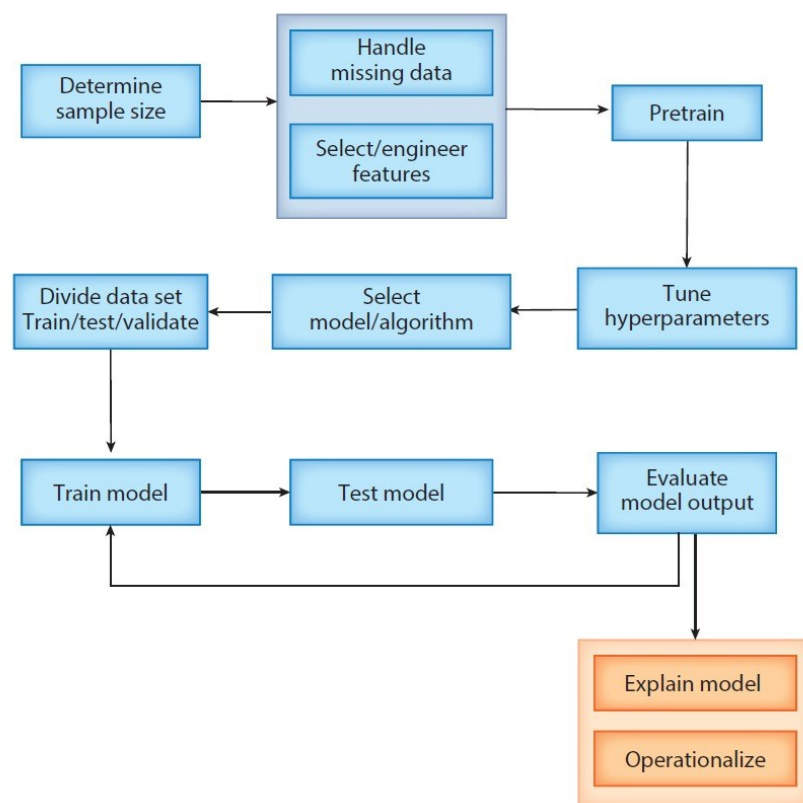
ML algorithms are typically categorized into three main types based on the nature of the learning process (64):

- **Supervised Learning:** the model is trained on labeled data, where both inputs (e.g., food intake data, lifestyle indicators) and known outputs (e.g., disease status, biomarker levels) are provided. This is widely used for classification (e.g., identifying individuals at high risk of diet-related diseases using logistic regression, random forests, or support vector machines) and regression tasks (e.g., predicting BMI or energy intake with linear regression or gradient boosting methods).
- **Unsupervised Learning:** the algorithm attempts to discover patterns or structures in unlabeled data without predefined outcomes. Common tasks include clustering (e.g., grouping individuals based on dietary patterns using k-means or hierarchical clustering) and dimensionality reduction [e.g., using Principal Component Analysis (PCA) to simplify food frequency questionnaire data while preserving variation].
- **Semi-supervised:** this approach combines labeled and unlabeled data and is useful in scenarios with limited annotations.

- **Reinforcement learning:** It involves agents learning optimal strategies through interactions with an environment and is more experimental in nutritional science, particularly in modeling longitudinal behavioral changes or adaptive dietary feedback systems.

The application of ML generally follows a structured workflow as shown in **Figure 1.2**: data preprocessing, model training, hyperparameter tuning, model evaluation, and deployment or interpretation. While this pipeline originates from supervised learning, many of its steps are also relevant to unsupervised or semi-supervised settings, with adapted strategies and goals.

Figure 1.2. End-to-end supervised machine learning workflow (63)



Data preprocessing

Before training, a critical phase involves preparing the dataset to ensure that the model learns from meaningful and high-quality inputs. This phase, known as data preprocessing, includes multiple steps that greatly influence model performance, interpretability, and generalizability (63,64).

- *Calculating Sample Size:* ML algorithms lack formal rules for sample size calculation, unlike traditional models based on p-values or effect sizes. Adequate size depends on model complexity, number of features, and class balance. In exploratory tasks like dietary

clustering, even small datasets can be informative, as seen in pattern detection from food logs in hospitalized populations (65,66).

- *Handling missing data*: many ML learning algorithms cannot operate with incomplete input, making data imputation essential. Imputation methods can range from simple mean replacement to more complex approaches like random forest–based imputers, which can account for nonlinear interactions and are particularly useful in epidemiological datasets (67,68).
- *Feature selection*: this step aims to identify the most relevant predictors while avoiding overfitting. Given that many datasets contain hundreds of variables, reducing dimensionality is crucial. Feature selection can be manual, based on clinical relevance, or automated using statistical techniques such as correlation analysis, feature importance scores, or algorithms (e.g., LASSO regression).
- *Feature engineering*: it aims at creating new variables from existing data to better capture latent relationships (e.g., nutrient ratios, dietary indices, or polynomial terms). More advanced methods, such as deep feature synthesis, allow automated construction of complex features through combinations of aggregations and mathematical primitives, enabling models to extract patterns that are not immediately visible in the raw data.
- *Contextual data integration*: external data sources (e.g., environmental, geographical, and socio-economic indicators) can be integrated during preprocessing to enrich the feature set and improve prediction accuracy. These supplementary features may capture unobserved confounders or contextual variables relevant to population-level analyses.

Model preparation and evaluation

Once data are processed, the next phase involves model development and validation (63).

- *Model Selection*: the selection of an appropriate machine learning algorithm depends on several factors including the nature of the data, the prediction task (e.g., classification vs. regression), and the interpretability or scalability needs. Common algorithms include decision trees (DTs), support vector machines (SVMs), k-nearest neighbors (k-NN), and artificial neural networks (ANNs). For each of these, the suitability must be evaluated in relation to domain-specific requirements such as sample size, data dimensionality, and outcome distribution (64)
- *Pretraining and Hyperparameter Tuning*: most ML models require tuning of hyperparameters [e.g., learning rate in neural networks, regularization parameters (C, sigma) in SVMs, or the number of neighbors (k) in k-NN] to optimize predictive

performance and to avoid underfitting or overfitting. Hyperparameter tuning typically uses a separate validation set or cross-validation, and can be performed via techniques such as grid search, random search, or Bayesian optimization. Tuning should always be done independently of the final test set to avoid data leakage. When dealing with class-imbalanced data—common in public health settings (e.g., few cases of rare diseases)—techniques like Synthetic Minority Over-sampling Technique (SMOTE) can be applied to the training data after the split.

- *Data Splitting*: after hyperparameters are tuned, the dataset is split into training and test sets. Although no universal rule exists, an 80/20 split is commonly used. Key considerations include sample size, number of features, and class distribution. Importantly, normalization or standardization (e.g., z-score scaling) of continuous features must occur after the data are split, and statistics used for normalization should be derived from the training set and applied to the test set to prevent leakage.
- *Training and Testing*: with a selected algorithm and optimal hyperparameters, the model is trained on the training set. This involves fitting the model to learn patterns in the data that relate inputs to the output labels. The test set is then used to assess generalizability on unseen data. For classification models, the class distribution in the test set should remain untouched to reflect real-world application. Cross-validation is a widely used technique for reliably evaluating the generalization ability of machine learning models. By repeatedly splitting the dataset into training and validation subsets—as in k-fold cross-validation—this approach provides a robust estimate of predictive performance that is independent of any single train/test split. Careful validation is essential to avoid two common pitfalls:
 - Overfitting: when a model learns noise and specificities of the training data rather than generalizable patterns. This results in excellent performance on training data but poor accuracy on new, unseen data.
 - Underfitting: when a model is too simplistic to capture the underlying structure of the data, leading to poor performance during both training and validation,
- *Evaluation of Performance*: model performance is assessed using metrics appropriate to the prediction task:
 - Regression: Common evaluation metrics include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics quantify the average difference between predicted and actual values, with MSE and RMSE penalizing larger errors more

heavily. MAPE is especially useful when interpretability in percentage terms is needed, although it may be unstable when true values are close to zero;

- Classification: key performance metrics include accuracy, precision, recall, F1-score, area under the ROC curve (AUC-ROC), and precision-recall curves. While accuracy is intuitive, it can be misleading in imbalanced datasets. Metrics like precision (positive predictive value) and recall (sensitivity) offer more insight into performance on the minority class, and the F1-score provides a balance between the two.

Model interpretability and explainability

Interpretability remains a critical issue in nutrition-related models because many ML models are considered black boxes, especially ensemble methods and neural networks. Therefore, tools like SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are now used to enhance interpretability by attributing feature contributions at the individual level (69).

Adaptations for unsupervised models

Although this pipeline is typically rooted in supervised learning, many components (e.g., data cleaning, feature selection and engineering, model selection, or hyperparameters tuning) are shared with unsupervised methods. However, steps like model training, testing, and performance evaluation rely on labeled data in supervised models, whereas unsupervised models (e.g., clustering or dimensionality reduction) are evaluated using internal metrics (e.g., silhouette score or cluster stability) and visual inspection. Therefore, while the structure of the workflow remains broadly similar, its implementation and assessment must be tailored to the learning context.

In conclusion, ML provides a robust and flexible framework to address a wide range of analytical tasks in nutrition research, from dietary pattern recognition to disease risk prediction. Its integration with domain knowledge, rigorous preprocessing, and transparent evaluation is essential to ensure both scientific validity and public health impact.

1.4.3 Deep Learning: principles and relevance in nutritional epidemiology

From Neural Networks to Deep Learning

Deep Learning (DL) originates from Artificial Neural Networks (ANNs), mathematical models inspired by the human brain, first proposed in the 1940s and refined over subsequent decades (70). Despite early promise, ANNs were long limited by computational and methodological constraints, resulting in fluctuating interest and adoption (63).

From the mid-2000s, increased computational capacity, large-scale datasets, and advances in optimization enabled the training of deep architectures with multiple hidden layers, giving rise to modern DL (64). A key feature of DL is its ability to automatically learn hierarchical representations from raw data, which has driven major advances in image recognition, speech processing, and natural language understanding. This representation-learning capability has made DL a state-of-the-art solution for high-dimensional analytical problems, including image-based dietary assessment and other applications in nutrition and nutritional epidemiology (70).

Deep Learning for image-based dietary assessment

DL is well suited to image-based dietary assessment because it integrates feature extraction and prediction within a single framework. Model parameters are optimized through backpropagation, iteratively minimizing a predefined loss function over multiple epochs and batches (64).

Compared with traditional approaches based on handcrafted features, DL can learn increasingly complex patterns directly from images. This is especially evident with the use of Deep Convolutional Neural Networks (DCNNs) and Vision Transformers (ViTs) (71), as well as with the integration of language supervision in multimodal image classification (72). When applied to food images (55,73–75), DL outperforms traditional algorithms in extracting features from both generic (76) and food-specific images (55), and has increasingly incorporated vision–language models into the analysis pipeline (77). Beyond nutrient estimation (78), DL has also been applied to generate realistic food images (79), create recipes (80), recognize flavors (81), and adapt recipes across cultures (82). These advancements often build upon classical computer vision problems. Specifically, these models can: (1) segment visual regions targeting specific food components (83); (2) identify ingredients (84) and link them to recipes (79,80), and (3) estimate portion sizes and related volumes (55,85). Several recent models have adopted a multi-task learning approach, combining ingredient recognition, food classification, and volume estimation within a unified framework (55). These systems frequently rely on instance

segmentation algorithms (e.g., Mask R-CNN) and may incorporate multi-view inputs and geometric priors to improve volume estimation. This has supported the development of specialized datasets designed for benchmarking and end-to-end training, including Food-101, Nutrition5k, and MetaFood3D (86–90). Such datasets have improved both model performance (91–94) and reproducibility in image-based dietary assessment. **Table 1.2** summarizes the main DL approaches used in image-based dietary assessment, highlighting their typical applications as well as key strengths and limitations.

Given its detailed annotations, image diversity, and explicit focus on nutrient estimation, the Nutrition5k dataset (95,96) was selected as the primary resource for this doctoral project. It provides a large-scale benchmark of real-world meals with paired food images, segmentation masks, and ground-truth nutrient values, enabling training and evaluating deep learning models for automatic dietary assessment. Nutrition5k includes multimodal data (i.e., multiple angles RGB video streams, depth images, and annotations on ingredient weights and nutritional values from the US FCDB (49) on over 5,000 real-world food dishes. Its structure and level of detail make it a suitable framework for investigating both algorithmic performance and data quality issues, which became central themes in the research presented in this thesis.

Limitations and challenges

Despite their strengths, DL approaches have several important limitations. Overfitting remains a possible concern, especially with limited or imbalanced datasets. Additionally, deep learning models are often criticized for their black-box nature, lacking transparency and interpretability compared to simpler models like regression or decision trees (63). The performance of DL models depends strongly on the quality and representativeness of the training data; therefore, data integrity, cultural representativeness, and well-documented metadata are essential for robust and transferable results (97,98). For example, nutritional differences across countries—driven by agricultural practices, processing methods, culinary traditions, and FCDB compilation standards—can limit model generalizability and accuracy when applied in new cultural contexts (32,99,100). In addition, variability in cooking methods, food presentation, lighting, cropping, and occlusion can reduce model robustness in real-world applications. These challenges underline the importance of dataset curation and standardized preprocessing when transferring DL models across populations. Finally, DL training and deployment remain computationally demanding, often requiring specialized hardware (GPUs) or cloud infrastructure (63). Moreover, unreliable annotations and inconsistent handling of missing

values may propagate bias and obscure performance, making accurate labeling and standardized preprocessing essential (67,68).

Overall, improving data integrity, cultural representativeness, and model generalizability is crucial for developing robust and equitable AI-based dietary assessment tools. These aspects align with the broader objectives of this doctoral research and will be further addressed in the following chapters.

Table 1.2. Deep learning approaches for image-based dietary assessment: applications, strengths, and limitations

Deep learning approach	Typical applications in dietary assessment	Strengths	Limitations and challenges
Deep Convolutional Neural Networks	Food classification; nutrient prediction; ingredient recognition	Strong performance in visual feature extraction; Efficient training; Widely validated architectures	Limited global context; sensitive to cropping/occlusion; Performance depends on dataset diversity
Vision Transformers	Food classification; Nutrient prediction; Ingredient recognition	Captures global context; Robust representations across images; Strong cross-domain performance	High data/computational requirements; Sensitive to annotation quality; Limited interpretability
Vision–language / multimodal models	Food recognition with semantic supervision; Improved ingredient–food linking; Integration with textual metadata	Better semantic grounding; Improved generalization via language supervision; Supports richer dietary information	Requires additional modalities/metadata; Increased pipeline complexity; Limited availability of standardized datasets
Portion/volume estimation models (RGB-Depth, multi-view)	Portion-size estimation; Volume reconstruction; Improved mass/nutrient estimation	Improves portion estimation compared with 2D-only approaches; Supports more realistic dietary quantification	Complex acquisition protocols; Limited scalability in free-living settings; Domain shift (controlled vs real-world images)
Multi-task learning frameworks	Joint prediction (food type + ingredients + volume + nutrients)	End-to-end pipeline; Improves coherence of outputs; Better use of shared information across tasks	Hard to balance objectives; Error propagation across tasks; Needs large, well-annotated datasets

1.5 THE INDACO PROJECT: INTEGRATING MACHINE LEARNING AND EPIDEMIOLOGY FOR CANCER RISK ASSESSMENT

1.5.1 General Overview

The INDACO project (Incorporating Nonadditivity and Nonlinearity within the Dietary Patterns and Cancer Risk Association) represents an innovative effort to overcome current methodological limitations in nutritional epidemiology. The project aims to explore the non-linear and non-additive relationships between dietary patterns and cancer risk by leveraging machine learning and advanced statistical approaches. INDACO is grounded in the idea that a more sophisticated modeling of dietary intake, combined with accurate tools for data collection, may improve our understanding of diet-disease associations, ultimately informing cancer prevention strategies. The structure of the INDACO project is illustrated in **Figure 1.3**.

The project is structured around four overarching objectives:

1. Modeling nonlinearity and nonadditivity in the association between dietary patterns and cancer risk using novel ML/statistical methods.
2. Validating the predictive performance of these models through external datasets and a newly collected dataset of clinical data and dietary habits from healthy Italian adults.
3. Exploring ML-based image recognition to support new tools for dietary assessment.
4. Transferring image-based ML systems from US-based datasets to Italian dietary contexts via a newly developed pilot dataset of Italian recipes.

1.5.2 Work Packages Overview

The INDACO project is structured around a series of interconnected Work Packages (WPs), each targeting a specific research objective. The overarching goal is to address the limitations of traditional approaches in nutritional epidemiology and enhance the understanding of diet–cancer associations through the integration of novel statistical and machine learning methods.

Assessing nonlinearity and nonadditivity in cancer risk through Machine Learning (WP1)

This WP focuses on the application of ML algorithms to developing novel machine learning approaches to exploring complex interactions among dietary variables and between diet and confounders in relation to cancer risk. Data harmonization is performed on over 24,000 subjects from a network of Italian and Swiss case-control studies. Feature selection is conducted from a

rich set of ~500 dietary and risk-related variables using standard and advanced ML techniques, including LASSO, conditional inference forests, and deep learning models such as ResNets and transformers.

Statistical approaches to nonlinearity and nonadditivity (WP2)

Complementing WP1, WP2 employs classical and Bayesian statistical tools to model nonlinear and synergistic effects of dietary patterns and confounders on cancer risk. These novel statistical approaches include multi-study factor analysis, spline modeling, and functional data analysis of anthropometric trajectories. A key innovation is the use of modeling strategies that incorporate uncertainty in model selection, enhancing the robustness of conclusions.

Cancer risk prediction in university employees (WP3)

This WP aims to evaluate cancer risk models on new data collected from ~300 healthy middle-aged university employees. Data collection includes lifestyle, anthropometry, and dietary information using a digitalized web-app linked to the BDA database (41). Anthropometric and body composition measures are collected alongside structured interviews. This new dataset serves as a validation cohort for prediction models developed in WP1 and WP2.

Training Machine Learning algorithms on food images (WP4)

WP4 is dedicated to developing and training a multitask DL model capable of ingredient recognition, segmentation, and mass/volume estimation from food images. The Nutrition5k dataset (96) is used as a training base, leveraging its annotated food videos and nutrient information. The approach includes transfer learning from models pretrained on ImageNet and evaluation of multiple model architectures.

External validation on Swiss case-control studies (WP5)

To assess generalizability, models from WP1 and WP2 are externally validated on Swiss case-control studies. These studies share the same design and dietary data collection tools as the Italian ones, allowing a reliable cross-country performance evaluation.

Integrative Analysis and Model Transferability (WP6)

Although not a standalone WP, WP6 involves the integrative analysis of results from WP3 and WP5 to assess the performance of prediction models across both newly collected and external

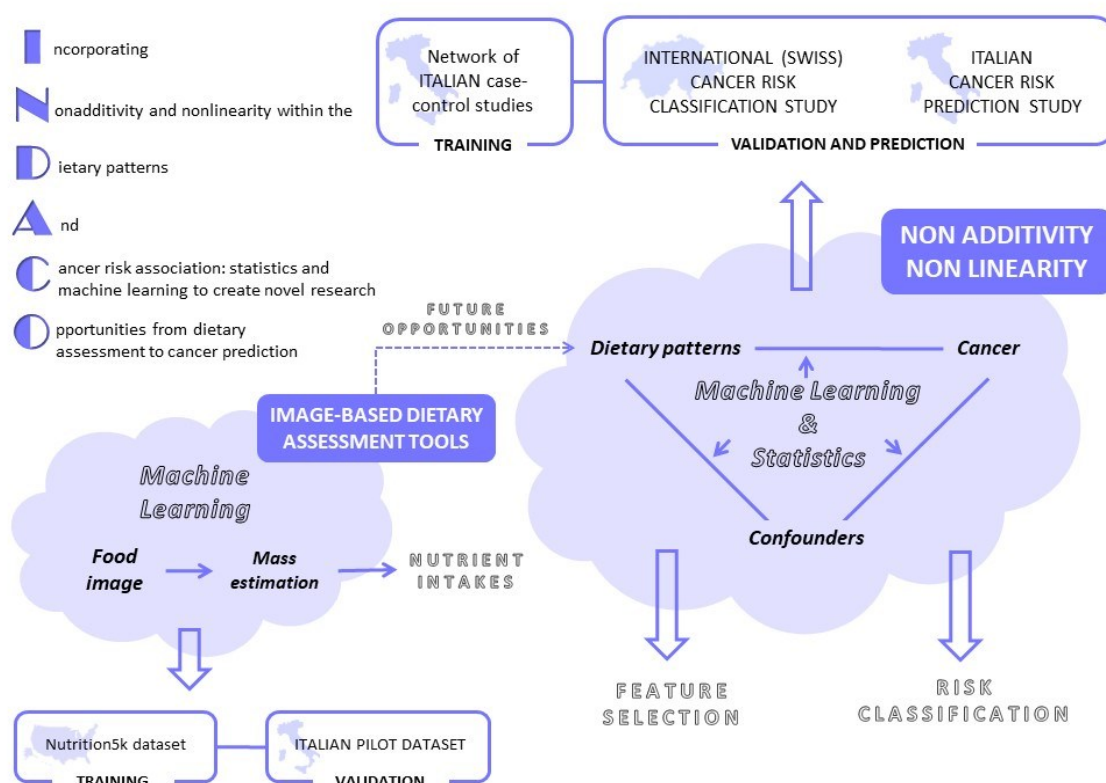
datasets. It also contributes to understanding model robustness and transferability across populations.

Fine-Tuning and Evaluation of Image-Based Models on Italian Foods (WP7)

WP7 includes the collection of a pilot dataset of 50 Italian dishes, annotated with recipes, weights, and depth images. The deep learning model developed in WP4 is fine-tuned on this dataset using transfer learning. Model performance is evaluated based on ingredient recognition, segmentation, and estimation tasks. To enhance accuracy, depth data integration and standardized image capture techniques (e.g., robotic devices) are explored.

Together, these WPs enable a multi-level investigation of diet and cancer risk, from advanced modeling of traditional dietary data to the development of image-based dietary assessment tools adapted to the Italian population. The interconnection between WPs ensures both methodological innovation and practical application, particularly within the doctoral research contributing to WP3, WP4, and WP7.

Figure 1.3. Overview of the INDACO project structure and methodological flow



Abbreviations: INDACO, Incorporating Nonadditivity and Nonlinearity within the Dietary Patterns and Cancer Risk Association.

2. AIMS

The overall goal of this doctoral research was to improve dietary assessment in the context of nutritional epidemiology by leveraging deep learning models trained on food images and integrating them with traditional epidemiological tools. To this purpose, the investigation was divided into four main objectives:

Objective 1: Defining the State of the Art in Dietary Pattern analysis within the Italian nutritional landscape

We aim to define the current state of the art in the identification of *a posteriori* dietary patterns and their associations with health outcomes within the Italian population.

Objective 2: Developing and evaluating deep learning models for image-based dietary assessment

We aim to train deep learning models on the publicly available Nutrition5k dataset (96) to perform food classification, ingredient recognition, and portion size estimation. In the next phase, these models will be fine-tuned and evaluated on a newly collected pilot dataset of Italian food images.

Objective 3: Creating a standardized, annotated pilot dataset of Italian dishes

We aim to create a novel pilot dataset consisting of ~50 complex Italian dishes, each annotated with detailed multimodal information, to serve as external validation set for evaluating deep learning model performance on culturally specific foods within the Italian context.

Objective 4: Supporting cancer risk prediction with improved dietary data

We will recruit ~300 healthy, middle-aged university employees and collect information about lifestyle, anthropometric, body-composition, and dietary measures, by using structured interviews and a new web-based FFQ linked to the BDA database.

3. DESCRIPTION OF THE THESIS STRUCTURE

This thesis is organized as follows:

Chapters 4 to 9 cover all the projects I pursued in my doctoral research. While Chapters 4 to 6 are adapted from peer-reviewed articles published during my doctoral studies, Chapters 7 to 9 present original, unpublished research written in the format of a scientific paper.

In Project 1 (Chapter 4), we aimed to achieve Objective 1. We conducted two systematic literature reviews of studies applying principal component analysis (PCA) or exploratory factor analysis (EFA) in Italian population, aiming to assess the methodological consistency, and dietary pattern characterization across studies conducted in a culturally diverse dietary landscape (101,102)

Objective 2 was addressed through Projects 2 (Chapter 5), 3 (Chapter 6), and 4 (Chapter 7). Despite advances in deep learning (DL) for image-based nutrient estimation, applying these methods across diverse dietary contexts remains challenging. To support the development of a culturally adapted image-based dietary assessment tool for Italy, I adopted a multi-phase strategy encompassing data harmonization, model evaluation, and ingredient-level recognition. This objective was pursued through three interconnected research steps, each developed within a dedicated project:

1. *Cross-country nutrient harmonization* (Project 2: Chapter 5): I investigated methodological and nutritional discrepancies arising when linking the Italian FCDB with US-based Nutrition5k food image datasets. This involved manual food matching, expert-driven ingredient-level integration, recalculation of nutrient content for each dish based on 86 components, and robust modeling to explore determinants of cross-database differences (103).
2. *Two-dimension direct prediction of mass and nutrients from food images* (Project 3: Chapter 6): We evaluated the prediction performance of multiple deep learning architectures across four ground-truth datasets differing in FCDB alignment and data curation. Key preprocessing steps, including ingredient-mass correction and frame filtering, were assessed for their impact on performance, and misclassified dishes were analyzed to inform model refinement (104).
3. *Ingredient recognition and nutrient prediction from curated food images* (Project 4: Chapter 7): We expanded upon findings of Project 3 by implementing top-performing

deep learning models and automated image quality control methods to enhance the accuracy of ingredient recognition and the estimation of mass, energy, and macronutrients, using both curated Nutrition5k images and nutritionally curated datasets as training data (105).

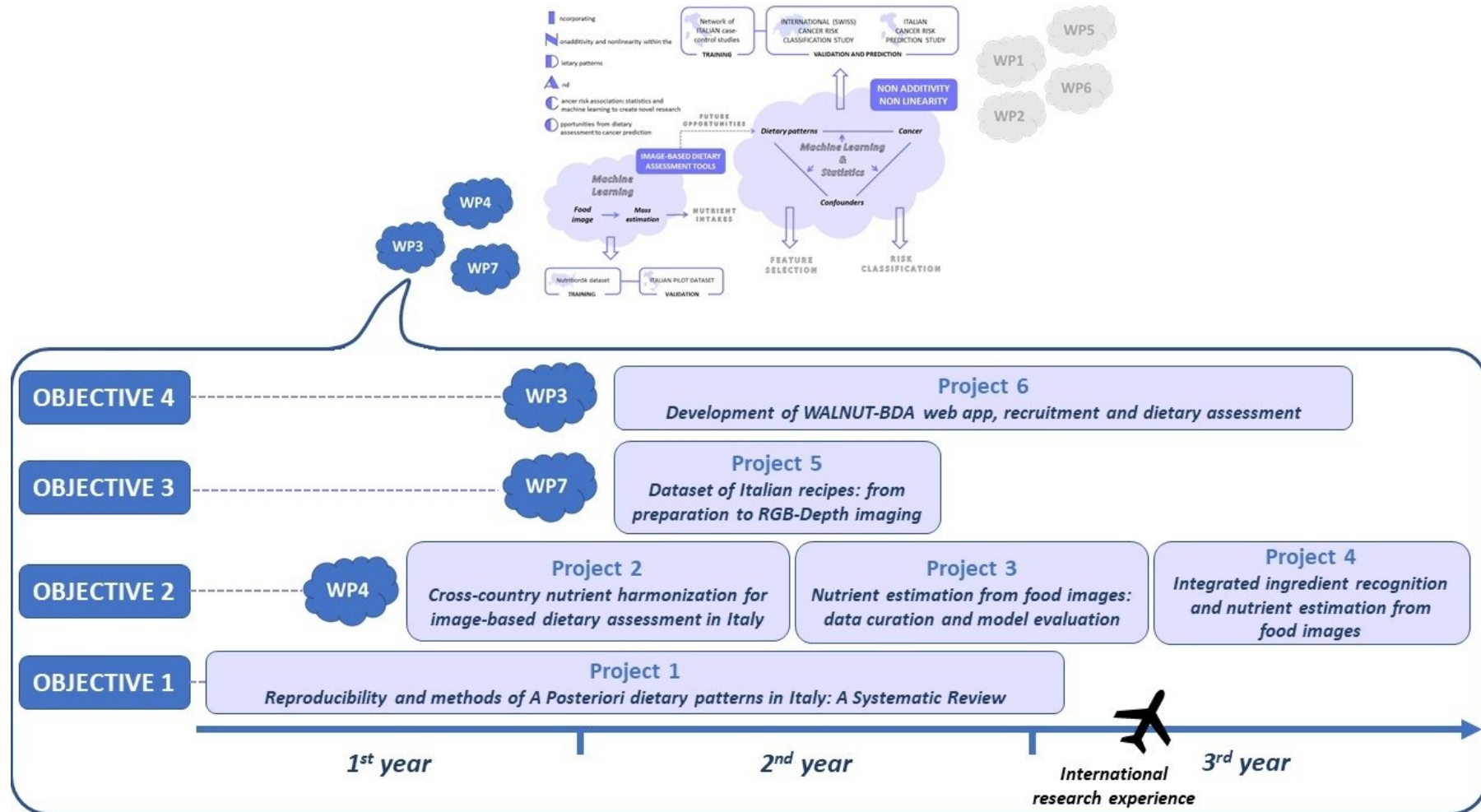
Objective 3 was achieved through Project 5 (Chapter 8), which involved the development of a curated pilot dataset comprising 54 traditional Italian recipes, each prepared in three standardized portion sizes. Nutritional information was computed using the Italian FCDB, and standardized images were collected using a robotic system equipped with an RGB-Depth camera.

Finally, Objective 4 was achieved through Project 6 (Chapter 9). The WALNUT-BDA web application was developed for digital FFQ administration with automated nutrient calculation from the Italian FCDB. It was used to collect dietary, anthropometric, and body composition data from ~300 university employees through standardized interviews and privacy-compliant data management.

Chapter 10 (Discussion and conclusion) provides a comprehensive interpretation of the findings across the entire work. This chapter will focus on the methodological advancements and challenges in image-based dietary assessment, particularly in the context of adapting deep learning approaches to culturally specific dietary data and supporting their application in nutritional epidemiology. Additionally, this chapter addresses the broad study limitations and offers some directions for future research directions.

Finally, Chapter 11 summarizes the international research visit carried out during the PhD. This chapter highlights the objectives, activities, and scientific relevance of these experiences within the broader research training path.

To provide a temporal and conceptual overview of the doctoral work, **Figure 3.1** illustrates the timeline of the six main research projects conducted over the three-year program. Each project is mapped to its corresponding PhD objective and aligned with the relevant work packages (WP3, WP4, and WP7) of the INDACO project to which it contributes. **Table 3.1** complements this overview by summarizing the structure of the thesis chapters and linking each chapter to the corresponding PhD objective, research project, INDACO work package, and related scientific publication.

Figure 3.1. Visual timeline of the doctoral research projects and their relation to doctoral objectives and INDACO project work packages¹

¹The figure illustrates the chronological distribution of the six PhD research projects across the three academic years. Each rectangle represents a specific project, with its duration scaled according to its actual development timeline. Rounded corner boxes (Objectives 1–4) refer to PhD objectives addressed by each project, while blue cloud-shaped labels (WP3, WP4, WP7) refer to the relevant work packages of the INDACO research program. Abbreviations: INDACO, Incorporating Nonadditivity and Nonlinearity within the Dietary Patterns and Cancer Risk Association.

Table 3.1. Overview of thesis chapters, PhD objectives, INDACO work packages, and related scientific publications.

Chapters	PhD thesis objective	Research project	Project objective	INDACO Work Package	Related publications
Chapter 1	Introduction				
Chapter 2	Aims				
Chapter 3	Description on the thesis structure				
Chapter 4	Objective 1	Project 1	1. Systematically review PCA/EFA-derived dietary patterns in Italian populations and evaluate cross-study methodological consistency and reproducibility 2. Characterize recurring reproducible dietary patterns in Italy and assess the consistency of their associations with health outcomes and determinants	-	(101,102)
Chapter 5	Objective 2	Project 2	Address methodological challenges in linking Italian FCDB data to Nutrition5k and compare Italian vs US FCDB nutrient estimates to identify sources of variation.	WP4	(103)
Chapter 6		Project 3	Evaluate how FCDB alignment and preprocessing procedures influence DL nutrient prediction performance under cross-cultural adaptation		(104)
Chapter 7		Project 4	Integration of ingredient recognition to the DL image-based nutrient prediction pipeline		(105)
Chapter 8	Objective 3	Project 5	Development of a pilot dataset of Italian recipes to support the validation of deep learning models for food recognition and nutrient estimation within the Italian context.	WP7	-
Chapter 9	Objective 4	Project 6	Implementation of WALNUT-BDA for digital FFQs and automated nutrient/energy estimation (Italian FCDB), and recruitment of healthy middle-aged adults with standardized lifestyle and anthropometric/dietary assessments	WP3	-
Chapter 10	Discussion and conclusion				
Chapter 11	Additional experiences: international research visit				

Abbreviations: DL, deep learning; EFA, exploratory factor analysis; FCDB, food composition database; FFQ, food frequency questionnaire; INDACO, Incorporating Nonadditivity and Nonlinearity within the Dietary Patterns and Cancer Risk Association; PCA, principal component analysis; WALNUT-BDA, Web Assessment on Lifestyle and NUTrition-BDA; WP, work package.

4. REPRODUCIBILITY AND METHODOLOGICAL INSIGHTS OF *A POSTERIORI* DIETARY PATTERNS IN THE ITALIAN POPULATION: A SYSTEMATIC REVIEW-BASED APPROACH

4.1 INTRODUCTION

Over the past two decades, *a posteriori* methods, such as Principal Component Analysis (PCA) and Exploratory Factor Analysis (EFA), have gained popularity in nutritional epidemiology for identifying dietary patterns (DPs) that reflect the complexity of real-world eating behaviors (5). These data-driven approaches synthesize correlated dietary variables into fewer, interpretable components, allowing researchers to move beyond isolated nutrient analysis and toward holistic representations of food consumption. Importantly, *a posteriori* DPs are not constrained by predefined models, but instead emerge from empirical data, making them particularly suited to capture context-specific dietary habits shaped by cultural, socioeconomic, and geographic factors (8).

The Italian population represents a particularly compelling setting for this type of investigation. Although traditionally considered adherent to a Mediterranean-style diet (106,107) recent consumption trends suggest a gradual shift away from its core features, with a marked decrease in plant-based food intake and a concurrent rise in meat, sweets, and processed food consumption (18,108). This evolution has occurred unevenly across Italian regions, further complicating the landscape of dietary analysis. As a result, characterizing common dietary patterns in Italy and evaluating the consistency with which they are identified becomes both scientifically and practically relevant for nutritional surveillance, public health, and policy-making.

To address these challenges, two systematic literature reviews were conducted as part of this PhD project (Objective 1). The first aimed to assess the methodological heterogeneity and cross-study reproducibility of dietary patterns derived using PCA and EFA in Italian populations, with a specific focus on variations in input variables, labeling criteria, and reproducibility metrics (101). The second review focused on characterizing the most frequently observed dietary patterns in terms of their content and associations with health-related outcomes, and on evaluating the consistency of these associations across studies (102). Together, these complementary analyses sought to explore whether certain dietary patterns emerge repeatedly and reliably across different Italian subpopulations, and whether their health implications are consistent.

In this chapter, the findings of these two systematic reviews are re-elaborated to provide a comprehensive overview of methodological practices, highlight reproducibility challenges, and discuss the cultural and nutritional implications of recurring dietary patterns in Italy.

4.2 OBJECTIVES

The aims of this chapter reflect the dual scope of the two systematic reviews carried out during this PhD project, both centered on *a posteriori* dietary patterns derived through PCA or EFA in Italian population studies. The reviews addressed two complementary research goals:

4.2.1 *Assessment of methodological consistency and reproducibility*

1. To systematically collect and describe PCA/EFA-based dietary patterns identified in Italian free-living populations.
2. To assess the methodological consistency across studies in terms of input variables, preprocessing, statistical procedures, and dietary pattern labeling.
3. To evaluate the cross-study reproducibility of identified dietary patterns using both qualitative (i.e., similarity plots built on original text descriptions and factor loadings) and quantitative (i.e., congruence coefficients) approaches.
4. To explore potential sources of agreement and discrepancy in reproducibility outcomes.

4.2.2 *Characterization of recurring patterns and associated outcomes*

Building on the subset of reproducible dietary patterns identified in the previous analysis, the second review investigated their relevance to public health outcomes and determinants. Specific objectives were:

1. To group dietary patterns based on reproducibility and characterize the most frequently recurring dietary profiles identified in Italian populations.
2. To evaluate the consistency of associations between reproducible dietary patterns and health outcomes, behavioral determinants, or population correlates.
3. To explore potential methodological sources of variation in these associations (e.g., type of dietary assessment tool, adjustment for confounding).

4.3 MATERIALS AND METHODS

The first systematic review (101) was conducted referring to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (109). The review protocol was registered in the International Prospective Register of Systematic Reviews (PROSPERO) database under the registration number CRD42022341037.

4.3.1 Search strategy

An electronic literature search was independently performed by two researchers on December 21, 2022, using three electronic databases: MEDLINE/PubMed, Embase, and Cochrane (CENTRAL and Reviews). The search strategy combined keywords and controlled vocabulary terms related to “dietary patterns,” “factor analysis,” “principal component analysis,” and “Italy.” No language restrictions were applied. Moreover, no filters were used to select for specific health outcomes, determinants, or correlates, provided that PCA- or EFA-based dietary patterns were identifiable in Italian populations. EndNote 20 (Thomson Reuters, New York, NY, USA) was used for reference management throughout the review process.

4.3.2 Eligibility criteria

Articles were considered eligible for inclusion if they (1) were original full-texts articles in peer-reviewed journals; (2) enrolled human subjects living in Italy; (3) identified DPs based on PCA and/or EFA on dietary data, independently of any additional analysis on health outcomes, determinants, or correlates. Articles were excluded if (1) they did not provide original data, or they were case reports, in vitro and in vivo animal studies, conference abstracts or posters; (2) the reference population lived outside Italy or, in international studies, it was not possible to distinguish the Italian-specific DPs, which are of interest in the current review; (3) results concerned single nutrients, single food items, or single food groups; (4) the term DP was used to identify dietary attitudes, perceptions, or patterns of meals; (5) DPs were identified using the a priori approach, the mixed-type approach, or the a posteriori approach but not following PCA or EFA; (6) PCA or EFA were applied on dietary behaviors or lifestyle variables. No restrictions were applied regarding publication year, participants’ characteristics, or health status.

4.3.3 Article selection

After removal of duplicates, titles and abstracts were screened for relevance. Eligible full-text articles were then reviewed in detail to determine final inclusion. Reference lists of included studies were also examined by hand-searching to identify additional eligible articles. All screening steps were carried out independently by two researchers, with disagreements resolved through discussion and consensus with a third reviewer.

4.3.4 Data extraction

Data extraction was independently performed by two researchers, and cross-checked by two additional investigators. A third investigator was consulted in cases of disagreement. Information extracted from each study included the following: (1) general characteristics of the studies; (2) study design; (3) dietary assessment tool used; (4) DP identification method; (5) number of DPs, proportion of variance explained, name, and composition; (6) statistical methods used to relate the identified DPs to disease outcomes/determinants/correlates, and (7) main results on the relationship between identified DPs and disease outcomes/determinants/correlates (corresponding to those statistical models adjusted for all the available confounders, if models were fitted).

4.3.5 Assessment of study quality

For each article that met the inclusion criteria, study quality was independently evaluated by two researchers by using the Quality Assessment Tools from the National Institutes of Health National Heart, Lung, and Blood Institute (110). Disagreements were resolved through discussion and consensus with a third reviewer. Based on the number of criteria met, as defined by each tool (range: 0–14 for cohort, cross-sectional studies, or trials; 0–12 for case-control studies), studies were rated using a four-tier system: “poor,” “fair,” “good,” and an additional “very good” category, introduced to further distinguish high-quality studies. Scoring thresholds were defined so that $\geq 25\%$ of positive responses (corresponding to 3 items) placed a study into a given category (110). Owing to the lack of previous evidence on reproducibility of DPs in Italy, we chose not to exclude studies based on their quality. Therefore, all the retrieved studies were considered in the analyses.

4.3.6 *Narrative synthesis and qualitative and quantitative assessments of reproducibility of DPs*

We first conducted a narrative synthesis of the included studies, focusing on study design, population characteristics, dietary assessment tools, DP identification methods, and descriptive summaries of the extracted patterns. To assess cross-study reproducibility, we then carried out a qualitative evaluation based on similarity plots, built from the original text descriptions and, when available, factor loadings. Factor loadings were used to determine the relative contribution of dominant food groups or nutrients, particularly in cases with detailed DP descriptions. In parallel, we performed a quantitative reproducibility assessment using the congruence coefficient (CC), the preferred metric to evaluate the similarity between PCA/EFA-derived patterns (range: -1 to 1) (111).

To ensure comparability and minimize subjectivity in defining a shared input matrix, CCs were calculated within small, highly comparable groups of studies that used the same type of input variables (i.e., either nutrients or food groups). We defined a CC of 0.85 – 0.94 as indicative of “fair similarity,” and values ≥ 0.95 as “equivalent” dietary patterns. The full distribution of CCs was examined to evaluate pairwise similarities. All quantitative analyses were performed using R (112) software and the “psych” package (113).

Lastly, a sensitivity analysis was conducted by restricting the reproducibility assessment to dietary patterns derived from data collected in more recent years (2013–2022). This aimed to explore potential shifts from traditional Mediterranean dietary profiles over time.

4.3.7 *Associations between individual Dietary Patterns and health-related outcomes: an aggregate-level synthesis of findings*

Following the reproducibility assessment, we extended the synthesis to explore whether individual DPs were consistently associated with health outcomes, behavioral drivers, or population correlates. The collected evidence was analyzed by examining the following aspects:

- 1) Target variables: based on the research question we categorized target variables (i.e., variables potentially related to the identified DPs) as:
 - i. correlates: when descriptive statistics (e.g., correlation coefficients, Cohen’s kappa, or Bland–Altman plots), possibly integrated with hypothesis testing, were used;
 - ii. drivers: when regression models treated the driver as the independent variable and DP scores as the dependent variables. In our framework, drivers are linked to—but not necessarily causal for—DPs, as causality would require specific study designs and Hill’s criteria (1965) (114);

- iii. health/disease outcomes: when DP scores were used as independent variables in models predicting health outcomes;

In each category, we grouped similar variables on a post-hoc basis. We clarified which variables were similar in a dedicated table and displayed them in adjacent columns in the graphical synthesis of findings;

- 2) Statistical methods: we assessed whether the analytical methods used to examine associations between DPs and target variables were consistent with the original study design and research questions;
- 3) Adjustment for confounders: we reviewed the lists of confounding variables across studies, comparing disease-oriented, driver-oriented, and correlate-oriented articles. We also examined whether confounders in disease-oriented studies reflected relevant drivers or correlates addressed in other studies;
- 4) Observed associations: taking into account study design, we summarized the number and percentage of statistically significant associations between individual DPs and:
 - i. any disease outcomes or DP drivers/correlates, regardless of the specific variables examined;
 - ii. similar disease outcomes or drivers/correlates investigated.

4.3.8 *Reproducible DPs and disease outcomes, DP drivers, or correlates: causal criteria and rules of inference*

To assess whether reproducible DPs were consistently associated with similar health outcomes, behavioral drivers, or population correlates, we expanded the synthesis using a structured set of criteria:

- 1) DP reproducibility: patterns were grouped using the same labels from the previous qualitative reproducibility assessment. Within each group, nutritionally similar DPs (as defined by color codes and supported by quantitative reproducibility metrics) were condensed for analysis.
- 2) Similarity of target variables: we examined whether the associated variables (i.e., disease outcomes, drivers, or correlates) were the same or sufficiently similar, based on the prior classification of target variables.
- 3) Consistency of analytical methods: we evaluated whether studies applied statistical methods appropriate to their research questions and study designs, in order to reduce bias from analytical inconsistencies.

- 4) Consistency of adjustment for confounders: we compared the confounding variables controlled for across studies investigating the same or similar target variables.
- 5) Consistency of associations: using a majority-rule approach (115), we examined whether over 50% of findings for a given DP-target combination were statistically significant and pointed in the same direction. “Same direction” was defined as:
 - i. Positive or inverse (linear) relationships, for correlate-oriented questions;
 - ii. Increasing or decreasing trends in driver means across increasing quantile-based categories of principal component/factor score, for driver-oriented studies;
 - iii. Higher or lower risks of disease/death/adverse health outcome were associated with increasing DP scores, for disease-oriented outcomes.

For each reproducible DP, we summarized the number of significant positive, significant negative, and non-significant findings across similar targets. Where the same target variable was assessed across studies, we conducted meta-analyses when feasible, collecting information on population, confounders, effect sizes, and confidence intervals. The feasibility of conducting single meta-analyses was assessed on a case-by-case basis, considering population comparability and overlap, the number of available effect estimates, and the measures used in each comparison, in line with the Cochrane Handbook and relevant references (116,117). In cases where meta-analyses were not feasible, we provided a narrative synthesis describing the heterogeneity of study designs and adjustments for confounders. Finally, we evaluated the criteria of “strength of association” and “dose–response.” For the “strength of association,” a statistically significant risk estimate that is a >20% increase or decrease in risk was considered a positive finding, with a 40%–50% change considered strong. For the “dose–response,” we assessed the presence of a statistically significant linear or otherwise regularly increasing trend, to further support the evidence for causality (115).

4.4 RESULTS

4.4.1 Article selection process and quality assessment

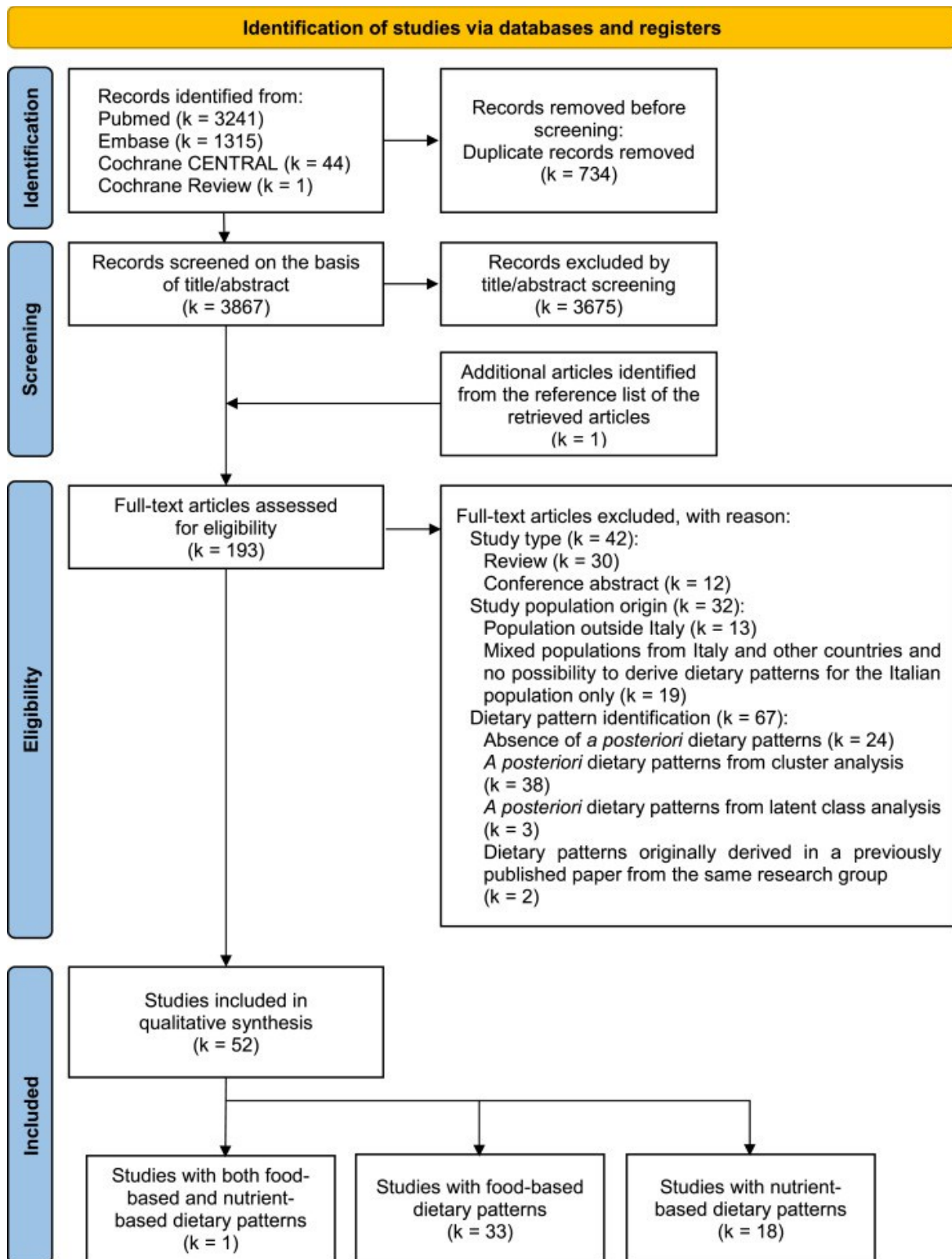
Figure 4.1 illustrates the PRISMA flowchart of the article selection process. The electronic database search yielded 4,601 records. After removing 734 duplicates, 3,675 records were excluded based on title and abstract screening. A total of 193 full-text articles—including one identified through reference list screening—were assessed for eligibility. Following the application of exclusion criteria, 52 articles (all published in English) were included in the final synthesis of this review (118–169). Reasons for exclusion are detailed in **Figure 4.1**. Among the included articles, 7 (13.5%) were based

on studies rated as “very good” quality, 35 (67.3%) as “good,” 8 (15.4%) as “fair,” and 2 (3.8%) as “poor,” both lacking outcome data. Across all studies, sample size justification was the most commonly unmet criterion (**Figure A1, Appendix A**).

4.4.2 Main characteristics of the included studies

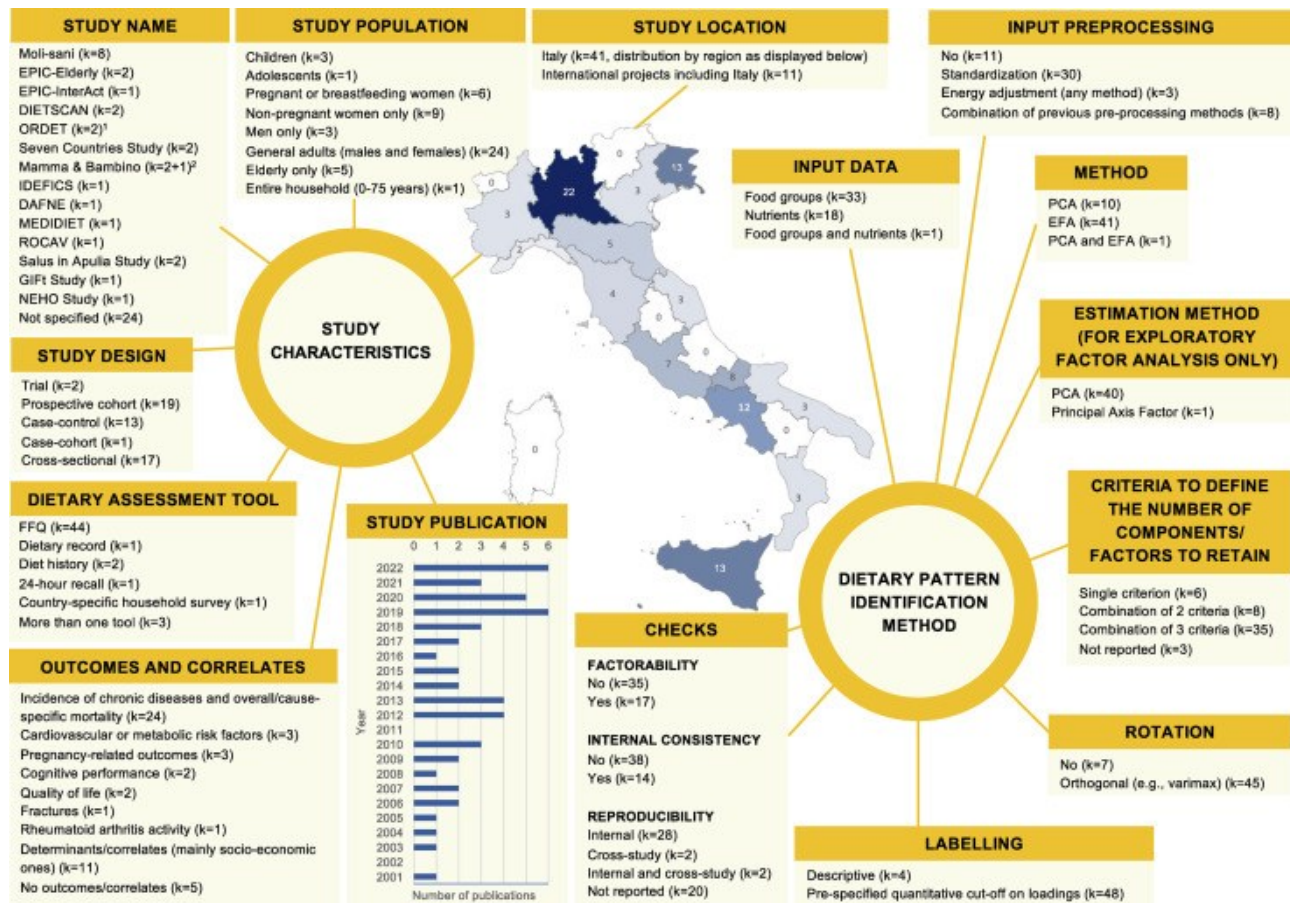
Figure 4.2 provides an overview of study design, dietary assessment tools, target variables, and DP identification methods used across the 52 included articles. The selected articles were published between 2001 and 2022 (with 79% published from 2010 onward), and covered 14 of the 20 Italian regions, with Lombardy, Friuli Venezia Giulia, Sicily, and Campania most frequently represented. Eleven articles (21%) were part of international studies that included Italy, 15 (29%) were based on Italian multicentric studies, and 26 (50%) involved single-center or single-region samples. Several articles referred to the same cohorts, such as Moli-sani (8 articles), Mamma & Bambino (3 articles), Salus in Apulia (2 articles), and “Ormoni e Dieta nell'Eziologia del Tumore della Mammella” (ORDET) (2 articles). International initiatives were also represented, including “Dietary Patterns and Cancer” (DIETSCAN) (2 articles), “European Prospective Investigation into Cancer and Nutrition” (EPIC)-Elderly (2 articles), EPIC-InterAct (1 article), and the “Seven Countries Study” (2 articles). The most frequent study design was the prospective cohort (19 articles, of which 8 performed cross-sectional analyses only), followed by the cross-sectional design (17 articles), and by the case–control (13 articles) one. The general population of adult males and females was included in 24 articles. Three articles focused exclusively on men, whereas 15 articles considered women, 6 of which specifically examined pregnant/breastfeeding women. Additionally, 10 other articles considered apparently healthy children or adolescents, community-dwelling elderly, and the entire household (0–75 y). In most studies, dietary habits were assessed once at recruitment, using a single FFQ, covering the period from 1965 to 2022. FFQs were predominantly interviewer-administered or self-administered, with reference periods typically of 1 or 2 years. Shorter periods were used during pregnancy or lactation. Except for few studies, FFQs were reported as valid and/or reproducible, or derived from validated tools. The number of items ranged from 31 to 217 (median: 95), with nearly half exceeding 100 items (**Table A1, Appendix A**).

Figure 4.1. Flow diagram of the study selection process (101)



Abbreviations: EMBASE, Excerpta Medica Database; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

Figure 4.2. General characteristics of the studies included in the systematic review and main steps in the dietary pattern identification process: a summary of findings from the systematic review (101)



¹The DIETSCAN project included one Italian cohort (ORDET) which recruited women only and it was therefore classified as “nonpregnant women only” instead of “general adults (males and females)”. ²The Mamma & Bambino birth cohort was also pooled together with MAMI-MED in another study. Abbreviations: DAFNE, Data Food Networking; DIETSCAN, Dietary Patterns and Cancer; EFA, exploratory factor analysis; EPIC, European Prospective Investigation into Cancer and Nutrition; FFQ, food frequency questionnaire; GIft, gestational intake of food toward healthy outcomes; IDEFICS, Identification and prevention of Dietary- and lifestyle-induced health Effects In Children and infants; NEHO, Neonatal Environment and Health Outcomes; ORDET, Ormoni e Dieta nell'Eziologia del Tumore della Mammella; PCA, Principal Component Analysis; ROCAV, Risk Of Cardiovascular diseases and abdominal aortic Aneurysm in Varese.

4.4.3 DP identification: statistical methods

DPs were identified using nutrients as input variables in 18 articles and food groups in 33 articles, while one article used both types of variables. The number of nutrients ranged from 10 to 37 (median: 28), and food groups from 8 to 57 (median: 37). Most articles applied EFA (k=41), a few used PCA (k=10), and one applied both; EFA was typically performed using PCA extraction. Input data were commonly standardized, and the number of factors/components retained was generally based on two or more criteria (i.e., eigenvalue threshold, Scree plot, interpretability). Varimax was the most used orthogonal rotation method (45 articles). Components were labeled quantitatively, with cut-offs ranging from 0.1 to 0.63 in absolute value (median: 0.30). About one-third of the studies checked matrix factorability, mostly by the same research team, which also assessed internal consistency

($k=14$) using Cronbach's alpha. Internal reproducibility was evaluated in 28 articles (~54%), most often via split-half or alternative scoring methods, while cross-study reproducibility was examined in four. Each article described between 2 and 6 DPs (median: 4), with explained variance ranging from 6.6% to 82% (median: 45.5%). Higher explained variance (>75%) was mainly reported in nutrient-based DP analyses (**Table A2** left columns, **Appendix A**).

4.4.4 Qualitative assessment of DP reproducibility: original descriptions

A total of 186 DPs were identified across all included articles, of which 102 food-based and 84 nutrient-based DPs. With the exception of 15 unlabeled DPs, the remaining 171 could be grouped based on their original names. The most frequent recurring names included: "Vitamins and Fiber" (14 articles, nutrient-based DPs), "Starch-rich" (13 articles, nutrient-based DPs), "Animal Products" (13 articles, nutrient-based DPs), "Prudent" (11 articles, food-based DPs), "Pasta and Meat" (10 articles, food-based DPs), "Western" (9 articles, food-based DPs), "Eggs and Sweets" and "Olive Oil and Vegetables" (8 articles each, food-based DPs), "Animal Unsaturated Fatty Acids" (AUFA) and "Vegetable Unsaturated Fatty Acids" (VUFA) (7 and 5 articles, respectively, nutrient-based DPs) (**Table A2** central columns, **Appendix A**). To account for subjective labeling, we used original text descriptions and factor loadings to harmonize the 186 DPs into 113 apparently different patterns (a 39.3% reduction), including 69 food-based and 44 nutrient-based patterns (**Figure 4.3**).

Food-based DPs

We organized the 69 food-based DPs into "Mediterranean-style" and "Western-style" macro-areas (**Figure 4.3**). The Mediterranean-style macro-area included 3 different groups of DPs that we defined as "Mixed-Salad," "Healthy-Protein Foods and Side Dish," and "Traditional" DPs. The "Mixed-Salad" group (in green) included DPs based on olive oil, raw (and sometimes cooked) vegetables (DPs named "Salad Vegetables") (118,119,145,146), with additional presence of legumes and fish (144), soup and turkey in the EPIC-Elderly study (142,143), and further inclusion of fruits and potatoes in the Moli-sani study (134–141). The "Healthy-Protein Foods and Side Dish" group (in blue) included DPs based on the presence of at least one source of healthy proteins (i.e., fish, poultry, nuts, and/or legumes) and a side dish represented mainly by cooked vegetables (142,143,151,156,165), potatoes and/or grains (160,166), or a combination of them (118,145–150,159,162). In addition, fruit loaded high on a "Prudent"-like DP in 5 articles (142,143,151,159,168). Four DPs of the "Healthy-Protein Foods and Side Dish" group presented a wider range of components in adults (157,161,169) or children/adolescents (155,156,162). The DPs

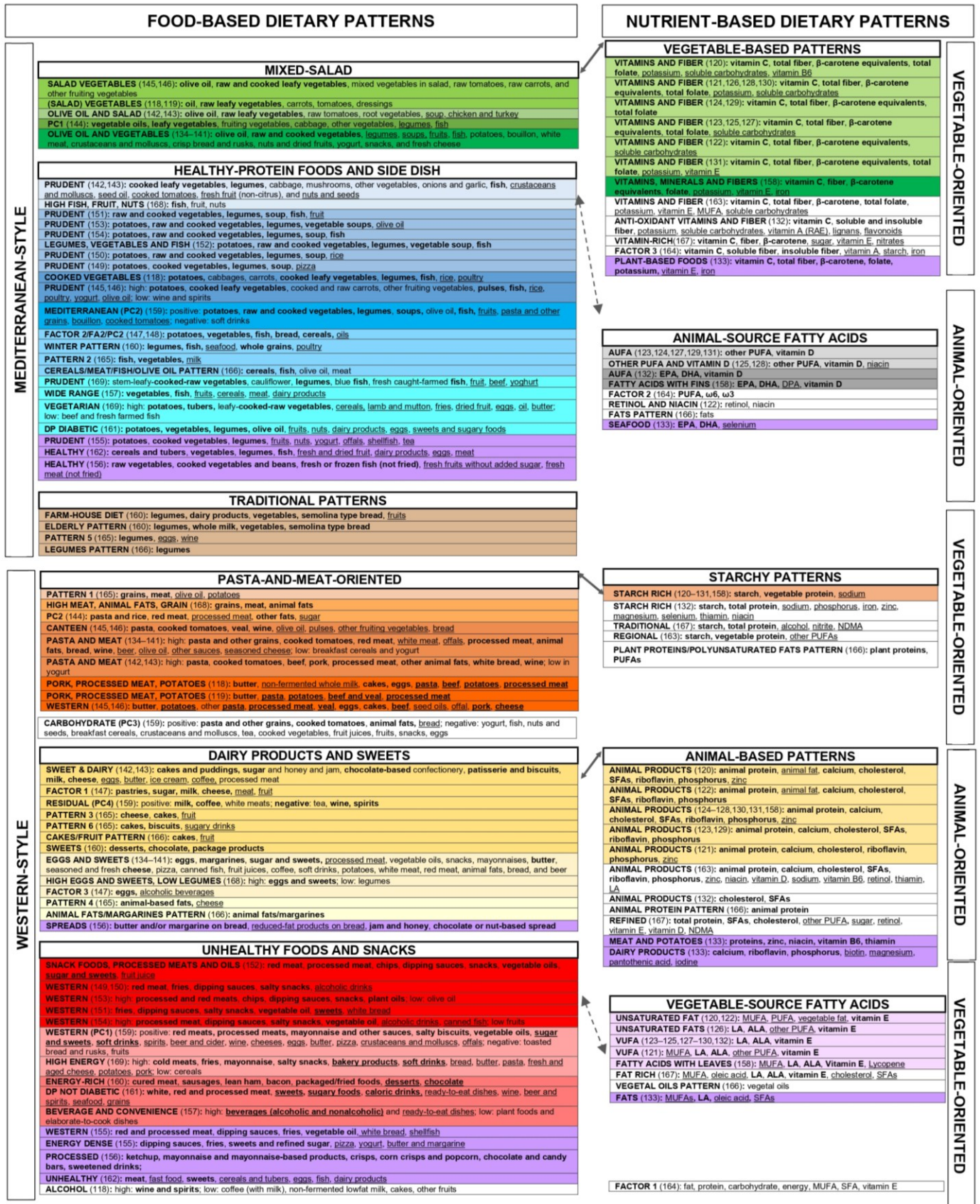
included in the “Traditional” group (in brown) characterized elderly populations from Apulia and Calabria (southern Italy) and shared consumption of legumes (166), integrated with semolina-type bread, dairy products, and other vegetables (160), or eggs and wine (165). The “Western-style” macro-area included the “Pasta-and-Meat oriented,” “Dairy Products and Sweets,” and “Unhealthy Foods and Snacks” groups of patterns. The “Pasta-and-Meat-oriented” group (in orange) included DPs loading high on grains (e.g., pasta and/or rice), (red) meat, and animal fats (118,119,134–146,168). Additional dominant food groups were cooked tomatoes, (white) bread, and wine (134–143,145,146). The “Dairy Products and Sweets” group (in yellow) included DPs loading high on sweets (160,165,166), dairy products (159,165) or spreads (166), and eggs (147), or a combination of them (134–143,147,156,165,168). The “Unhealthy Foods and Snacks” group (in red) included DPs loading high on processed foods, like snacks or salty snacks, dipping sauces, deli meats, desserts or sugary/soft drinks, and ready-to-eat dishes, as identified in adults (including pregnant women), or children/adolescents (149–157,159–162,169). In addition, 5 DPs of this group also included alcoholic beverages (149,150,154,155,157,159,161). Although alcoholic beverages have been previously identified in the “Traditional,” “Pasta-and-Meat-oriented,” and “Unhealthy Foods and Snacks” groups as consumed at mealtime, one article identified an “Alcohol” DP alone, likely because the DIETSCAN project provided DPs based on a parallel analysis of international studies (118).

Nutrient-based DPs

With the exception of a single DP (164) representing the overall diet, we organized the 44 nutrient-based DPs into the “Animal-oriented” and “Vegetable-oriented” macro-areas (**Figure 4.3**). The “Animal-oriented” macro-area included 2 different groups of DPs, “Animal-based Patterns” and “Animal-source Fatty Acids”. Within the “Animal-based Patterns” group (in yellow) the “Animal Products” DP was characterized in most articles by animal protein, calcium, cholesterol, SFAs, riboflavin, phosphorus, and zinc (124–128,130,131,158). Although 3 DPs showed a richer DP composition in adults (“Animal Products” DP (163)) and children (“Dairy products” and “Meat and Potatoes” DPs (133)), another 2 were poorly characterized (132,166). Finally, the “Refined” DP (167) suggested shifting toward more processed foods. Within the “Animal-source Fatty Acids” group (in gray), most DPs from the same research group were labeled “AUFA” and were mainly characterized by vitamin D and other PUFAs (123,124,127,129,131). In another 3 articles, eicosapentaenoic acid, docosahexaenoic acid (132,133), and/or docosapentaenoic acid (158), omega-3 and omega-6 (164) were found as dominant nutrients, due to a different classification of fats. Three additional articles also included niacin among the “AUFA” DP-based dominant nutrients (122,125,128). The “Vegetable-oriented” macro-area included 3 different groups of DPs that we

defined as “Vegetable-based Patterns,” “Vegetable-source Fatty Acids,” and “Starchy Patterns”. Within the “Vegetable-based Patterns” group (in green), most DPs from the same research group were labeled “Vitamins and Fiber” and were all characterized by vitamin C, total fiber, and β -carotene equivalents; additional dominant nutrients were total folate, potassium, vitamin B6, vitamin E, and soluble carbohydrates, alone or in combination (120–131). In other articles, additional dominant nutrients included MUFAs, iron, nitrates, lignans, vitamin A, flavonoids, starch, or a combination of some of them (132,133,158,163,164,167). Within the “Vegetable-source Fatty Acids” group (in lilac), most DPs from the same research group were labeled “VUFA” and were all characterized by linoleic acid, α -linolenic acid, and vitamin E (123–125,127–130,132). A different classification of fats allowed to identify vegetable fat as an additional dominant nutrient in 2 articles from the same research group (120,122). The joint presence of vegetable and animal sources of fatty acids mainly characterized the “Unsaturated Fats” (126), the “VUFA” (121), and the “Fat-rich” (167) DPs in adults, as well as the “Fats” DP in children (133). Within the “Starchy Patterns” group (in orange), the “Starch-rich” DPs from the same research group were all characterized by starch, vegetable protein, and sodium (120–131,158); additional nutrients included various minerals and vitamins (132), as well as PUFAs/other PUFAs (163,166). Similarly, the “Traditional” DP (167) included nitrites, alcohol, and N-nitrosodimethylamine, together with starch and total protein.

Figure 4.3. Qualitative assessment of reproducibility for all the available dietary patterns: dietary patterns identified using principal component analysis or exploratory factor analysis in Italy from 1965 to 2022, in groups based on original text descriptions and loadings (101)¹



¹Dietary patterns with similar profile (based on factor loadings and text description) were grouped and consistently indicated with the same color code. Virtually identical patterns were merged into a single cell, while white rows denote patterns too dissimilar to be grouped. Variants of the same color indicate different subgroups of dietary patterns within the same group, with loadings showing modest but nutritionally relevant differences across color-specific subgroups. Results were separately displayed for food-based (left) and nutrient-based (right) patterns and for adults and children/adolescents (consistently indicated in violet). Food-based and nutrient-based patterns were juxtaposed based on correlation coefficients between nutrient-based dietary patterns and selected food groups, as provided in most of the original articles. Solid and dashed arrows represent stronger and weaker similarities, respectively, between pattern groups. Abbreviations: ALA, α -linolenic acid; AUFA, Animal Unsaturated Fatty Acids; DHA, docosahexaenoic acid; DP, dietary pattern; DPA, docosapentaenoic acid; EPA, eicosapentaenoic acid; FA, factor analysis (factor name from original articles); LA, linoleic acid; MUFA, monounsaturated fatty acid; NDMA, N-nitrosodimethylamine; PC, principal component (analysis) (principal component names from original articles); PUFA, polyunsaturated fatty acid(s); RAE, Retinol Activity Equivalent; SFA, saturated fatty acid(s); VUFA, Vegetable Unsaturated Fatty Acids.

Nutrient-based DPs Food-based and nutrient-based DPs: an overall picture

Based on correlation coefficients reported in the original articles (124–131), we compared nutrient-based and food-based DPs to identify similarities between them (**Figure 4.3**, solid lines).

Specifically, we observed the following overlaps:

1. “Mixed-Salad” and “Vegetable-based patterns”,
2. “Pasta-and-Meat-oriented” and “Starchy patterns”,
3. “Dairy Products and Sweets” and “Animal-based patterns”.

Some nutrient-based patterns were more difficult to match clearly with food-based ones (**Figure 4.3**, dashed lines). For example, the “AUFA” pattern included both healthy (fish) and less healthy (red meat, liver) foods but lacked side dishes. The “VUFA” pattern was associated with seed oils and some animal foods, suggesting possible links to fried food consumption, although other typical “Unhealthy Foods and Snacks” group items (e.g., processed meat, sugary drinks) were not consistently present.

4.4.5 Quantitative assessment of DP reproducibility: congruence coefficients

We calculated 215 CCs across 68 DPs (36.6% of 186) identified as apparently similar in 18 studies (~ 35% of 52) that used the same type of input variables (either nutrient- or food-based) (121,123–131,135–137,139–141,152,153). All CCs indicated at least “fair similarity” ($CC \geq 0.85$), and 80.9% met the threshold for “equivalence” ($CC \geq 0.95$). When grouping DPs based on fair similarity, the 68 DPs collapsed into 13 genuinely distinct DPs. If only equivalent patterns were grouped, 30 DPs collapsed into 6 distinct patterns, suggesting a strong reduction of redundancy (up to 80%).

Separate summary statistics of CCs by research group and DP labels are provided in **Table 4.1** and corresponding “equivalent” DPs are summarized in **Figure 4.4**.

Within the 10 multicenter case–control studies on diet and cancer (121,123–131), the following patterns showed consistent equivalence across studies:

- “Animal Products” and “Vitamins and Fiber”: 100% of CCs ≥ 0.95 .
- “AUFA”: 75% of CCs ≥ 0.95 .
- “Starch-rich” and “VUFA”: 50% of CCs ≥ 0.95 .

In the Moli-sani study (135–137,139–141), which used different input lists across publications, three patterns (i.e., “Pasta and Meat,” “Olive Oil and Vegetables,” and “Eggs and Sweets”) were separately compared:

- With 43 food groups (135–137,139): “Pasta and Meat” showed full equivalence (minimum CCs ≥ 0.95); “Olive Oil and Vegetables” and the “Eggs and Sweets” DPs showed “equivalence” in 75% and $\geq 25\%$ of their CCs, respectively.
- With 46 food groups (140,141): all the three patterns were equivalent.

In two companion articles from a Sicilian research group (152,153), the DPs were similar but did not reach equivalence.

Finally, we assessed correspondence between food-based and nutrient-based patterns using CCs from selected studies. The following pairings showed strong equivalence:

- “Vitamins and Fiber” / “Olive Oil and Vegetables” $\rightarrow 98\%$ of CCs ≥ 0.95 .
- “Animal Products” / “Eggs and Sweets” $\rightarrow 92\%$ of CCs ≥ 0.95 .
- “Pasta and Meat” / “Starch-rich” $\rightarrow 71\%$ of CCs ≥ 0.95 .

Table 4.1. Quantitative assessment of dietary pattern reproducibility for those dietary patterns identified on the same list of input variables: summary statistics on congruence coefficients¹ between loadings of pairs of apparently similar dietary patterns

Multicentric case–control studies on diet and cancer at several sites, articles presenting the same list of 28 nutrients as input variables (121,123–131)						
Nutrient-based dietary pattern	Number involved articles	Minimum	First quartile	Median	Third quartile	Maximum
Animal Products	10	0.95	0.98	0.99	0.99	1.00
Vitamins and Fiber	10	0.95	0.97	0.98	0.99	0.99
Starch-rich	10	0.88	0.93	0.98	0.99	1.00
AUFA ²	7	0.91	0.96	0.97	0.98	0.99
VUFA ³	9	0.88	0.93	0.96	0.97	0.99
Moli-sani study, articles presenting the same list of 43 food groups as input variables (135–137,139)						
Food-based dietary pattern	Number involved articles	Minimum	First quartile	Median	Third quartile	Maximum
Olive Oil and Vegetables	4	0.94	0.95	0.95	0.98	1.00
Pasta and Meat	4	0.97	0.97	0.98	0.99	1.00
Eggs and Sweets	4	0.92	0.93	0.94	0.98	1.00
Moli-sani study, articles presenting the same list of 46 food groups as input variables (140,141)						
Food-based dietary pattern	Number involved articles	Congruence coefficient				
Olive Oil and Vegetables	2	0.98				
Pasta and Meat	2	0.98				
Eggs and Sweets	2	0.97				
Research group from Sicily, articles presenting the same list of 39 food groups as input variables (152,153)						
Food-based dietary pattern	Number involved articles	Congruence coefficient				
Snack foods, processed meats and oils/Western ⁴	2	0.91				
Legumes, vegetables and fish/Prudent	2	0.90				

¹Congruence coefficients range between 0 and 1 (in absolute value), with values between 0.85 and 0.94 indicating fair similarity, and values ≥ 0.95 indicating equivalence of corresponding dietary patterns; ²Three articles (121,126,130) did not contribute to the congruence coefficient-based analyses as the AUFA DP was not identified in those articles; among the DPs here named AUFA, the 2 from (125,128) were originally named Other PUFAs and Vitamin D; ³One article (131) did not contribute to the congruence coefficient-based analyses as the VUFA DP was not identified in that article; among the dietary patterns here named Vegetable Unsaturated Fatty Acids, the one from (126) was originally named Unsaturated Fats; ⁴Minor inconsistencies were detected in the names of the food groups: in the current analysis, vegetable oils in (153) was considered equivalent to plant oil in (152); sugar, sweets in (153) was considered equivalent to sweet and processed sugar in (152). Abbreviations: AUFA, Animal Unsaturated Fatty Acids; VUFA; Vegetable Unsaturated Fatty Acids

Figure 4.4. Quantitative assessment of reproducibility for those dietary patterns identified on the same list of input variables and evaluated to be equivalent (101)

FOOD-BASED DIETARY PATTERNS		NUTRIENT-BASED DIETARY PATTERNS	
MEDITERRANEAN-STYLE	MIXED-SALAD 43 FOOD GROUP INPUT LIST OLIVE OIL AND VEGETABLES (135, 137, 139) OLIVE OIL AND VEGETABLES (136)* *(136) was also equivalent to (137, 139) 46 FOOD GROUP INPUT LIST OLIVE OIL AND VEGETABLES (140,141)	VEGETABLE-BASED PATTERNS VITAMINS AND FIBER (121, 123–131)	VEGETABLE-ORIENTED
	HEALTHY-PROTEIN FOODS AND SIDE DISH PRUDENT (153) LEGUMES, VEGETABLES AND FISH (152)	ANIMAL-SOURCE FATTY ACIDS AUFA (123–125,127–129)* AUFA (131) *(125) was also equivalent to (131)	ANIMAL-ORIENTED
	PASTA-AND-MEAT-ORIENTED 43 FOOD GROUP INPUT LIST OLIVE OIL AND VEGETABLES (135–137, 139) 46 FOOD GROUP INPUT LIST OLIVE OIL AND VEGETABLES (140,141)	STARCHY PATTERNS STARCH RICH (123-130)* STARCH RICH (121) STARCH RICH (131) *(125,128) were also equivalent to (121)	VEGETABLE-ORIENTED
	DAIRY PRODUCTS AND SWEETS 43 FOOD GROUP INPUT LIST EGGS AND SWEETS (135, 137, 139) EGGS AND SWEETS (136)* *(136) was also equivalent to (137, 139) 46 FOOD GROUP INPUT LIST EGGS AND SWEETS (140,141)	ANIMAL-BASED PATTERNS ANIMAL PRODUCTS (121, 123–131)	ANIMAL-ORIENTED
WESTERN-STYLE	UNHEALTHY FOODS AND SNACKS WESTERN (153) SNACK FOODS, PROCESSED MEATS AND OILS (152)	VEGETABLE-SOURCE FATTY ACIDS VUFA (123–125, 127–129) VUFA (121, 126, 130)* *(130) was also equivalent to (123)	VEGETABLE-ORIENTED

Abbreviations: AUFA, animal unsaturated fatty acids; VUFA, vegetable unsaturated fatty acids.

4.4.6 Qualitative and quantitative assessment of DP reproducibility: a comparison

We compared the results of the qualitative synthesis (**Figure 4.3**) with the quantitative assessment based on CCs (**Figure 4.4**) to evaluate the consistency between the two approaches. Key findings included:

1. For the “Animal Products” and “Vitamins and Fiber” DPs, different cells in **Figure 4.3** were indicated to be all “equivalent” based on CCs, so nuances in **Figure 4.3** did not end up into genuinely different DPs in **Figure 4.4**
2. For the “AUFA” DP, most CCs ($\approx 76\%$) indicated equivalence, with all the “fairly similar” evaluations related to the bladder cancer study (131). However, the “AUFA” DP for bladder cancer was not clearly separated in the qualitative map, despite being less reproducible.
3. The “Starch-rich” pattern appeared homogeneous in **Figure 4.3** but showed only moderate equivalence (67%) based on CCs, with all “fairly similar” evaluations given by gastric and bladder cancer studies (121,131).
4. The “VUFA” pattern had 61% of CCs above the equivalence threshold, with all the “fairly similar” evaluations related to the pancreatic and gastric cancer studies (121,126) (which showed “equivalence” between the corresponding “VUFA” DPs); this finding was reflected in part by **Figure 4.3**, where gastric- and pancreatic-cancer “VUFA” DPs weren’t grouped together despite their equivalence.
5. For “Pasta and Meat” and “Olive Oil and Vegetables” patterns, both identified from different food group lists in the Moli-sani study, the qualitative and quantitative assessments aligned well: all CCs showed equivalence, except one in the “Olive Oil and Vegetables” DP on the 43 food groups.
6. The Eggs and Sweets pattern was confirmed as equivalent using the 46-food-group list (140,141), but showed lower consistency (33%) with the 43-food-group list (135–137,139). The discrepancies were due mainly to DPs linked to nutrition knowledge or media exposure, which were nonetheless equivalent based on CCs.
7. Finally, the two DPs identified by the Sicilian research group (152,153) were in different cells in the qualitative synthesis but were only “fairly similar” based on CCs, confirming a moderate level of reproducibility.

4.4.7 Sensitivity analysis: qualitative and quantitative assessments of reproducibility for the most recently identified DPs

Between 2013 and 2022, twenty studies identified PCA/EFA-derived dietary patterns (DPs) from Italian datasets. Of these, 4 studies (20%) examined children, adolescents, or university students (133,155,162,164); 6 (30%) focused on pregnant or breastfeeding women (150,151,158,168,169); 3 (15%) investigated nonpregnant women (~ 40 years old) attending clinical labs in Sicily (152–154), and 4 (20%) included elderly populations (159,161,165,166). Only 3 studies (15%) included middle-aged adults of both sexes, mostly with existing health conditions (131,132,163). In the most recent

synthesis, 68 DPs were identified and consolidated into 65 apparently distinct patterns (a 4.4% net reduction), of which 38 were food-based and 27 nutrient-based.

Compared to all previously identified patterns (**Figure 4.3**), the most notable changes included:

- Complete disappearance of the “Mixed-Salad” group (100% reduction);
- A 78% reduction in “Pasta-and-Meat-oriented” patterns;
- A 50% reduction in “Traditional,” “Vegetable-source fatty acids,” and “Vegetable-based” patterns;
- A reduction of 25% or less for “Starchy,” “Unhealthy Foods and Snacks,” and “Animal-source fatty acids” patterns.

4.4.8 Single DPs and disease outcomes, drivers, or correlates: statistical analysis and main results

With the exception of 6 articles (118,152,161,163,164,169), all DPs identified were examined in relation to health outcomes, DP drivers, or correlates (102). Most studies (45/52) used regression models tailored to the study design, with principal component/factor scores treated either as independent variables (in disease-oriented analyses) or as dependent variables (in driver-oriented analyses). Specifically:

- In longitudinal analyses of cohort studies, Cox proportional hazards models were used to estimate hazard ratios;
- In case-control studies logistic regression was applied to estimate odds ratios;
- In cross-sectional studies or in cross-sectional analyses of cohort studies, linear or logistic regression models were employed.

Driver-oriented studies used linear regression, logistic regression, or ANOVA depending on the type of score and variable (**Figure 4.5**, left side).

All models except two (142,158) included adjustment for confounding variables (median: 7; range: 0–14). All studies, except two that applied automatic covariate selection (165,166), adjusted for age, sex, or center/geographical area, when appropriate. Adjustments for socioeconomic characteristics (notably education, income, and socioeconomic status) were applied in 86% of the relevant analyses. Among lifestyle-related factors, smoking was the most frequently considered (80%), followed by physical activity (30%, mainly from the Moli-sani study), and alcohol intake (27%, mostly from case-control studies). Anthropometric variables, such as BMI or height, were included in 75% of analyses,

while total energy intake was adjusted for in 52%, although many case–control studies excluded it due to the simultaneous inclusion of multiple DPs in the models. Driver-oriented studies often adjusted for a broader range of socioeconomic variables, while disease-oriented studies focused more narrowly on education as the key socioeconomic confounder. In studies on hormone-related cancers, additional adjustments for age at menarche, parity, menopausal status, and oral contraceptive use were applied, aligning with prior evidence (**Figure 4.5**, left side).

In total, 455 combinations of individual DPs and target variables were analyzed. Of these, 121 combinations concerned DP drivers or correlates, and 334 concerned health/disease outcomes. Statistically significant associations were found in 60% (73/121) of the possible combinations of investigated DPs and any of their drivers/correlates. This percentage increased to 67% (65/97) when the analysis was restricted to drivers only. The identified associations with drivers/correlates were limited to cross-sectional analyses of food-based DPs that did not fall under the “Traditional Patterns” group (**Figures 4.5** and **4.6**). Statistically significant associations were found in 42% (139/334) of the possible combinations of identified DPs and any available disease outcomes (food-based DPs: 39%, nutrient-based DPs: 44%). The identified associations with disease outcomes encompassed all groups of reproducible DPs and available study designs (**Figures 4.5**, **4.7**, and **4.8**).

Among the drivers/correlates, socioeconomic variables (i.e., education, school performance, income, socioeconomic status, mass media exposure, nutritional knowledge and culture, household occupation, composition, and geographical location) (**Table 4.2**) accounted for 42% (57/121) of the tested associations, with 54% (31/57) showing statistically significant results. When present, these associations followed expected direction: putatively unhealthy DPs were linked to lower socioeconomic indicators, and protective DPs to higher ones. These findings were consistent across children (155,156), adults (135–138,149,151,157), and the elderly (142) (**Figure 4.6**). Regarding health outcomes, 91% (305/334) of the combinations involved chronic disease incidence, mortality, cardiometabolic risk, pregnancy/lactation outcomes, or elderly-related outcomes (**Table 4.2**). Significant associations were found in 43% (132/305) of these combinations, including 48% for chronic disease incidence, 36% for overall/cause-specific mortality, 51% for cardiovascular and/or cardiometabolic risk factors in adults and children, 39% for pregnancy/breastfeeding-related outcomes, and 30% for elderly-related outcomes. When significant, the associations aligned with expectations: detrimental DPs were associated with higher risk, and protective DPs with lower risk of adverse health outcomes (**Figures 4.7** and **4.8**). Notably, all cardiometabolic findings and most results on pregnancy and elderly health came from cross-sectional studies (**Figure 4.5**).

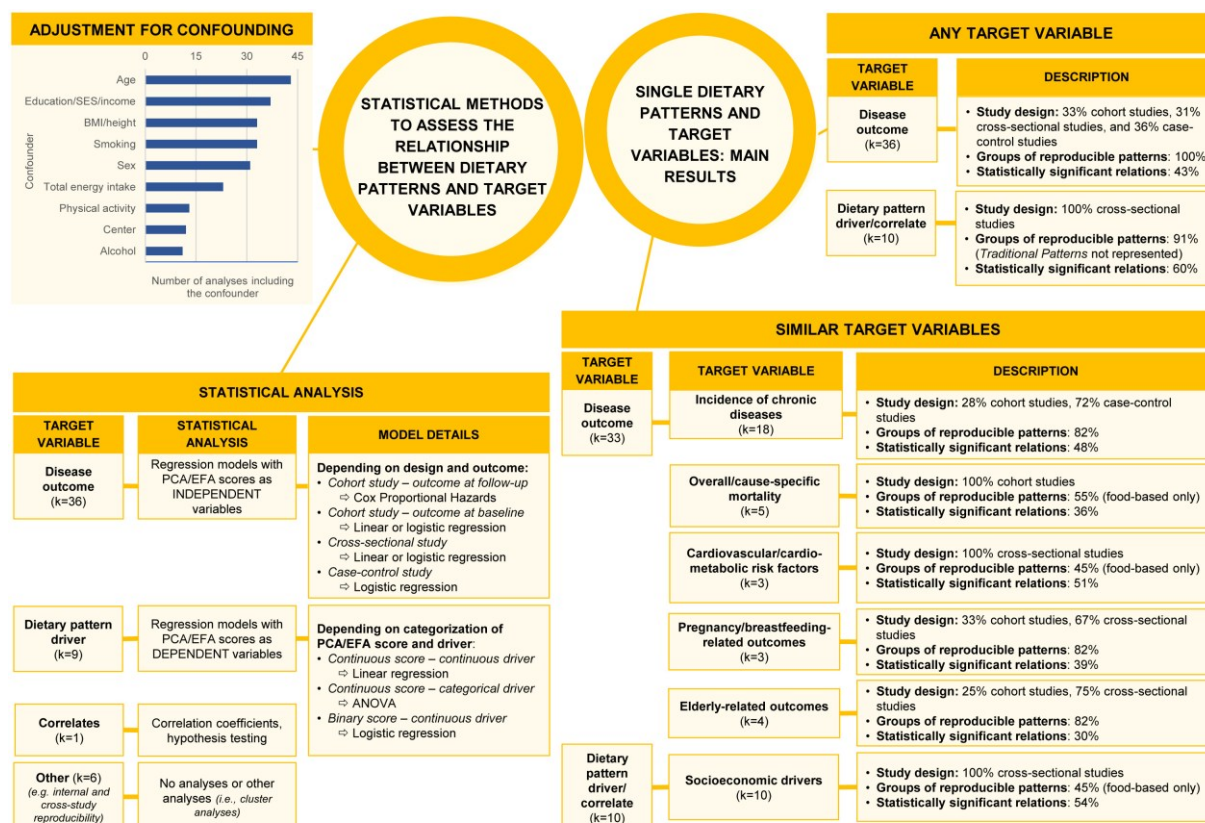
Table 4.2. Available dietary pattern drivers, correlates of interest, and health or disease outcomes, in groups of similar target variables to facilitate evidence synthesis

Target variable type	Groups of similar target variables		Same target variable available in at least two included articles	Same target variable available for the same group of reproducible dietary patterns
Disease outcome	Incidence of chronic diseases	Cancer incidence (several sites)	Cancer incidence	Cancer incidence
		CHD incidence	CHD incidence	
		Type-2 diabetes incidence		
	Cardiovascular and/or metabolic risk factors	Blood glucose	Blood glucose	Blood glucose
		Blood pressure – SBP	Blood pressure – SBP	Blood pressure – SBP
		Blood pressure – DBP	Blood pressure – DBP	Blood pressure – DBP
		Blood pressure – mean		
		Hypertension		
		Inflammatory markers (CRP, leucocytes)	Inflammatory markers (CRP, leucocytes)	
		Tryglicerides		
		Cholesterol – total	Cholesterol – total	Cholesterol – total
		Cholesterol – LDL	Cholesterol – LDL	Cholesterol – LDL
		Cholesterol – HDL		
		BMI		
		Smoking		
		CUORE CVD risk		
	Overall and cause-specific mortality	Overall mortality	Overall mortality	Overall mortality
		CHD mortality	CHD mortality	
		CVD mortality		
		Cancer mortality		
	Elderly-related outcomes	Bone mineral density		
		Fractures		
		Cognitive deterioration		
		Psychological resilience		
		Quality of life (physical/mental health)		
	Pregnancy/breastfeeding-related outcomes	Pre-gestational BMI		
		Gestational age at delivery		
		Maternal biomarkers during pregnancy (concentrations of serum vitamin D and plasma hepcidin)		
		Foremilk composition (SFA, MUFA, AA,		

		omega3, ALA, EPA, DHA, DPA)		
	Childhood-related outcomes	Cognitive performance		
Dietary pattern driver/ correlate	Socio-economic drivers	Education (adults)	Education	Education
		School performance in adolescents (correlate)		
		Socio-economic status		
		Income		
		Mass media exposure		
		Nutritional knowledge		
		Food label reading		
		Education (household)	Education	Education
		Occupation (household)		
		Locality (household)		
		Composition (household)		
	Pregnancy-related drivers	Pre-gestational BMI		
		Education (pregnancy)	Education	Education
		Age		
		Current smoking status		
		Covid-19 pandemic		
	Lifestyle drivers	Physical activity level		
		Dietary modifications		
		Recruitment center		
	Anthropometric drivers	BMI		
		Waist-hip ratio		
	Cardiovascular and/or cardio metabolic drivers	Hyperlipidemia		
		Hypertension		

Abbreviations: AA, arachidonic acid; ALA, α -linolenic acid; BMI, body mass index; CHD, coronary heart disease; COVID-19, Coronavirus disease 2019; CRP, C-reactive protein; CVD, cardiovascular disease; DBP, diastolic blood pressure; DHA, docosahexaenoic acid; DPA, docosapentaenoic acid; HDL, high-density lipoprotein; LDL, low-density lipoprotein; MUFA, monounsaturated fatty acid(s); SBP, systolic blood pressure; SFA, saturated fatty acid(s).

Figure 4.5. Associations between identified dietary patterns and selected disease outcomes, dietary pattern drivers, and correlates of interest: summary of the second set of findings from the systematic review as presented in this paper. The statistical analysis methods, adjustment for confounding factors, and main results on the associations between single dietary patterns and available target variables were summarized (102)



Abbreviations: ANOVA, analysis of variance; EFA, exploratory factor analysis; PCA, principal component analysis; SES, socioeconomic status.

Figure 4.6. Identified food-based dietary patterns grouped according to textual description and original factor loadings, and related associations with drivers/correlates of interest (102). Separate panels represented the following target populations: (A) adults and (B) entire household, pregnant women, and children/adolescents

A		ADULTS																
							Pala, 2006 (142) (DRIVERS)											
							Physical activity level											
							Waist-hip ratio											
							BMI											
							Hyperlipidemia											
							Hypertension											
							Recent modification of habitual diet											
							High school education											
							Recruitment center											
							Food label reading											
							Nutritional knowledge in categories											
							Mass media exposure in categories											
							Income in categories											
MIXED-SALAD		OLIVE OIL AND SALAD (142) ¹					Ms≠; Fs≠	Ms-; Fs-	Ms≠,↑; Fs≠,↑	Ms-; Fs-	Ms-; Fs≠,↑	Ms≠,↑; Fs-	Ms≠,↓; Fs≠,↓	Ms-; Fs≠,↑				
		OLIVE OIL AND VEGETABLES (135–138)																
HEALTHY-PROTEIN FOODS AND SIDE DISH		PRUDENT (142)																
PASTA-AND-MEAT- ORIENTED		PASTA AND MEAT (135–138); PASTA AND MEAT (142)					=	≠,↓*	-	≠,↓	Ms≠; Fs≠	Ms≠,↓; Fs≠,↓	Ms≠,↓; Fs≠,↓	Ms-; Fs-	Ms≠,↓; Fs≠,↓	Ms≠,↑; Fs≠,↑	Ms≠,↑; Fs≠,↑	Ms≠,↑; Fs-
DAIRY PRODUCTS AND SWEETS		SWEET & DAIRY (142)									Ms≠; Fs≠	Ms-; Fs≠,↑	Ms≠,↓; Fs≠,↓	Ms-; Fs-	Ms≠,↓; Fs≠,↓	Ms -; Fs ≠,↓	Ms-; Fs≠,↓	Ms-; Fs≠,↑
		EGGS AND SWEETS (135–138)					≠,↓*	=	-	≠,↓								

B		ENTIRE HOUSEHOLD					PREGNANT WOMEN					CHILDREN/ADOLESCENTS																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																											
		Naska, 2006 (157) (DRIVERS)										Magnano San Lio, 2022 (151) ² (DRIVER)					Maugeri, 2019 (149) (DRIVERS)					COVID-19 pandemic					Pre-gestational BMI					Current smoking status					Age					Medium-low education level					Education (reference: elementary)					Occupation (reference: manual)					Locality (reference: rural)					Household composition (reference: single adult)																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																									
HEALTHY- PROTEIN FOODS AND SIDE DISH		PRUDENT (151); PRUDENT (149) ¹										↓																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																											

¹Similar dietary patterns (based on text descriptions and factor loadings) were displayed in the same rows and shared the same color. If patterns in a row have different names, all names with their references are listed and separated by semicolons; if the name is identical, only the references are separated by semicolons. Color variants across rows denote subgroups with modest but nutritionally relevant differences; white rows indicate patterns too dissimilar to assign to any group. Each cell reports significant results from the overall analysis for the main dietary pattern driver/correlate. Symbol key: in logistic/Cox models: “↑” = significant risk factor, “↓” = significant protective factor, and “-” = nonsignificant association with risk; in hypothesis testing/analysis of variance models: “≠” = significant difference in means of the dietary pattern driver/correlate of interest across quantile-based categories of principal component/factor score and “=” nonsignificant difference, and “≠,↑”, “≠,↓”, and “≠,?” indicated an increasing, decreasing, or an unclear trend across quantile-based categories. ²In Magnano San Lio et al. 2022 (151), to make results consistent across articles, results were expressed in terms of COVID-19 pandemic (yes compared with no). Abbreviations: BMI, Body Mass Index; Fs, females; Ms, males.

Figure 4.7. Identified food-based dietary patterns grouped according to textual description and original factor loadings, and related associations with disease outcomes (102). Separate panels represented the following outcomes: (A) incidence of chronic diseases and overall/cause-specific mortality; (B) cardiovascular/ cardiometabolic risk factors and maternal biomarkers, and (C) mental and physical health

A

		ADULTS/ELDERLY																
		Männistö, 2005 (119)	Sieri, 2004 (145)		Sant, 2007 (146)		Barchitta, 2018 (153)	Barchitta, 2019 (154) ²	Jannasch, 2019 (144)	Menotti, 2018 (148)					Menotti, 2012 (147)	Zupo, 2020 (160)	Masala, 2007 (143)	Bonaccio, 2016 (140)
		Breast cancer incidence	Breast cancer incidence	Breast cancer incidence, HER2+	Breast cancer incidence, HER2-	High-grade cervical cancer	High-risk HPV infection	Chromosomal instability	Type-2 diabetes incidence	CHD mortality, 40ys	CHD mortality, 40ys	CHD incidence, 20ys	Cancer mortality, 40ys	CVD mortality, 40ys	Overall mortality, 40ys	Overall mortality	Overall mortality	Overall mortality in diabetic subjects
MIXED-SALAD	SALAD VEGETABLES (145,146); (SALAD) VEGETABLES (119) ¹	-	↓	↓	-													
	OLIVE OIL AND SALAD (143)																↓	
	PC1 (144)								-									
	OLIVE OIL AND VEGETABLES (140)																	-
HEALTHY-PROTEIN FOODS AND SIDE DISH	PRUDENT (143)																-	
	PRUDENT (153); (154)					-	-	↓										
	PRUDENT (145,146)		-	-	-													
	FACTOR 2/FA2/PC2 (147,148); WINTER PATTERN (160)									↓	↓	↓	↓	↓	↓	-		
TRADITIONAL PATTERNS	FARM-HOUSE DIET (160); ELDERLY PATTERN (160)															↑; -		
PASTA-AND-MEAT-ORIENTED	PC2 (144)								-									
	CANTEEN (145,146); PASTA AND MEAT (143); (140)		-	-	-												-	-
	PORK, PROCESSED MEAT, POTATOES (119); WESTERN (145,146)	-	-	-	-													
DAIRY PRODUCTS AND SWEETS	SWEET & DAIRY (143); FACTOR 1 (147); SWEETS (160)										-	-	-	-	-	-	-	
	EGGS AND SWEETS (140); FACTOR 3 (147)										-	-	↓	-	↓			-
UNHEALTHY FOODS AND SNACKS	WESTERN (153); (154)					-	-	-										
	ENERGY-RICH (160)															-		

B

[illegible]

C

		ADULTS/ELDERLY							
		Bonaccio, 2013 (139)	Bonaccio, 2018 (141)			Colica, 2017 (165)			Mazza, 2017 (166) ³
		SF-36 score, mental health component	SF-36 score, physical health component	Psychological resilience (25-item Connor- Davidson Psychological Resilience Scale)	Whole body bone mineral density	Past fractures (≥1 vs. no fractures)	Past fractures (≥2 vs. 1 fracture)	Cognitive deterioration (ADAS-Cog, 12 months follow-up)	Cognitive deterioration (MMSE, 12 months follow-up)
MIXED-SALAD	OLIVE OIL AND VEGETABLES (139,141) ¹	↑	↑	↑					
HEALTHY-PROTEIN FOODS AND SIDE DISH	PATTERN 2 (165); CEREALS/MEAT/FISH/OLIVE OIL PATTERN (166)				↑	-	-	-	-
TRADITIONAL PATTERNS	PATTERN 5 (165); LEGUMES PATTERN (166)				-	↓	-	↓	↓
PASTA-AND-MEAT- ORIENTED	PATTERN 1 (165) PASTA AND MEAT (139,141)	-	↓	-	↑	-	↓		
DAIRY PRODUCTS AND SWEETS	PATTERN 3 (165); PATTERN 6 (165); CAKES/FRUIT PATTERN (166)				-; -	-; -	-; -	-	-
	EGGS AND SWEETS (139,141)	↓	↑	-					
	PATTERN 4 (165); ANIMAL FATS/MARGARINES PATTERN (166)				-	-	-	-	-

¹Similar dietary patterns (based on text descriptions and factor loadings) were displayed in the same rows and shared the same color. If patterns in a row have different names, all names with their references are listed and separated by semicolons; if the name is identical, only the references are separated by semicolons. Color variants across rows denote subgroups with modest but nutritionally relevant differences; white rows indicate patterns too dissimilar to assign to any group. The background color of column headings indicates the study design and type of analysis: dark gray for cohort studies, light gray for case-control studies, and white for cross-sectional studies/cross-sectional analyses of cohort studies. Each cell reports significant results from the overall analysis for the main outcome. Symbol key: in logistic/Cox models: “↑” = significant risk factor, “↓” = significant protective factor, and “-” = nonsignificant association with risk. ²In Barchitta et al. 2019 (154), average LINE-1 CpG methylation (i.e., an inverse marker of chromosomal instability and aberrant genome function) was assessed; for consistency across articles, results are reported here in terms of chromosomal instability. ³In Mazza et al. 2017 (166), higher ADAS-Cog indicates greater cognitive impairment, whereas higher MMSE indicates better performance. For cross-article consistency, “↓” denotes a protective effect against cognitive deterioration. Abbreviations: ADAS-Cog, Alzheimer’s Disease Assessment Scale–Cognitive subscale; CHD, coronary heart disease; CVD, cardiovascular disease; DP, dietary pattern; FA, factor analysis; Fs, females; HER2, human epidermal growth factor receptor 2; HPV, human papilloma virus; MMSE, Mini-Mental State Examination; Ms, males; PC, principal component analysis; PWV, pulse wave velocity; SF-36, Short Form Healthy Survey 36.

Figure 4.8. Identified nutrient-based dietary patterns grouped according to textual description and original factor loadings, and related associations with disease outcomes (102). Separate panels represented the following combinations of target populations: (A) adults/elderly; (B) breastfeeding women and children

		ADULTS/ELDERLY													
		Palii, 2001 (167): gastric cancer incidence	Edefonti, 2008 (120): breast/ovarian cancer incidence	Bertuccio, 2009 (121): gastric cancer incidence	Edefonti, 2010 (122): oral cavity cancer incidence	Bravi, 2010 (123): colorectal cancer incidence	Edefonti, 2010 (124): laryngeal cancer incidence	Bravi, 2012 (125): esophageal cancer incidence	Bosetti, 2013 (126): pancreatic cancer incidence	Rosato, 2014 (127): prostatic cancer incidence	Bravi, 2015 (128): endometrial cancer incidence	Edefonti, 2015 (129): nasopharyngeal cancer incidence	Daimatello, 2020 (130): renal cancer incidence	Edefonti, 2020 (131): bladder cancer incidence	Mazza, 2017 (166) ² : – ADAS-Cog – MMSE
ANIMAL-BASED PATTERNS	ANIMAL PRODUCTS (120); (121); (122); (123,129); (124–128,130,131) ¹		breast↓; ovarian–	↑	↑	colon–; rectum–	↑	↑	↑	↑	↑	↑	–	–	
	ANIMAL PRODUCTS (132)														
	ANIMAL PROTEIN PATTERN (166)														
	REFINED (167)	–													
ANIMAL-SOURCE FATTY ACIDS	AUFA (123,124,127,129,131); OTHER PUFA AND VITAMIN D (125,128)					colon↓; rectum–	↑	↓		↑	↑	↑	–		
	AUFA (132)													↓	–
	RETINOL AND NIACIN (122)				–										
	FATS PATTERN (166)														–
VEGETABLE-BASED PATTERNS	VITAMINS AND FIBER (120); (121,126,128,130); (122); (123,125,127); (124,129); (131)		breast–; ovarian↓	↓	↓	colon–; rectum↓	↓	↓	↓	–	–	–	–	↓	
	ANTIOXIDANT VITAMINS AND FIBER (132)														–
	VITAMIN-RICH (167)	↓													
VEGETABLE-SOURCE FATTY ACIDS	UNSATURATED FAT (120,122); UNSATURATED FATS (126); VUFA (121); (123–125,127–130,132); FAT RICH (167)		breast↓; ovarian–	–	↓	colon↓; rectum–	–	–	–	–	–	↑	↓		↓
	VEGETAL OILS PATTERN (166)	–													–
STARCHY PATTERNS	STARCH-RICH (120–131)		breast↑; ovarian↑	↑	↓	colon↑; rectum↑	–	–	↑	↑	–	↑	↑	–	
	STARCH-RICH (132)														–
	TRADITIONAL (167)	↑													–
	PLANT PROTEINS/ POLY-UNSATURATED FATS PATTERN (166)														↓

B

B	BREASTFEEDING WOMEN													CHILDREN		
	Bravi, 2021 (158): foremilk composition													Mainoni, 2022 (133): cognitive performance		
		LAV DHA	AA/ DHA	AA/ EPA	omega6/ omega3	DPA	DHA	EPA	ALA	omega3	AA	MUFA	SFA	PRI	VCI	PSI
ANIMAL-BASED PATTERNS	ANIMAL PRODUCTS (158) ¹	=	≠, ?*	≠, ?*	=	=	=	=	≠, ?*	≠, ?*	≠, ↑*	=	=	- ; - ; - ;	↓ ; ↓ ;	↓ ;
	MEAT AND POTATOES (133); DAIRY PRODUCTS (133)															
ANIMAL-SOURCE FATTY ACIDS	FATTY ACIDS WITH FINS (158)	≠, ↓*	≠, ↓*	≠, ↓*	≠, ↓*	≠, ↑*	≠, ↑*	≠, ↑*	=	≠, ↑*	=	=	=	-	↑	-
	SEAFOOD (133)															
VEGETABLE-BASED PATTERNS	VITAMINS, MINERALS AND FIBERS (158)	≠, ↓*	≠, ↓*	≠, ↓*	≠, ↓*	≠, ↑*	≠, ↑*	≠, ↑*	=	≠, ↑*	=	=	=	-	-	-
	PLANT-BASED FOODS (133)															
VEGETABLE-SOURCE FATTY ACIDS	FATTY ACIDS WITH LEAVES (158)	=	=	=	=	=	=	=	≠, ↑*	=	=	≠, ↑*	≠, ↓*			
	FATS (133)															
STARCHY PATTERNS	STARCH-RICH (158)	=	=	=	=	=	=	=	=	=	=	=	=			

¹Similar dietary patterns (based on text descriptions and factor loadings) were displayed in the same rows and shared the same color. If patterns in a row have different names, all names with their references are listed and separated by semicolons; if the name is identical, only the references are separated by semicolons. Color variants across rows denote subgroups with modest but nutritionally relevant differences; white rows indicate patterns too dissimilar to assign to any group. The background color of column headings indicates the study design and type of analysis: dark gray for cohort studies, light gray for case-control studies, and white for cross-sectional studies/cross-sectional analyses of cohort studies. Each cell reports significant results from the overall analysis for the main outcome. Symbol key: in logistic/Cox models: “↑” = significant risk factor, “↓” = significant protective factor, and “–” = nonsignificant association with risk; in hypothesis testing/analysis of variance models: “≠” = significant difference in means of the dietary pattern driver/correlate of interest across quantile-based categories of principal component/factor score and “=” nonsignificant difference, and “≠,↑”, “≠,↓”, and “≠,?” indicated an increasing, decreasing, or an unclear trend across quantile-based categories. ²In Mazza et al. 2017 (166), higher ADAS-Cog indicates greater cognitive impairment, whereas higher MMSE indicates better performance. For cross-article consistency, “↓” denotes a protective effect against cognitive deterioration. Abbreviations: AA, arachidonic acid; ADAS-cog, Alzheimer’s Disease Assessment Scale–Cognitive subscale; ALA, α-linolenic acid; AUFA, animal unsaturated fatty acids; EPA, eicosapentaenoic acid; DHA, docosahexaenoic acid; DP, dietary pattern; DPA, docosapentaenoic acid; DAS28, Disease Activity Score on 28 joints; DPA, docosapentaenoic acid; LA, linoleic acid; MMSE, Mini-Mental State Examination; MUFA, monounsaturated fatty acid; PRI, perceptual reasoning index; PSI, processing speed index; RA, rheumatoid arthritis; SDAI, Simplified Disease Activity Index; SFA, saturated fatty acid(s); VCI, verbal comprehension index; VUFA, Vegetable Unsaturated Fatty Acids.

4.4.9 Reproducible DPs in relation to the same disease outcomes/DP drivers/correlates of interest: main results

Figure 4.9 summarizes the combinations of reproducible dietary DPs and target variables for which over 50% of the associations were either statistically significant and directionally consistent, or nonsignificant. The results by DP group are as follows:

1. **Mixed-Salad** group was positively associated with socioeconomic characteristics in 67% of the combinations and inversely related to cardiovascular and cardiometabolic risk factors in 89% of cases among adults. It also showed protective associations with psychological resilience and quality of life in the elderly in 100% of the combinations.
2. **Healthy-Protein Foods and Side Dish** group was linked to a reduced risk of overall or cause-specific mortality in 71% of the combinations and to lower cardiometabolic risk factors in 54% of the comparisons involving both adults and children.
3. **Traditional Patterns** group was associated with protective effects on elderly-related outcomes such as cognitive function and fracture risk in 60% of the combinations.
4. **Pasta-and-Meat-oriented** group was associated with lower socioeconomic status in 67% of comparisons (adults only), with higher cardiometabolic risk in 78% (also adults), and with poorer pregnancy or breastfeeding outcomes in 100% of cases.
5. **Dairy Products and Sweets** group was mostly unrelated to health or disease outcomes, with 78% of the associations showing no significant results across a range of outcomes including chronic disease incidence, mortality, cardiometabolic risk, pregnancy and elderly outcomes. It was also mostly unrelated to socioeconomic factors.
6. **Unhealthy Foods and Snacks** group was associated with lower socioeconomic characteristics in 59% of comparisons (in adults, children/adolescents, and entire households) and with increased cardiometabolic risk in adults in 54% of comparisons.
7. **Animal-based Patterns** group was linked to a higher risk of chronic diseases such as cancer in 53% of the combinations, all in adult populations.
8. **Animal-source Fatty Acids** group was positively associated with improved pregnancy and breastfeeding outcomes (e.g., foremilk composition) in 67% of the combinations.
9. **Vegetable-based Patterns** group showed protective effects against chronic diseases like cancer in 60% of the combinations and were associated with improved pregnancy and breastfeeding outcomes in 67% of cases.

10. ***Vegetable-source Fatty Acids*** group was largely unrelated to disease outcomes, with 69% of the associations nonsignificant for both cancer and pregnancy/breastfeeding outcomes, although a few protective effects were noted.
11. ***Starchy Patterns*** group was associated with an increased risk of chronic diseases, especially cancer, in 67% of the comparisons.

In total, statistically significant associations were found in 46% (157/342) of the combinations of groups of reproducible DPs and similar target variables.

Figure 4.9. Summary of associations between reproducible dietary patterns and similar disease outcomes, DP drivers, or correlates (102)¹

GROUPS OF REPRODUCIBLE DIETARY PATTERNS		SIMILAR TARGET VARIABLES WHERE >50% STATISTICALLY SIGNIFICANT FINDINGS IN THE SAME DIRECTION OR NON-SIGNIFICANT FINDINGS	
NUMBER OF COMBINATIONS WITH SIMILAR TARGET VARIABLES FOR EACH GROUP OF REPRODUCIBLE DIETARY PATTERNS	25 Mixed-Salad	Incidence of chronic diseases (n=5) – 60%; ↓40% Cardiovascular/cardiometabolic risk factors (n=9) ↓89%; – 11% Elderly-related outcomes (n=3) ↑100% Socio-economic characteristics (n=6) ↑67%; – 33%	5
	50 Healthy-Protein Foods and Side Dish	Incidence of chronic diseases (n=5) – 80%; ↓20% Overall/cause-specific mortality (n=7) ↓71%; – 29% Cardiovascular/cardiometabolic risk factors (n=13) ↓54%; – 46% Pregnancy/breastfeeding-related outcomes (n=4) – 75%; ↓25% Elderly-related outcomes (n=5) – 80%; ↑20% Socio-economic characteristics (n=16) – 56%; ↑38%; ↓7%	6
	7 Traditional Patterns	Elderly-related outcomes (n=5) ↑60%; – 40%	2
	34 Pasta-and-Meat-oriented	Incidence of chronic diseases (n=8) – 100% Overall/cause-specific mortality (n=2) – 100% Cardiovascular/cardiometabolic risk factors (n=9) ↑78%; – 22% Pregnancy/breastfeeding-related outcomes (n=3) ↓100% Socio-economic characteristics (n=6) ↓67%; – 33%	6
	60 Dairy Products and Sweets	Incidence of chronic diseases (n=2) – 100% Overall/cause-specific mortality (n=11) – 82%; ↓18% Cardiovascular/cardiometabolic risk factors (n=21) – 71%; ↑24%; ↓5% Pregnancy/breastfeeding-related outcomes (n=3) – 100% Elderly-related outcomes (n=16) – 88%; ↑6%; ↓6% Socio-economic characteristics (n=7) – 57%; ↓29%; ↑14%	6
	38 Unhealthy Foods and Snacks	Cardiovascular/cardiometabolic risk factors (n=13) ↑54%; – 46% Socio-economic characteristics (n=22) ↓59%; – 41%	5
	27 Animal-based Patterns	Incidence of chronic diseases (n=15) ↑53%; – 40%; ↓7% Pregnancy/breastfeeding-related outcomes (n=12) – 58%; ≠ 42%	2
	21 Animal-source Fatty Acids	Pregnancy/breastfeeding-related outcomes (n=12) ↑67%; – 33%	2
	27 Vegetable-based Patterns	Incidence of chronic diseases (n=15) ↓60%; – 40% Pregnancy/breastfeeding-related outcomes (n=12) ↑67%; – 33%	2
	26 Vegetable-source Fatty Acids	Incidence of chronic diseases (n=14) – 64%; ↓29%; ↑7% Pregnancy/breastfeeding-related outcomes (n=12) – 75%; ↑25%	2
	27 Starchy Patterns	Incidence of chronic diseases (n=15) ↑67%; – 27%; ↓7% Pregnancy/breastfeeding-related outcomes (n=12) – 100%	2
		NUMBER OF AVAILABLE SIMILAR TARGET VARIABLES FOR EACH GROUP OF REPRODUCIBLE DIETARY PATTERNS	

¹For each DP group, the number of available combinations (left), similar target variables with >50% consistent associations (center), and the total number of similar variables assessed (right) are reported. Dashed lines indicate groups with >50% nonsignificant findings. Arrows indicate the direction of statistically significant associations (↑ positive, ↓ inverse, ≠ difference, – nonsignificant). Some totals do not match due to residual combinations being exactly 50% or targeting unique variables

4.4.10 Reproducible DPs in relation to the same disease outcomes/DP drivers/correlates of interest: main results

Reproducible DPs were identified in relation to several disease outcomes and DP drivers or correlates, including education, cancer incidence, overall mortality, systolic and diastolic blood pressure, total and LDL cholesterol, and glucose (**Table 4.2**).

Among DP drivers, education showed inconsistent associations. Specifically, it was significantly associated with two DPs from the “*Unhealthy Foods and Snacks*” group—one suggesting increased risk and one indicating a protective association—as well as with three DPs from the “*Healthy-Protein Foods and Side Dish*” group, where one was associated with higher risk, one with lower risk, and one showed no significant association (**Figure 4.6B**). As for disease outcomes, cancer incidence emerged as the most frequently investigated endpoint. Nutrient-based DPs from the “*Animal-based Patterns*” group were significantly associated with increased cancer risk in 53% of the available comparisons (**Figure 4.8A**), although no corresponding evidence was available from the food-based DPs in the “*Dairy Products and Sweets*” group (**Figure 4.7A**). Similarly, 67% of the nutrient-based DPs in the “*Starchy Patterns*” group were positively associated with cancer incidence (**Figure 4.8A**), in contrast with the “*Pasta-and-Meat-oriented*” food-based DPs, which showed no significant associations across all comparisons (**Figure 4.7A**). Conversely, increasing scores of 60% of the nutrient-based DPs in the “*Vegetable-based Patterns*” group were linked to a decreased risk of cancer (**Figure 4.8A**), although the corresponding food-based “*Mixed-Salad*” DPs did not yield consistent results (**Figure 4.7A**). Additional analyses of reproducible DPs from other groups provided mixed or null findings. For cancer incidence, nutrient-based DPs from the “*Animal-source Fatty Acids*” group yielded inconsistent results (4 at-risk, 2 protective, 3 nonsignificant out of 9), while Vegetable-source Fatty Acids were mostly nonsignificant (64%), with only a few protective (4) or at-risk (1) associations (**Figure 4.8A**). No significant associations were reported for food-based DPs in the “*Healthy-Protein Foods and Side Dish*” group (4/4 nonsignificant) (**Figure 4.7A**) (102).

The risk of overall mortality was significantly reduced in 50% of the food-based DPs from the “*Mixed-Salad*” group, in 33% of those from the “*Healthy-Protein Foods and Side Dish*” group, and in 20% of those from the “*Dairy Products and Sweets*” group. The remaining DPs in these groups showed no significant associations with mortality risk. All DPs from the “*Pasta-and-Meat-oriented*” group were consistently unrelated to overall mortality (**Figure 4.7A**).

Regarding cardiovascular and cardiometabolic risk factors, all reproducible food-based DPs from the “*Healthy-Protein Foods and Side Dish*” group were significantly associated with lower glucose levels (blood glucose in adults and capillary glucose in children). In contrast, results for the “*Unhealthy Foods and Snacks*” group were inconsistent: one DP showed a significant detrimental association in adults, while the other was not significantly associated with glucose in children. For the “*Dairy Products and Sweets*” group, all associations with systolic and diastolic blood pressure, total and LDL cholesterol, and glucose were consistently nonsignificant (**Figure 4.7B**).

Notably, in 84% of the combinations examined (38 out of 45), more than half of the results showed nonsignificant associations with the same disease outcomes. This pattern was particularly evident for cancer incidence, overall mortality, and cardiometabolic risk factors, where most DPs yielded null findings (102).

4.4.11 Reproducible DPs in relation to the same disease outcomes/DP drivers/correlates of interest: evaluation of causal criteria and rules of inference

Following the assessment of associations between reproducible DPs and various target variables, we explored whether the available evidence allowed for quantitative synthesis through meta-analysis. Across 15 articles, 53 associations involving 9 groups of DPs and 9 target variables (disease outcomes or DP drivers) were identified as potentially suitable. On average, there were 2 DPs per target variable, with consistent study designs within each comparison (e.g., cohort studies were available for breast cancer incidence and overall mortality) (**Table 4.2**).

Most studies accounted for relevant confounding variables, typically including age, sex, and total energy intake. In 87% of cases, additional confounders such as education, BMI, or socioeconomic indicators were also considered. However, control for confounding varied across studies, especially in comparisons involving education as a DP driver, which were based on cross-sectional studies with heterogeneous adjustment strategies and effect measures.

Although some outcome–DP combinations, such as breast cancer incidence, had appropriate designs and confounding control, the lack of independent data prevented formal meta-analyses. For gastric cancer incidence, four comparisons were available from two case–control studies using similar adjustments, which supported meaningful comparisons. Comparable limitations

applied to associations with glucose, blood pressure, and cholesterol, where three cross-sectional studies provided estimates with variable adjustment levels.

Among available results, the “*Healthy-Protein Foods and Side Dish*” group showed consistent inverse associations with glucose, though based on different confounding strategies. As for overall mortality, associations were investigated for four groups of reproducible DPs across multiple populations (e.g., elderly, diabetics, general population), but due to population differences and small numbers of comparisons, meta-analysis was not feasible. Nevertheless, the criterion of “strength of association” was met for the “*Vegetable-based Patterns*” group, which consistently showed odds ratios for gastric cancer close to 0.5 with confidence intervals excluding 1. The “*Starchy Patterns*” group also showed significant associations with gastric cancer risk, with odds ratios above 1.5 and evidence of a dose–response relationship.

In summary, while formal meta-analyses were not possible due to heterogeneity in study design, population, and confounding control, some reproducible DPs (e.g., “*Vegetable-based*” and “*Starchy Patterns*”) met key criteria for causal inference, particularly in relation to cancer risk.

4.4.12 Overview of results from the systematic review on reproducibility of DPs in Italy and their consistent associations with disease outcomes, DP drivers, or correlates

These systematic reviews (101,102) examined PCA/EFA-derived DPs identified in Italy, focusing on two main aspects: their reproducibility across studies and the consistency of their associations with disease outcomes, drivers, and correlates.

Regarding cross-study reproducibility, the following observations were made (101):

- 1) population, study design, and dietary assessment tool: observational studies including comparable populations of adults, pregnant women, and the elderly were utilized, with 48% of cross-sectional analyses; reproducible and valid FFQs with a 1- or 2-y reference period were commonly employed;
- 2) DP identification method: similarities were found in the preprocessing of input variables, rotation techniques, and quantitative labeling of DPs, but the lists of input variables varied in terms of number of variables and included variables (nutrients or food groups);
- 3) DP cross-study reproducibility: the 186 identified DPs representing the Italian diet over the last 30 y were condensed into 11 groups of reproducible DPs targeting the following combinations: pasta/meat, healthy-protein foods/side dish, fruits/vegetables, cheese/deli

meats, processed/ready-to-eat foods, animal sources of fats, vegetable sources of fats, and legumes/bread/dairy products.

Regarding the consistency of associations (102):

- 1) statistical methods and adjustment for confounding: regression models were appropriately applied in 98% of the included articles to address the original research questions within the specific study designs; adjustment for confounding was proposed in 96% of articles applying regression models, by including a median number of 7 confounders;
- 2) consistency of associations: when similar target variables were considered, 9 groups of reproducible DPs showed >50% of statistically significant associations going in the same direction. Exceptions were groups targeting dairies/sweets and vegetable sources of fats. However, 54% of nonsignificant findings were found across combinations of reproducible DPs and similar target variables. Together with population comparability issues, this prevented us from reliably performing meta-analyses and assessing related heterogeneity and publication bias.

4.5 DISCUSSION

These systematic reviews (101,102) provide the first comprehensive synthesis of methodological approaches and reproducibility of PCA/EFA-derived DPs across Italian studies. Based on 52 articles published between 2001 and 2022, the first review (101) captures dietary data spanning from 1965 to 2022, with most DPs derived using EFA applied to food groups from FFQ-based data. A dual assessment strategy was adopted: a qualitative evaluation of textual descriptions and factor loadings, and a quantitative analysis using 215 CCs among 68 DPs from 18 studies based on the same input variables.

The findings highlight a moderate-to-high level of reproducibility among DPs with similar names or compositions. For example, ~81% of CCs indicated "equivalent" patterns, particularly for DPs such as *"Vitamins and Fiber"* / *"Olive Oil and Vegetables"* (98% equivalent) and *"Animal Products"* / *"Eggs and Sweets"* (92%). However, methodological inconsistencies emerged, including the absence of standardized procedures for DP derivation, substantial subjectivity in labeling, and limited reporting of key statistical details. To address these limitations, the review (101) emphasized the need to test matrix factorability before applying PCA/EFA, to adopt more robust strategies for assessing internal reproducibility, and to

implement more transparent labeling practices. Ultimately, 186 DPs were grouped into 11 reproducible categories reflecting core elements of the Italian diet.

Building on these findings, a second systematic review (102) was conducted to assess whether the identified reproducible DPs show consistent associations with disease outcomes, DP drivers, or sociodemographic correlates across the Italian population. To overcome challenges in interpreting *a posteriori* DPs, associations were evaluated using selected Hill's criteria for causal inference (i.e., namely consistency, strength, and dose–response) applied within a framework of statistical and nutritional rigor.

Despite the structured approach, the potential for formal meta-analysis was limited due to heterogeneity in study populations, designs, and outcome definitions. Notably, only two DP groups (i.e., “*Starchy Patterns*” and “*Vegetable-based Patterns*”) showed strong and opposing associations with gastric cancer risk, with the former meeting the dose–response criterion. Regression models were generally well-constructed and appropriately adjusted for confounders, although awareness of key confounding variables (e.g., physical activity) has evolved over time, possibly influencing earlier findings.

Overall, most reproducible DPs were consistently associated with one or more similar target variables, including cardiometabolic outcomes, mortality, pregnancy-related outcomes, and indicators of social inequality. Detrimental patterns (e.g., high in processed or starchy foods) were associated with lower socioeconomic status and poorer health, whereas healthier patterns (e.g., vegetable- or fish-based) showed protective trends. However, a significant portion (54%) of associations were non-significant, likely reflecting underpowered analyses or true null findings. The lack of sample size calculations in most studies, combined with heterogeneous populations and regression models with multiple categorical variables, further limits interpretability. Finally, the review acknowledged several methodological shortcomings: measurement error was rarely assessed, interactions between DPs and confounders were often ignored, and meal-based DPs—potentially more reflective of actual eating behavior—were excluded. The synthesis also relied on statistical significance thresholds and did not fully account for overlapping study samples, particularly in large cohort studies such as Moli-sani. Unlike the stricter approach used in the reproducibility analysis, this second review (102) employed more flexible inclusion criteria, combining descriptive and CC-based evidence to enable broader comparisons. Future efforts will focus on reconstructing DPs from independent studies using harmonized input variables, paving the way for more robust comparisons across both national and international datasets.

4.6 CONCLUSION

Taken together, the findings from both systematic reviews highlight critical limitations in the standardization, reproducibility, and interpretability of PCA/EFA-derived dietary patterns within the Italian context. In particular, inconsistencies in labeling, input data structures, and statistical power limited the comparability of findings across studies. These findings also highlight the inherent limitations of traditional assessment tools, such as FFQs, which are prone to subjectivity, recall bias, and inconsistent nutrient mapping. Although widely used, these tools lack the objectivity and granularity needed to reliably capture dietary behavior across diverse populations and over time. This underscores the growing need for scalable, automated approaches, such as AI-based image recognition systems, that can support standardized, reproducible, and culturally adaptable dietary data collection. These insights informed the subsequent development of Objective 2 of this thesis, which explores the development and evaluation of image-based deep learning methods for food recognition and nutrient estimation. By integrating food composition data, curated image datasets, and state-of-the-art prediction models, the subsequent projects aim to address the reproducibility and scalability challenges identified in traditional dietary pattern research. Further details are introduced in the following chapters.

5. CROSS-COUNTRY NUTRIENT HARMONIZATION FOR IMAGE-BASED DIETARY ASSESSMENT IN ITALY: CHALLENGES AND COMPARATIVE EVALUATION

To address the limitations identified in traditional dietary pattern research (Objective 1), Objective 2 of this thesis explored the development of scalable, culturally relevant, and reproducible image-based dietary assessment methods. This objective was pursued through a multi-phase strategy encompassing three interconnected projects: (1) nutrient data harmonization between countries, (2) prediction model evaluation, and (3) ingredient-level recognition. The current chapter (Project 2) focuses on the first of these steps: the harmonization of nutrient data between the US-based Nutrition5k dataset and the Italian FCDB. Establishing accurate nutritional correspondence between these datasets was essential to ensure that the deep learning models developed in subsequent projects (Chapters 6 and 7) could be adapted to the Italian context. This chapter describes in detail the methods, challenges, and findings related to cross-country data integration and provides the foundation for the image-based nutrient prediction models evaluated in the following stages of this research.

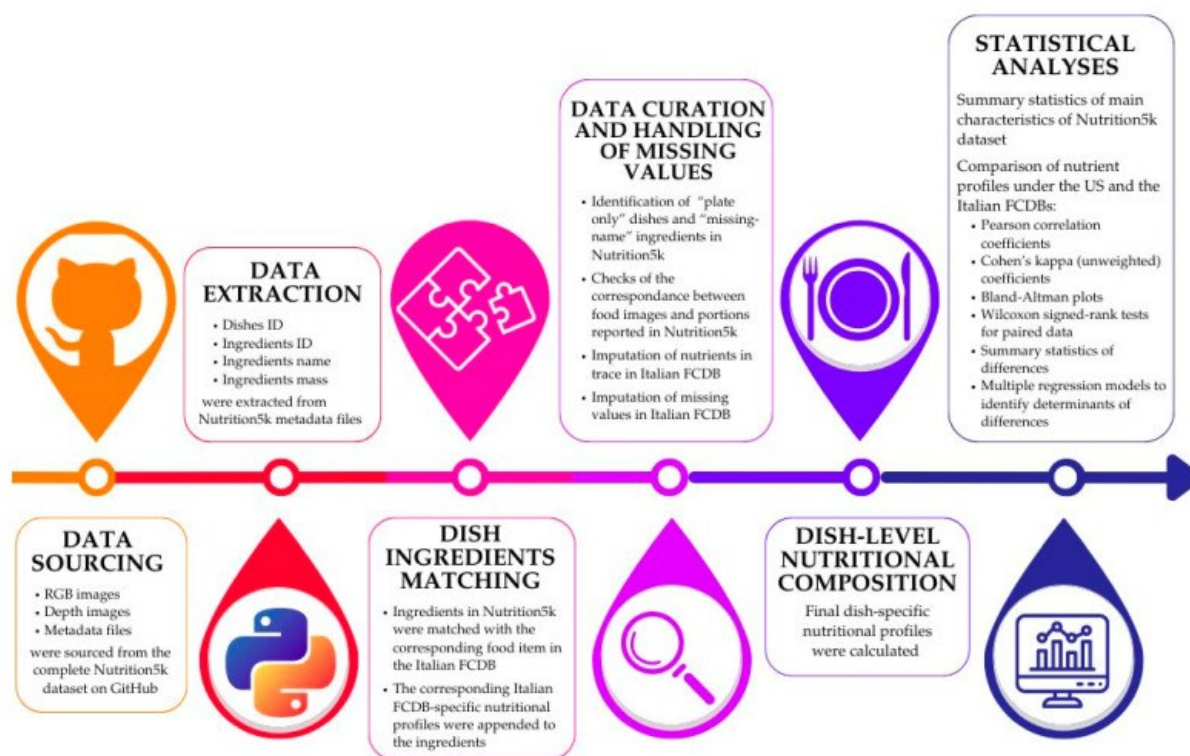
5.1 RATIONALE AND AIM

In recent years, the comparability of FCDBs across culturally diverse countries has become increasingly important for global nutrition research. While traditional dietary assessment tools (e.g., 24-hour recalls, FFQs, and food diaries) remain widely used, they suffer from limitations related to time, respondent burden, and data quality (1,27). Emerging technologies, particularly those based on deep learning and food image recognition, offer promising alternatives with greater scalability and precision. The Nutrition5k project provides a unique open-access dataset combining food images with detailed nutritional metadata from the US FCDB, and has been used to train DL models for portion size and nutrient estimation (95). However, applying such models to other populations, like the Italian one, requires harmonizing nutrient data across FCDBs due to differences in ingredients, portion sizes, and culinary practices. Within this context, the present study (103): 1) Explores the methodological challenges and solutions in linking Italian food composition data with the Nutrition5k image dataset; and 2) Compares nutrient estimates across the Italian and US FCDBs to identify key sources of variation.

5.2 MATERIALS AND METHODS

The harmonization process was handled by a team of nutritionists with different expertise and seniority who shares the management of the Italian FCDB. **Figure 5.1** shows the workflow of the analysis, including data extraction, data curation, the matching between dish ingredients in Nutrition5k and food items in the Italian FCDB, the derivation of Italian-FCDB-specific nutritional compositions, and the statistical analyses needed to compare the nutrient content obtained for each dish under the Italian and US FCDBs. Additional details are provided in the following paragraphs.

Figure 5.1 Comprehensive work plan related to research data acquisition and processing (103)



Abbreviations: FCDB, Food Composition Database; RGB, Red, Green, and Blue.

5.2.1 Data extraction and preliminary data management

We downloaded the metadata files *dish_metadata_cafe1.csv*, *dish_metadata_cafe2.csv*, and *ingredients_metadata.csv* from the Nutrition5k project to extract nutritional information at both the dish and ingredient level. In these files, each dish is reported in a single row and includes: a unique ID, total mass (i.e., the portion size served, in grams), number of ingredients, and energy and macronutrient content (*dish_id*, *total_mass*, *total_calories*, *total_fat*, *total_carb*, *total_protein*, *num_ingrs*). Each row also contains ingredient-level details, including the ID,

name, mass (in grams), and corresponding energy and macronutrients (*ingr_id*, *ingr_name*, *ingr_grams*, *ingr_calories*, *ingr_fat*, *ingr_carb*, *ingr_protein*). Each dish may include one or more ingredients, which can represent either single foods or composite recipes. Nutritional values in Nutrition5k were automatically derived by matching each ingredient with the US FCDB (49). From the metadata files, we extracted dish and ingredient IDs, ingredient names, and their respective masses. To facilitate the matching with Italian-FCDB-specific nutritional values, we reshaped the dataset from wide to long format, creating a separate row for each ingredient within a dish.

5.2.2 *Exact and indirect matching of ingredients with their nutritional composition*

We matched each ingredient from the Nutrition5k dataset (96) with the corresponding food item in the Italian FCDB and assigned the Italian nutrient values (expressed in terms of 86 components, including energy (2 components), water, alcohol, and macro- and micro-nutrients) to each ingredient. To ensure consistency in definitions, we cross-checked each nutrient across the Italian and US food composition databases (41,49).

Although the Nutrition5k metadata provide energy and macronutrients only, the underlying US FCDB used for nutrient estimation includes 477 components. These broader nutrient definitions were taken into account during the harmonization process. Specifically, we applied the following conversions to align the Italian nutrient definitions with those from the US FCDB (41,49):

- *Available carbohydrates* = carbohydrate by difference – total dietary fiber;
- *Vitamin A components*:
 - β -carotene equivalents = 1 β -carotene + 0.5 α -carotene + 0.5 β -cryptoxanthin;
 - Retinol equivalent = retinol + 1/6 β -carotene equivalents;
- *Alpha-tocopherol equivalents* = α -tocopherol + 0.4 β -tocopherol + 0.1 γ -tocopherol + 0.01 δ -tocopherol + 0.3 α -tocotrienol + 0.05 β -tocotrienol + 0.01 γ -tocotrienol;
- *Short-chain saturated fatty acids* = butyric fatty acid (C4:0) + caproic fatty acid (C6:0) + caprylic fatty acid (C8:0) + capric fatty acid (C10:0).

In addition, the Italian FCDB included a variable for “Other Polyunsaturated Fatty Acids (PUFAs)” that was missing in the US FCDB; we derived it by summing the relevant individual fatty acids available in the US database.

Because the Italian FCDB expresses all nutrient values per 100 g of edible portion, we converted them to a gram-specific basis to match the per-ingredient mass values in Nutrition5k. Furthermore, given that Nutrition5k dataset nutrient content is derived from ingredient masses (measured by a scale under the plate) and volumes (captured via depth imaging), we assumed that both ingredient and dish values referred to cooked foods. Therefore, we preferentially matched each ingredient to its *cooked* equivalent in the Italian FCDB. When a cooked version was not available, we used the corresponding raw item instead (e.g., matching cooked salmon in Nutrition5k dataset to raw salmon in the Italian FCDB).

We identified five matching criteria (53) between the Nutrition5k-specific ingredients and Italian-FCDB-specific food items, as described in the following:

1. **Exact matching:** a match was considered exact when:
 - the Nutrition5k ingredient had the same name as the Italian FCDB item (e.g., *eggplant – melanzane, salmon – salmone, or butter – burro*), or
 - the names were slightly different but clearly referred to the same food (e.g., *celery root – celeriac, or green beans – French beans*).

If no exact match was available, we applied one of the following indirect matching strategies.

2. **Similarity-based matching:** when a similar food was available in the Italian FCDB (in terms of definition, appearance, description, or nutrient composition), it was used as a substitute. If multiple items were suitable, we chose the one closest in calories, macronutrients, and water content.
3. **Missing foods in the Italian FCDB:** if a Nutrition5k ingredient was not present in the Italian FCDB and no suitable Italian alternative could be found, we referred to items from the US FCDB. We selected the best match by comparing nutritional composition.
4. **Generic ingredients:** when the Nutrition5k ingredient was too generic (e.g., *cheese* or *berries*), we considered variability across dishes (e.g., "cheese" might refer either to cheddar or to mozzarella) and identified a group of plausible matches in the Italian FCDB. We then calculated the average nutrient values across these foods.
5. **Composite recipes:** if the Nutrition5k ingredient was a recipe not listed in the Italian FCDB, we recreated it using the *Atlante Fotografico Alimentare* (19) or popular Italian cooking websites (170,171). For generic or culturally uncommon recipes (e.g., *tuna salad, coleslaw*), dish images were also used to guide the composition.

5.2.3 *Manual data curation*

To ensure accuracy and consistency in the dataset, several manual data curation steps were applied:

1. **Removal of empty dishes and identification of missing-name ingredients:** dishes labeled as “plate only” (i.e., with no visible ingredients) were removed after confirming that the plate was indeed empty. For ingredients identified only by a numerical ID and lacking a name in the dish metadata files (*dish_metadata_cafe1.csv*, *dish_metadata_cafe2.csv*), we used the supplemental *ingredients_metadata.csv* file or referred to the dish images to identify the missing ingredient.
2. **Checks of the ingredient portion:** we reviewed the distribution of ingredient mass values across the dataset (minimum, 1st quartile, median, 3rd quartile, maximum, mean, and standard deviation,). When ingredient mass appeared unrealistically high, we inspected the corresponding dish images to estimate more plausible portions and adjusted the values accordingly.
3. **Handling of trace nutrient values:** the Italian FCDB (41) flags trace amounts of nutrients (i.e., those present in very small quantities that cannot be reliably quantified) using specific thresholds (<0.6 , <0.06 , or <0.006) depending on the analytical method (32). Therefore, we imputed trace values with 0.5, 0.05, or 0.005 according to the methodology proposed by Greenfield and Southgate (32). For example, we indicated a retinol trace content <0.6 μg as 0.5 μg , a vitamin D trace content <0.06 μg as 0.05 μg , a tocopherol trace content <0.006 mg as 0.005 mg, and so on for each nutrient-specific criterion.

5.2.4 *Missing values*

Several food items in the Italian or US FCDBs showed missing values for some nutritional components. To increase the comparability between the two FCDBs, we handled missing values by using a standardized approach (32), as described below:

- *Imputation by similar food items:* missing values were replaced with other values based on a similar food item (e.g., values for blueberries used for raspberries), or another form of the same food (e.g., values for “boiled” used for “steamed”);

- *Imputation by calculation*: missing values were imputed by calculation from incomplete or partial analyses of a food (e.g., carbohydrates or fats by difference, or chloride calculated from the value for sodium);
- *Imputation by assumption*: when the source or origin of the values may be referred to as “assumed” or “presumed” zero (e.g., vitamin B12 in vegetables), missing values were replaced with zero;
- *Imputation by recipe calculation*: missing values were substituted with values derived from recipes, calculated from the nutrient content of the ingredients and corrected for preparation factors (i.e., yield and retention factors);
- *Imputation by borrowed values*: when original sources were adequate, missing values were replaced with values taken from other tables and databases (46–50). In some cases, the borrowed values were adapted to the different macronutrient content (e.g., calculation based on a reference profile for individual fatty acids, and/or individual soluble carbohydrates, and/or individual amino acids).

5.2.5 Dish-level nutritional composition

After dishes and ingredients were checked and missing values were imputed, final dish-specific nutritional information including mass, energy, macro- and micro-nutrient content (86 components plus mass) was calculated by summing the corresponding nutrient content for each dish.

5.2.6 Statistical analysis

We calculated the summary statistics (minimum, 1st quartile, median, 3rd quartile, mean, standard deviation, and maximum values) for the distributions of the number of ingredients, mass, energy (here expressed in kcal), and the remaining 85 components across all dishes.

We then compared the energy and macronutrient values (i.e., protein, fat, and carbohydrates) obtained using the Italian FCDB with those originally provided in Nutrition5k (based on US FCDB). This comparison was restricted to energy and macronutrients, because this is the only information provided in Nutrition5k. We also accounted for any corrections made to ingredient mass (see **Section 5.2.3**) to avoid overestimating the differences due to data errors already fixed.

To assess the level of agreement or discrepancy between the two databases, we used multiple statistical methods:

1. Scatterplots of each nutrient's distributions under the two FCDBs and Pearson correlations coefficients to examine how closely values from the two databases align, with hypothesis testing on the correlation coefficients;
2. Quintile classification: we evaluated how often dishes fell into the same nutrient quintile using both databases, and measured agreement using Cohen's kappa (unweighted). Cut-offs for quintiles were calculated separately for each database, and kappa values were interpreted according to strict criteria (172);
3. Bland–Altman plot for each nutrient and corresponding 95% limits of agreement;
4. Distribution of differences: for each nutrient, we computed the raw differences (Italian FCDB – US FCDB), calculated summary statistics, plotted their distributions, tested for normality (Kolmogorov–Smirnov test), and applied the Wilcoxon signed-rank test since none of the differences followed a normal distribution;
5. Top 25 differences: we also identified the 25 dishes with the largest absolute differences for each nutrient, regardless of direction.

To further investigate potential determinants of disagreement between the two FCDBs, we fitted a series of multiple regression models. For each macronutrient, we used the difference between the two databases as the outcome and included the following variables as predictors: (1) total dish mass (continuous); (2) number of ingredients per dish (discrete); (3) presence of recreated recipes in each dish (categorical, with “no” (reference category), “yes” categories); and (4) differential use of raw and cooked ingredients in each dish (categorical, with “no difference” (reference category), “one ingredient”, and “more than one ingredient” categories). We also included an interaction term between (3) and (4), based on expert nutritionists' knowledge. Violations of ordinary least-squares model assumptions suggested using the robust MM estimator (173) in the final analyses.

All statistical tests were two-sided with $\alpha = 0.05$. We used Python (v3.10) (174) for data preparation and R (v4.3.2) (112) for the analyses, with appropriate packages for robust regression, ANOVA, and hypothesis testing (175–179). Food matching was performed in Microsoft Excel© (2016).

5.3 RESULTS

5.3.1 *Data curation of dishes and dish ingredients in Nutrition5k*

A total of 5006 dishes were available in the Nutrition5k dataset: 4,768 from *café 1* and 238 from *café 2*. These dishes included 28,455 ingredient entries, corresponding to 249 unique ingredients (counting each ingredient once, regardless of how many times it appeared). We removed the “plate only” item (which appeared twice), leaving us with 5,004 dishes and 248 unique ingredients. Among the ingredient entries, one item appeared 110 times without a name. By cross-referencing this with the *ingredients_metadata.csv* file, we recovered 6 ingredients used 79 times. Additionally, we manually reviewed the images of these missing-name ingredients and identified two more: watermelon and apples with peel, which had been labeled as “deprecated” in the metadata file and occurred 31 times. In total, we were able to impute all eight missing-name ingredients. This brought the final count to 255 unique ingredients across 28,453 total ingredient entries.

5.3.2 *Exact and indirect matching between ingredients in Nutrition5k and food items in the Italian FCDB*

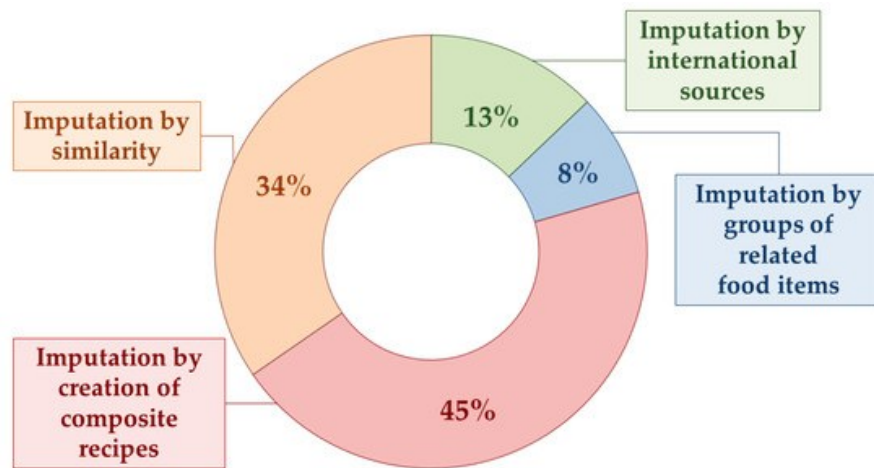
The Italian food composition data were linked to each of the 255 distinct ingredients identified in Nutrition5k using either exact or indirect food matching (see **Section 5.2.2** for details). Of these, 177 ingredients (approximately 69%)—corresponding to 23,834 individual ingredient entries (about 84% of the total)—were matched exactly to their Italian FCDB counterparts, regardless of differences in naming conventions between the two databases.

Indirect matching was required for 78 ingredients, accounting for 4,619 total entries. Details are shown in **Figure 5.2** and in the following bullet-pointed list; the full set of indirectly matched ingredients is available in **Tables B1-B4 (Appendix B)**. Among these:

1. 27 ingredients (~34%) had no direct equivalent but were replaced with similar foods available in the Italian FCDB;
2. 10 ingredients (~13%) had no suitable Italian alternatives and were instead retrieved from the US FCDB;
3. 6 generic ingredients (~8%) were matched by averaging the nutrient values of multiple corresponding Italian food items;

4. 35 composite ingredients (~45%) were recreated as new recipes, formulated to reflect their use in Nutrition5k.

Figure 5.2. Indirect matching: imputation strategies and related frequencies (103)



5.3.3 Manual data curation: ingredient portion checks

Four ingredients (i.e., olives, lemon, asparagus, and white rice) emerged as outliers based on the summary statistics of ingredient mass across dishes. Upon visual inspection of the food images, we found that their original portion sizes, which should have been just a few grams, had been mistakenly reported in kilograms. For example, olives and lemon were listed as 7,974 g instead of 7.974 g, asparagus as 3,324 g instead of 3.324 g, and white rice as 2,991 g instead of 2.991 g. We corrected these values by updating the ingredient mass to match the realistic quantities observed in the food images.

5.3.4 Handling of missing values

After linking each ingredient in Nutrition5k with the corresponding nutritional composition from the Italian FCDB, we identified a total of 2,621 missing values that required imputation. The proportion of missing data varied widely across nutrients, ranging from none to as high as 91.1% for vitamin K, with a median missing rate of 2.6% (IQR: 0–40.1%). Several micronutrients showed particularly high rates of missingness. Among the vitamins, substantial gaps were observed for biotin (42.2%), pantothenic acid, and vitamin B12 (both 40.1%). Similarly, a number of minerals were frequently missing, especially iodine (41.7%), chloride (40.6%), manganese, selenium, copper, magnesium (each around 40.1%), and sulfur (36.5%).

Even though total carbohydrates, starch, and soluble carbohydrates had very low rates of missing data (0–0.5%), some of their individual sugar components showed more substantial gaps. For instance, galactose was missing in 33.3% of cases, while glucose, fructose, lactose, maltose, and sucrose each had missing values in about 40.6% of instances. Similar issues were found across fatty acid subtypes, including several polyunsaturated (e.g., docosaesaenoic acid: 42.2%, eicosapentenoic acid: 42.7%, arachidonic acid: 41.1%), monounsaturated (e.g., palmitoleic acid: 42.2%, myristoleic acid: 51.0%), and saturated fatty acids (e.g., palmitic acid: 40.1%, behenic and arachidic acids: 54.7%). To address these gaps, we applied different imputation strategies. The majority of missing values (1771, or 67.5%) were filled using values from similar food items, either by direct substitution or by leveraging additional data provided after the initial release of the Italian FCDB. Other missing values were imputed by nutrient difference calculations (439 values, 16.9%), recipe-based estimations (183 values, 7.1%), or assumed zeros for nutrients logically absent in certain foods (140 values, 5.3%). A smaller share (88 values, 3.4%) was filled using borrowed values from other national FCDBs. After manual data curation of ingredients, food matching, linkage of nutritional compositions, and imputation of missing values, the dataset was ready for the statistical analyses, including descriptive and inferential statistics procedures.

5.3.5 *Distribution of dish ingredients by frequency of use and mass*

Dish complexity in Nutrition5k ranged from a single ingredient to up to 34 ingredients, with a median value of 3 ingredients per dish (IQR: 1–9). The most frequently used ingredients were olive oil, salt, garlic, vinegar, pepper, onions, and lemon juice, with a cumulative frequency of 25% (7,127 out of 28,453); in addition to condiments, other frequently used ingredients were broccoli, carrots, arugula, parsley, cherry tomatoes, raw spinach, cucumbers, and shallots, with a cumulative frequency of ~14% (3,296 out of 28,401) (**Figure 5.3**). **Figure 5.4** provides a clearer view of the most common ingredients by mass. At the top of the list were mainly protein-rich foods like eggs, meat, fish, and tofu (together accounting for 25%), followed by fruits (e.g., apple, pineapple, watermelon), starchy foods (e.g., potatoes, corn, pizza), and some vegetables like carrots and broccoli. Due to corrections of mass errors, ingredients such as olives, lemon, and white rice dropped in the ranking compared to the original Nutrition5k dataset.

Figure 5.3. Top 30 ingredients by frequency of use in Nutrition5k after data curation (103)

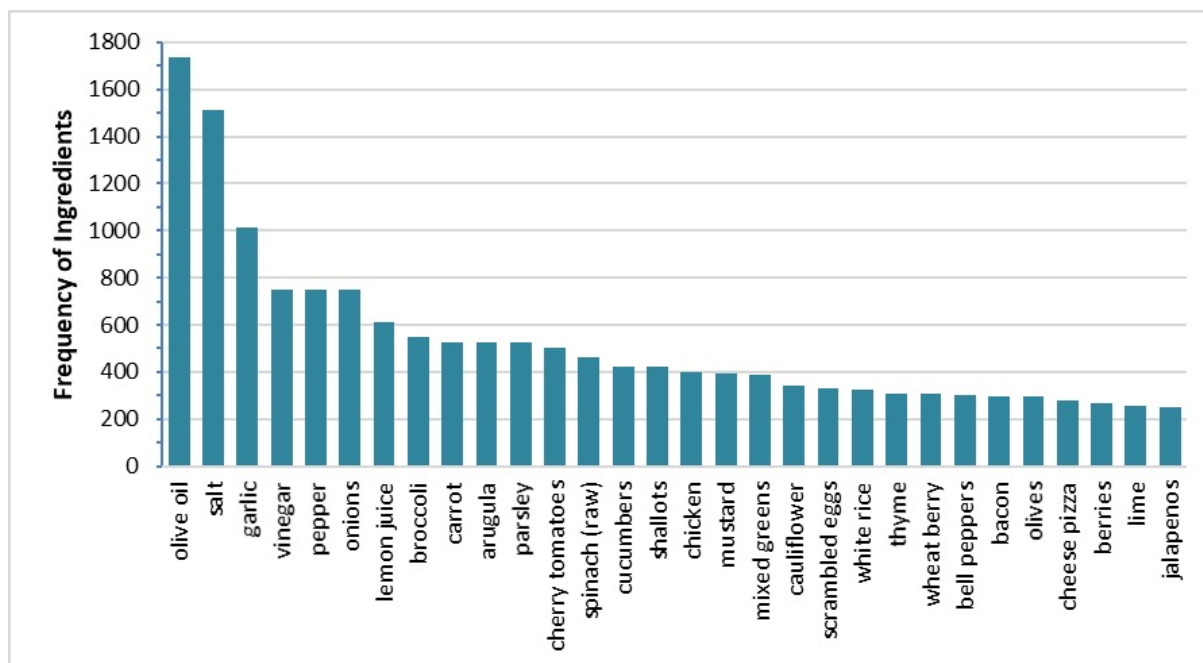
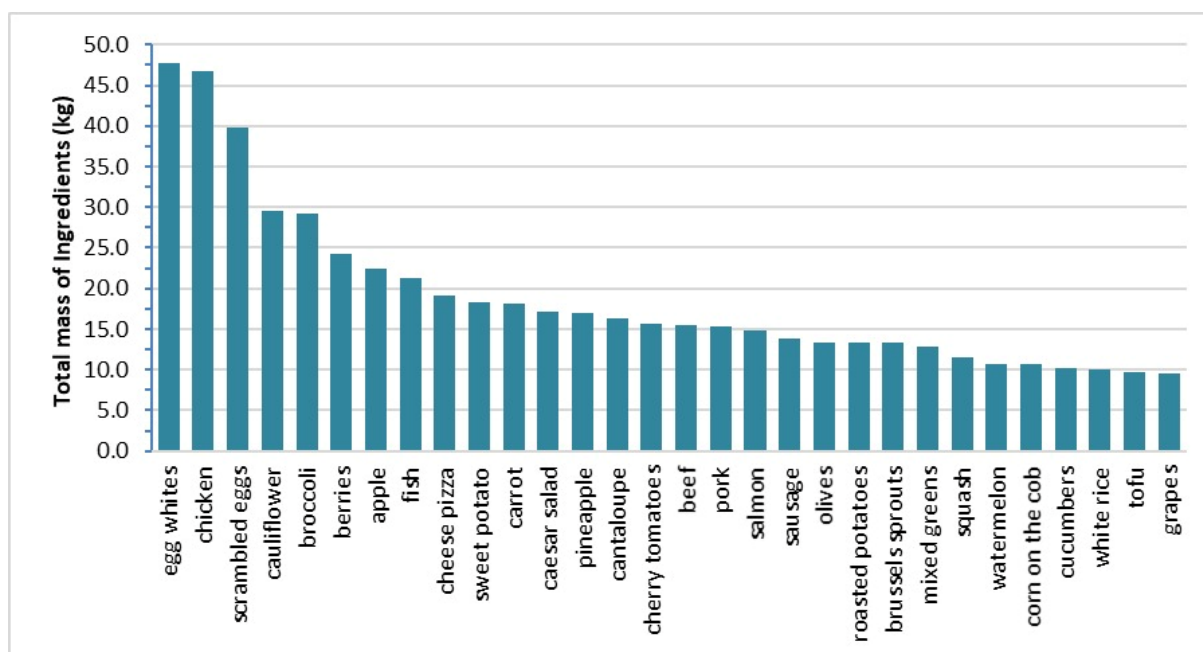


Figure 5.4. Top 30 ingredients by total mass (kg) across dishes in Nutrition5k after data curation (103)



5.3.6 *Distribution of mass, energy and macronutrient contents across available dishes in Nutrition5k after Italian nutritional values were linked*

Table 5.1 reports the distribution of mass, energy, and macronutrients across all dishes after assigning Italian FCDB values to Nutrition5k ingredients. Most distributions were right-skewed, with wide variability across dishes. The smallest dish (3 g) consisted of a single grape and had 0 g of protein. The lowest energy value was 1.1 kcal (asparagus-only dish). Median values were 145 g for mass, 162.7 kcal for energy, 8.0 g for protein, 7.0 g for fat, and 9.2 g for available carbohydrates. Several dishes had 0 g of fat (99 dishes) or carbohydrates (201 dishes). The highest values were 1102 g for mass, 1488.4 kcal for energy, 133.7 g for protein, 130.7 g for fat, and 117.7 g for carbohydrates (103).

Table 5.1. Descriptive statistics for mass, energy and macronutrient contents of dishes after attributing Italian-FCDB-specific nutritional values to dishes from Nutrition5k

	Mass (g)	Energy (kcal) ¹	Proteins (g)	Fats (g)	Carbohydrates (g)
Minimum	3.0	1.1	0.0	0.0	0.0
1st quartile	73.0	62.5	1.9	0.6	2.7
Median	145.0	162.7	8.0	7.0	9.2
3rd quartile	257.0	324.7	21.7	17.1	20.3
Maximum	1102.0	1488.4	133.7	130.7	117.7
Mean	182.7	220.8	14.5	11.5	14.2
SD	143.1	205.7	17.3	13.9	15.5

¹In the Italian FCDB, the energy content of each dish included fiber; therefore, for each dish, the sum of the calories provided by total proteins, total fats, and available carbohydrates was not equal to the total energy

5.3.7 *Nutrition5k dataset with Italian versus US nutritional values: a comparison*

After having performed manual data curation checks and imputation of missing values, we compared the nutrient content (energy, proteins, fats, and carbohydrates) between the Italian and US FCDBs through measures of agreement and differences. Correlation coefficients were equal to ~0.90 for fats and carbohydrates, 0.95 for energy, and 0.98 for proteins (all p-values < 0.001), indicating the presence of a strong linear relationship between corresponding nutrients under the Italian and US FCDBs (**Figure B1, Appendix B**).

Percentages of perfect agreement ranged from 68% (carbohydrates) to 84% (proteins); percentages of switching between adjacent quintiles ranged from 16% (proteins) to 30% (carbohydrates). When accounting for agreement by chance, Cohen's kappa coefficients still ranged from 0.60 (carbohydrates) to 0.80 (proteins), indicating moderate or strong agreement between corresponding nutrients (**Table 5.2**).

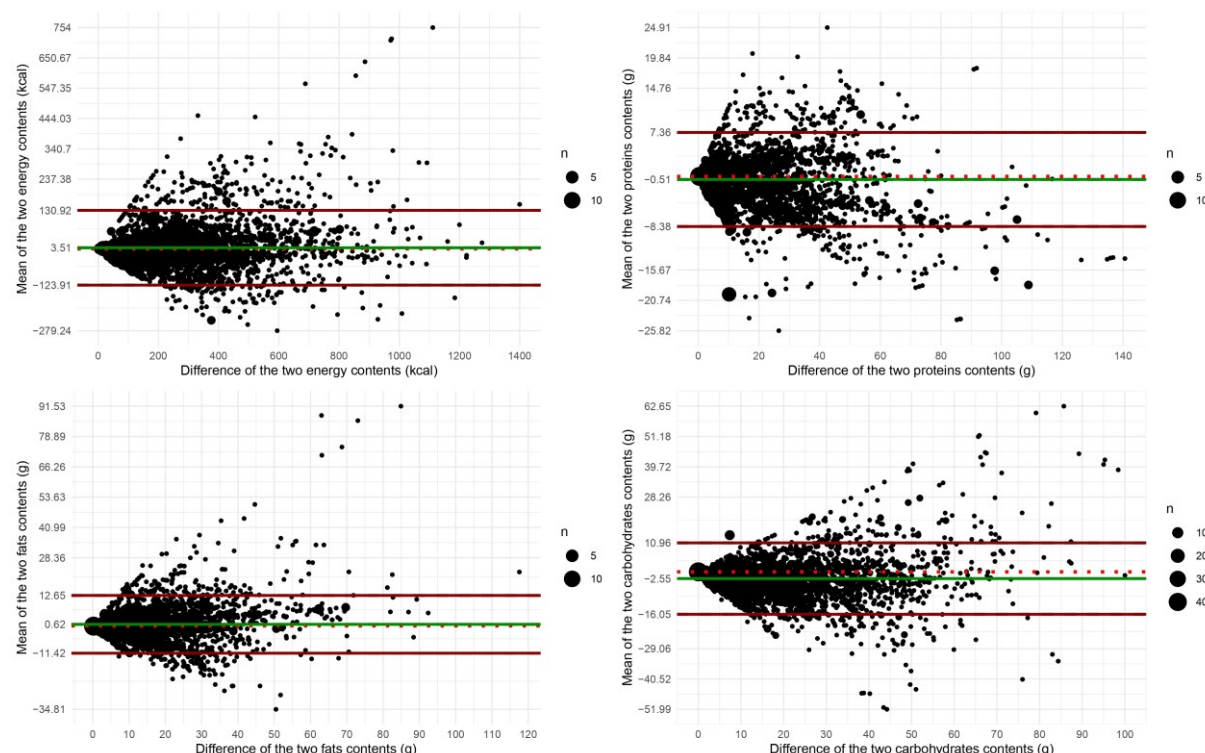
Table 5.2. Classification of dishes into quintiles and Cohen's kappa coefficient under the Italian and the US FCDBs

Energy (kcal)							Proteins (g)						
		US FCDB							US FCDB				
		Q1	Q2	Q3	Q4	Q5			Q1	Q2	Q3	Q4	Q5
Italian FCDB	Q1	18.17	1.84	0.0	0.0	0.0	Italian FCDB	Q1	18.35	1.44	0.0	0.22	0.0
	Q2	1.56	15.61	2.84	0.0	0.0		Q2	1.66	16.15	2.22	0.02	0.0
	Q3	0.28	2.26	14.13	3.30	0.02		Q3	0.0	2.30	15.47	2.14	0.04
	Q4	0.0	0.26	2.80	13.63	3.32		Q4	0.0	0.14	2.26	15.67	1.94
	Q5	0.0	0.06	0.22	3.06	16.67		Q5	0.0	0.0	0.02	1.96	18.03
kappa: 0.73							kappa: 0.80						
Fats (g)							Carbohydrates (g)						
		US FCDB							US FCDB				
		Q1	Q2	Q3	Q4	Q5			Q1	Q2	Q3	Q4	Q5
Italian FCDB	Q1	17.81	2.20	0.0	0.0	0.0	Italian FCDB	Q1	16.89	3.02	0.12	0.0	0.0
	Q2	2.28	13.97	3.56	0.20	0.0		Q2	2.70	12.17	4.40	0.70	0.02
	Q3	0.0	2.94	12.19	4.76	0.10		Q3	0.20	4.50	11.07	4.00	0.22
	Q4	0.0	0.64	3.76	11.15	4.46		Q4	0.22	0.36	4.08	11.75	3.62
	Q5	0.0	0.18	0.48	3.90	15.45		Q5	0.0	0.0	0.30	3.56	16.13
kappa: 0.63							kappa: 0.60						

Figure 5.5 shows the Bland–Altman plots for each nutrient, with corresponding 95% limits of agreement. The mean difference in nutrient content under the two FCDBs was 3.51 kcal for energy, −0.51 g for proteins, −0.62 g for fats, and −2.55 g for carbohydrates. In addition, the variability was not consistent across the plots for all investigated nutrients: the scatter around the bias line was larger as the mean on the x-axis became higher.

Although kernel density plots of the nutrient differences between the Italian and US FCDBs revealed a clear concentration of values around zero, particularly for energy, proteins, and fats, the distribution of differences was far from normally distributed (**Figure B2, Appendix B**). The Kolmogorov–Smirnov test confirmed significant deviations from normality (all p-values < 0.001), and the Wilcoxon signed-rank test detected non-zero shifts in the central location for all nutrients. These shifts were generally modest: values of median difference were exactly equal to 0 g for proteins and fats and −0.73 kcal for energy. Carbohydrates, however, showed more variability: the median difference was −2.10 g over a median content of 9.2 g (**Table 5.3**).

Figure 5.5. Bland–Altman plots representing the raw absolute difference between Italian- and US-specific content (x-axis) versus the mean of the Italian- and US-specific content for each nutrient (y-axis), with corresponding 95% limits of agreement (103)¹



¹The green line indicates the mean difference, while the red lines indicate the limits of agreement; the dotted red line indicates the reference value of 0

Table 5.3. Summary statistics of raw differences (i.e., nutrient in Italian FCDB – nutrient in US FCDB) in content of energy and macronutrients across Italian FCDB-specific and US FCDB -specific values

	Energy difference (kcal)	Proteins difference (g)	Fats difference (g)	Carbohydrates difference (g)
Minimum	-279.24	-25.82	-34.81	-52.00
1st quartile	-18.08	-1.46	-0.73	-5.08
Median	-0.73	0.0	0.0	-2.10
3rd quartile	15.59	0.83	1.80	-0.27
Maximun	754.0	24.91	91.53	62.65
Mean	3.50	-0.51	0.62	-2.54
SD	65.01	4.02	6.14	6.89

Abbreviations: FCDB, Food Composition Database.

An in-depth look at the dishes with the most extreme differences revealed that these were often due to a few recurring factors: discrepancies between the reconstructed recipe and the actual dish composition in Nutrition5k, the lack of cooked equivalents in the Italian FCDB, and the use of reconstructed recipes. For example, the dish showing the largest discrepancies in both

energy and fat content (*dish_1567714934*) contained Caesar dressing—a recreated recipe in the Italian FCDB with higher fat values due to the use of full-fat ingredients. Similarly, a dish with bacon showed the highest protein difference (*dish_1558115364*), largely because bacon was only available as a raw food item in the Italian FCDB, altering both fat and protein estimates when used in its cooked form (**Tables B5-B8, Appendix B**).

Table 5.4 presents the results of multiple robust regression models, where the difference in nutrient values between the Italian and US FCDBs was used as the outcome. The predictors included dish mass, number of ingredients, presence of recreated recipes, differences in the use of raw vs. cooked ingredients, and their interaction. For energy content, we found that the combination of recreated recipes and differences in raw/cooked ingredients was associated with a significantly larger mismatch between the two FCDBs ($p < 0.001$). Specifically, the energy difference increased by about 17–19 kcal when both conditions were present. In contrast, dish mass and number of ingredients did not meaningfully affect the energy difference. For carbohydrates, a higher dish mass was associated with smaller nutrient differences (-0.37 g every 25 g increase), while a greater number of ingredients led to slightly larger differences ($+0.11$ g per ingredient). Dishes that used raw and cooked forms of the same ingredient differently also showed larger differences, especially when multiple ingredients were involved. However, whether a recipe was recreated or not did not significantly influence carbohydrate differences. For proteins and fats, the patterns were somewhat reversed. An increase in dish mass was associated with larger differences for both nutrients ($+0.10$ g), while having more ingredients was linked to smaller differences (-0.15 g for proteins and -0.04 g for fats). Again, dishes with both recreated recipes and differences in ingredient preparation showed significantly larger discrepancies for fats ($p < 0.001$) and proteins ($p = 0.002$), although the effect for proteins became non-significant when multiple preparation differences were present.

Table 5.4. Beta coefficients and corresponding 95% confidence intervals (95% CI) from the multiple robust regression models¹

Characteristic	N	Difference of energy content (kcal)			Difference of proteins content (g)			Difference of fats content (g)			Difference of carbohydrates content (g)		
		Beta	95% CI	p-value	Beta	95% CI	p-value	Beta	95% CI	p-value	Beta	95% CI	p-value
Intercept	5004	-0.48	-1.15, 0.19	0.550 ²	-0.16	-0.19, -0.12	<0.001 ²	0.03	-0.02, 0.09	0.600 ²	-1.50	-1.59, -1.42	<0.001
Total mass (25 g increase)	5004	0.02	-0.06, 0.10	0.811 ²	0.10	0.10, 0.11	<0.001 ²	0.10	0.10, 0.11	<0.001 ²	-0.37	-0.38, -0.35	<0.001 ²
Number of ingredients	5004	0.00	-0.09, 0.08	0.969 ²	-0.15	-0.16, -0.15	<0.001 ²	-0.04	-0.04, -0.03	<0.001 ²	0.11	0.10, 0.12	<0.001 ²
Differential use of raw/cooked ingredients				<0.001 ³			<0.001 ³			<0.001 ³			<0.001 ³
<i>No difference in ingredients</i>	1768	—	—		—	—		—	—		—	—	
<i>One ingredient difference</i>	1500	-2.87	-3.81, -1.93	0.011 ²	0.13	0.08, 0.18	0.036 ²	-0.53	-0.61, -0.46	<0.001 ²	0.51	0.39, 0.62	<0.001 ²
<i>More ingredients difference</i>	1736	-10.87	-12.17, -9.57	<0.001 ²	-0.21	-0.28, -0.13	0.020 ²	-1.83	-1.94, -1.73	<0.001 ²	1.54	1.38, 1.69	<0.001 ²
Recreated recipes in dish				<0.001 ³			<0.001 ³			<0.001 ³			0.351 ³
<i>No</i>	3661	—	—		—	—		—	—		—	—	
<i>Yes</i>	1343	-4.06	-7.89, -0.23	0.375 ²	0.66	0.46, 0.85	0.005 ²	0.71	0.41, 1.02	0.050 ²	0.52	0.17, 0.88	0.217 ²
Interaction between differential use of raw/cooked ingredients and recreated recipes	5004			<0.001 ³			0.002 ³			<0.001 ³			0.252 ³
<i>One difference: Yes</i>	399	18.99	14.85, 23.14	<0.001 ²	0.60	0.39, 0.81	0.018 ²	1.04	0.71, 1.37	0.008 ²	-0.49	-0.89, -0.09	0.304 ²
<i>More differences: Yes</i>	863	16.73	12.67, 20.79	0.001 ²	0.42	0.21, 0.63	0.098 ²	1.88	1.56, 2.21	<0.001 ²	-0.69	-1.07, -0.30	0.136 ²

¹Estimates were obtained by including each nutrient's difference as the dependent variable and dish mass, number of ingredients per dish, presence of recreated recipes in each dish, and differential use of raw and cooked ingredients in each dish, as well as the interaction term between differential use of raw and cooked ingredients and presence of recreated recipes in each dish; ²This p-value derived from the robust tests for the single level of each variable; ³ This p-value derived from the robust ANOVA tests for the single variable.

5.4 DISCUSSION

To develop a novel image-based dietary assessment tool tailored to Italian foods, one crucial step was linking dish images from the US Nutrition5k dataset to nutritional values from the Italian FCDB (41). To our knowledge, this is the first attempt at harmonizing food composition data across countries specifically for image-based machine learning applications.

The harmonization process required several steps, including a thorough manual review of the Nutrition5k dishes and ingredients, exact and indirect matching with Italian FCDB food items, the creation of 35 new recipes, identification of discrepancies in the use of raw and cooked ingredients, and the imputation of over 2,600 missing values. This work ultimately allowed us to assign around 90 nutritional components to more than 5,000 dishes, enabling descriptive and inferential statistical analyses.

Overall, agreement between energy and macronutrients estimated from the US and Italian FCDBs was good, confirming the general consistency of the two databases. However, Bland–Altman plots showed that variability increased with higher nutrient values, a pattern also observed in a previous publication involving international FCDBs (172). Among the three macronutrients, carbohydrates were the most problematic: they showed the lowest correlation coefficients and agreement levels and the largest mean and median differences. This was largely expected due to methodological differences: while the US FCDB (49) calculates total carbohydrates by difference (including fiber), the Italian FCDB (41) defines "available carbohydrates" as the sum of starch and sugars, excluding fiber. As a result, values from the Italian FCDB were generally lower.

Further insights came from analyzing the top 25 dishes with the most extreme differences in nutrient values. These dishes often involved recreated recipes (e.g., Caesar salad, scrambled eggs, vinaigrette), ingredients with no cooked equivalent in the Italian FCDB (e.g., bacon, tuna, millet), or a high number of ingredients, which are signs of structural differences in the way the same recipe is represented across the two databases. These observations led us to formally test the role of several dish-level features (i.e., mass, number of ingredients, use of recreated recipes, and presence of raw/cooked mismatches) in explaining nutrient differences. Regression models confirmed that each factor contributed significantly to discrepancies, especially when both recipe reconstruction and raw/cooked mismatches were present in the same dish.

This project has several strengths. In the absence of standardized procedures, we followed best practices from EUROFIR (180) and FAO (53) and relied on expert nutritionist judgment. We also went beyond automated processes originally used in Nutrition5k, leveraging dish photos to refine matching, recover missing ingredients, and correct errors in mass values. Moreover, we introduced

robust statistical models to investigate determinants of nutrient differences, offering deeper insights than previous studies (172).

Nonetheless, some limitations remain. The Nutrition5k dataset includes dishes specific to US or multicultural contexts, some of which were not fully represented in the Italian FCDB. This led to substitutions or recipe reconstructions that may have increased discrepancies. In some cases, only raw versions of cooked ingredients were available, introducing bias, especially for carbohydrate-rich or protein-rich foods, which change weight differently when cooked (52). Additionally, we could not apply yield factors due to missing data on cooking methods or because the Italian FCDB does not systematically include them. Our comparison was also limited to macronutrients, since micronutrient data are not available in Nutrition5k, and these are known to be even harder to compare across FCDBs. Finally, although many missing values were carefully imputed, this issue remains a known limitation in food composition databases.

5.5 CONCLUSION

This study represents a fundamental step for the development of an Italian image-based dietary assessment tool powered by machine learning. By addressing the methodological challenges of linking a US-based food image dataset to an Italian FCDB, we demonstrated that cross-country harmonization is both feasible and informative, yet far from trivial. Our findings showed overall moderate to high agreement between the two FCDBs for energy and macronutrients, but also highlighted specific areas of divergence, mainly due to structural and definitional differences across databases, and to key determinants of nutritional discrepancies.

This harmonization process was not only necessary to adapt existing data for use in an Italian context, but also essential to generate reliable ground truth datasets for the next phase of our work: the direct prediction of mass and nutrient content from food images using deep learning (Project 3). Understanding how these preprocessing decisions affect model performance will be fundamental to refining prediction accuracy and ensuring generalizability across countries and dietary cultures.

6. PREDICTING DISH NUTRITIONAL COMPOSITION FROM FOOD IMAGES: DEEP LEARNING PERFORMANCE AND DATA CURATION BEYOND NUTRITION5K

Following the harmonization work (Project 2; Chapter 5), this chapter (Project 3) moves from dataset curation to model evaluation. We created multiple versions of curated and original ground-truth datasets, differing in FCDB alignment and preprocessing, and used them to test deep-learning models, assessing how cross-cultural adaptation and preprocessing affect prediction performance. Structured as a stand-alone research article, the chapter examines the impact of ingredient–mass correction, frame filtering, and FCDB differences on accuracy, thus linking the harmonization completed in Project 2 with the technical evaluation of DL algorithms for culturally adaptive dietary assessment.

6.1 RATIONALE AND AIM

In recent years, DL has increasingly been applied to estimate nutritional values from food images, offering more accurate and scalable alternatives to traditional tools. Nonetheless, variability in food appearance, image quality, and differences among national food databases limit model generalizability (55). We systematically evaluated convolutional and transformer-based architectures for predicting dish-level mass, energy, and macronutrients (104). We compared model performance across four curated versions of the Nutrition5k dataset (96), which differ in FCDB alignment (US vs. Italian) and preprocessing steps (i.e., ingredient–mass correction and test-set frame filtering). The analysis identifies model–dataset combinations with better performance and highlights dish types that remain difficult to predict, guiding refinement of image-based dietary tools across cultural settings.

6.2 MATERIALS AND METHODS

6.2.1 *Analytical framework and ground truth datasets for analysis*

This article built upon previous work on adapting the nutritional composition of Italian foods to align with the US Nutrition5k dataset for food image recognition (103) (Project 2, Chapter 5). In the current application (104), video frames from the Nutrition5k dataset were used to train and evaluate several standard DL algorithms for food image recognition. The goal was to predict the mass and nutritional composition of dishes in the test set. Since these outputs are continuous variables, the task was framed as a regression problem (55). Training and performance evaluation were conducted across four

distinct datasets, created from Nutrition5k by combining ingredient-mass correction with Italian-FCDB-specific nutritional values. Specifically, we have the following:

- 1) US FCDB–no correction: based on US-FCDB-specific nutritional values, without ingredient–mass correction;
- 2) US FCDB–correction: same as above, but with ingredient–mass correction applied;
- 3) IT FCDB–no correction: based on Italian-FCDB-specific nutritional values, which implied identifying and naming missing-name ingredients, as well as imputing traces and missing values for food items in the Italian FCDB, but without ingredient–mass correction;
- 4) IT FCDB–correction: same as above, but with ingredient-mass correction applied.

In the previous work (103), we compared dish-level mass, energy, and macronutrient values between datasets (2) and (4) to evaluate the impact of substituting US-FCDB with IT-FCDB nutritional values. In this study, we expand that analysis by evaluating both predicted values and model performance across all four available datasets. In particular, we examine how ingredient–mass correction affects prediction accuracy, both within the US-based and Italian-based datasets. We also assess how this correction step influences the performance of different DL models in estimating dish mass and nutrients from food images.

6.2.2 *Splitting data into training, validation, and test sets*

To ensure reproducibility with results from Thames et al. (95), we adopted the same train/test split as in the original Nutrition5k project, based on the *rgb_train_ids.txt* and *rgb_test_ids.txt* files (96). The initial split included 4,059 dishes for training and 709 for testing, all from the *dish_metadata_cafel.csv* file (96). However, we removed 129 training dishes and 33 test dishes that were missing video frames, leaving 3,930 training dishes and 676 test dishes in the final dataset. Unlike our previous analysis (103), we kept one “plate only” dish in both the training and test sets. Notably, all dishes in the same incremental scan were included in the same split in Nutrition5k (95). To optimize weights learning and evaluate generalization performance during training, we further split the training set into 90% for training and 10% for validation. To reduce the effect of randomness (e.g., how the multi-layer perceptron (MLP) used for the problem-solving part is initialized, or how the training data is ordered), we implemented a k-repeated shuffled validation strategy, varying the 90/10 train/validation split across each of the k runs.

6.2.3 *Selecting the architecture and pre-training weights for the automatic feature extraction*

We explored the official PyTorch repository (Vision Models 2.1.2) (181) to select suitable deep learning architectures for predicting mass and nutrients from food images. Our selection was based on four main criteria: (1) previous use in the Nutrition5k project (95); (2) popularity in multidisciplinary research (measured by number of citations) (182); (3) good balance between model size and dataset size (in terms of number of parameters and computational cost) (181); (4) accuracy (181). We first looked for the original algorithm used in Nutrition5k (95), InceptionV2 (IncV2), and found its updated version, InceptionV3 (IncV3) (183), available in PyTorch. We used this as our benchmark algorithm in our analysis. We then selected other widely used and efficient models, including Residual Network (ResNet) (184) and Vision Transformer (ViT) (185), all known for their good performance and high citation rates (181). Since Nutrition5k is a relatively small dataset, we avoided overly large models that require large amounts of training data. Instead, we focused on compact architectures (i.e., those with fewer than 75 million parameters and top-1 accuracy on ImageNet of at least 78.8%—the reported accuracy of IncV3 (183)) to ensure both competitive accuracy and computational efficiency, particularly for potential mobile deployment. Finally, we performed some preliminary experiments on a larger pool that also included ResNet18, ResNet34, and ViT-B-32, but based on results, we selected and used the following pre-trained models from ImageNet: Inception_V3_IMAGENET1K_V1 (benchmark), ResNet101_IMAGENET1K_V2, ResNet50_IMAGENET1K_V2, and ViT_B_16_IMAGENET1K_SWAG_E2E_V1. Unlike the original Nutrition5k study, which used the private JFT-300M dataset (186) for pretraining, we relied entirely on open-source ImageNet weights (1 million annotated generic images). Further details on each model are provided in (104).

6.2.4 *Extracting and preprocessing frames*

Each dish in the Nutrition5k dataset was recorded from up to four cameras, resulting in multiple video frames. During training and validation, we followed the Nutrition5k procedure and selected one frame out of every five to reduce memory usage and computational cost, while still introducing variability between batches and epochs. For testing, we used all available frames to improve prediction stability and reduce the risk of errors due to image artifacts. The final prediction for each dish was obtained by averaging the results across all frames. All selected frames were then preprocessed according to the neural network used. This included resizing, extracting a central crop, scaling pixel values to the [0,1] range using MinMax, and normalizing based on the mean and standard deviation from the ImageNet dataset (187).

6.2.5 *Setting the architecture for problem solving*

The pre-processed images were converted into fixed-size feature vectors using the last layer of each neural network: 2048 dimensions for ResNet and InceptionV3, and 768 dimensions for ViT (184,185). These vectors were then passed to an MLP, which predicted the dish’s mass, energy, and macronutrient content. On top of each feature extractor, we tested two variants of the MLP, here referred to as “2+1” and “2+2”, for the problem-solving part of the algorithm. In both variants, the input vector was first processed through two fully connected layers, interleaved by a nonlinear activation function (i.e., Rectified Linear Unit, ReLU). The resulting output was then processed in parallel through three trainable functions designed to predict mass, energy, and the three macronutrients together, as previously suggested in Thames et al. (95). In “2+1” variant, each head used one final layer; in “2+2” variant, each used two layers with ReLU. The “2+2” setup was based on the original Nutrition5k model, while “2+1” was a lighter version to test performance with fewer parameters. In total, we compared eight algorithms (**Table 6.1**) with IncV3_2+2 which was taken as our benchmark algorithm.

Table 6.1. Model name abbreviations used in tables and figures

Original Model Identifier ¹	Label Used in Tables and Figures ²
Inception_V3_IMAGENET1K_V1_2+1	IncV3_2+1
Inception_V3_IMAGENET1K_V1_2+2	IncV3_2+2
ResNet101_IMAGENET1K_V2_2+1	R101_2+1
ResNet101_IMAGENET1K_V2_2+2	R101_2+2
ResNet50_IMAGENET1K_V2_2+1	R50_2+1
ResNet50_IMAGENET1K_V2_2+2	R50_2+2
ViT_B_16_IMAGENET1K_SWAG_E2E_V1_2+1	ViT-B-16_2+1
ViT_B_16_IMAGENET1K_SWAG_E2E_V1_2+2	ViT-B-16_2+2

¹Model identifiers for the feature extraction part as provided by the original model sources (i.e., PyTorch Vision Models (181)) are listed in the left column. ²Abbreviated labels (right column) are used for clarity and brevity throughout the tables and figures in the main text and supplementary material

6.2.6 *Setting the optimization of the loss function for feature extraction and problem solving*

As in Nutrition5k (95), we selected the loss function given by the average of the single mean absolute errors (MAEs) calculated for the three tasks (i.e., prediction of mass, energy, and macronutrients, respectively). Training was carried out over 5 runs and 100 epochs, with a batch size of 64 (reduced to 32 for ViT-B-16 due to memory limits). We kept the number of epochs fixed to ensure comparability across models, although results showed that loss values usually stabilized well before 100 epochs (**Figure C1, Appendix C**). We used the Adam optimizer with a learning rate of 0.001.

For each run, the model weights that performed best on the validation set were used for testing. In the case of ViT-B-16, only the MLP layers were trained, while the pre-trained backbone was kept frozen, as training the entire ViT led to worse results and these models typically require much larger datasets to perform well (104).

6.2.7 *Setting the performance metrics for problem solving*

Following the approach proposed in Nutrition5k (95), we assessed model performance on the three prediction tasks (mass, energy, macronutrients) using three error metrics:

1. MAE (mean absolute error), showing the average prediction error in original units;

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i|$$

2. MAPE (mean absolute percentage error), which expresses the error as a percentage of the mean ground truth value, making it easier to compare across tasks;

$$MAPE = \frac{1}{N} \sum_{i=1}^N \frac{|\hat{y}_i - y_i|}{\bar{y}} \times 100$$

3. RMSE (root mean squared error), which emphasizes larger errors and is useful for detecting the impact of extreme prediction mistakes;

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2}$$

$\hat{y}_i$ and y_i represents the predicted and the ground truth values, respectively, and $\bar{y}$ is the average of the N ground truth values.

We hypothesized that using a combination of metrics would provide a more comprehensive evaluation by capturing different aspects of error performance metrics. Finally, for each metric, target variable, and algorithm, performance was averaged over the five available runs.

6.2.8 *Predicting mass, energy, and macronutrient content with and without ingredient–mass correction and Italian nutritional value calculation*

After standardizing file formats, column names, and frame folder structures, we applied the processing steps outlined in previous sections to each ground truth dataset individually (US FCDB–no correction, US FCDB–correction, IT FCDB–no correction, IT FCDB–correction). For each dataset, we generated dish-specific predictions for five target variables (i.e., mass, energy, protein, fat, and carbohydrates) using eight DL algorithms (IncV3_2+1, IncV3_2+2, R101_2+1, R101_2+2, R50_2+1, R50_2+2, ViT-B-16_2+1, and ViT-B-16_2+2). As for performance metrics, predictions

were averaged over the five available runs. This resulted in a total of 160 predictions per dish (5 target variables $\times$ 4 datasets $\times$ 8 algorithms). Statistical analyses were conducted on both ground truth (indicated as observed from now onwards) and predicted values for all dishes in the test set ($n = 676$).

6.2.9 Sensitivity Analysis: Comparison of Predicted Versus Calculated Energy Content in 4-Task and 5-Task Scenarios

Nutritionists usually estimate total energy intake (kcal) using this formula: $4 \times \text{protein (g)} + 9 \times \text{fat (g)} + 4 \times \text{carbohydrates (g)} + 2 \times \text{fiber (g)} + 7 \times \text{alcohol (g)}$ (17,32). Similarly, energy content of a dish can be calculated by summing macronutrient values multiplied by their respective factors. This raises the question of whether energy content should be directly predicted by DL algorithms or instead calculated from predicted available macronutrients. Moreover, since these tasks are interrelated, including energy prediction as a task may enhance the performance of DL models on macronutrient prediction. To explore this, we assessed the agreement between the three available scenarios: (1) *5-task predicted energy* (energy directly predicted by the model), (2) *5-task computed energy* (energy calculated from the macronutrients predicted by the same 5-task model), and (3) *4-task computed energy* (energy calculated from macronutrients predicted by a 4-task model, excluding energy).

6.2.10 Statistical analysis and visual inspection of frames

We calculated summary statistics (minimum, 1st quartile, median, 3rd quartile, mean, standard deviation, and maximum values) for the observed and predicted values of the target variables across all dishes in the test set. For predicted values, we also computed these statistics separately for each algorithm. We then repeated the same analysis on a merged dataset that included all observed values from the four versions of the ground truth.

Dish-specific (raw, absolute) differences between predicted and observed values of the target variables were evaluated across datasets and algorithms by considering the following: (1) percentages of perfect, adjacent, and opposite agreement among quartile-based categories, along with unweighted Cohen's kappa statistics, to take into account the possibility of agreement occurring by chance; and (2) Bland–Altman plots and corresponding 95% limits of agreement.

To identify top-performing algorithms for comparison with our benchmark (IncV3_2+2), we calculated the median metrics for each target variable across the available datasets. Although all metrics were examined, the algorithm with the best median MAPE was first selected, or MAE in the event of a tie.

Furthermore, we defined incorrectly predicted dishes across target variables and datasets as those that satisfied both the following conditions for 7 or 8 DL algorithms: (1) exceeded the limits of agreement in the Bland–Altman plots and (2) had the highest 5% of absolute differences (regardless of sign) between observed and predicted values. A visual inspection of dish frames from the four available cameras was conducted to identify potential issues with images and related ingredient labels that could distort performance and mask the true nutritional characteristics of the ingredients responsible for the poorest results.

Finally, in the sensitivity analysis, we evaluated the agreement between the following scenarios: (1) 5-task predicted energy content (i.e., main analysis); (2) 5-task computed energy content; and (3) 4-task computed energy content, across datasets and algorithms, by calculating percentages of perfect, adjacent, and opposite agreement among quartile-based categories, and corresponding unweighted Cohen’s kappa statistics. Performance metrics were then compared across the three scenarios using median values across the available datasets.

All statistical analyses were two-sided with $\alpha = 0.05$. We used Python (v3.10) (174) for data preparation and computation of error metrics, and R (v4.3.2) (112) for the analyses, with appropriate packages (175,176,188,189).

6.3 RESULTS

6.3.1 *Descriptive statistics on observed and predicted values from the test set with and without ingredient-mass correction and Italian nutritional value calculation*

Table 6.2 shows summary statistics of the observed values in the test set for each target variable, both for individual datasets and the merged dataset. In the merged dataset (**Table 6.2**, right column), the median dish had 142 g of mass, 164.5 kcal of energy, 8.3 g of protein, 6.9 g of fat, and 11.3 g of carbohydrates. The ingredient-mass correction notably reduced the maximum values in both US and Italian FCDBs, except for protein. **Table C1 (Appendix C)** reports summary statistics of the predicted values by target variable, algorithm, and dataset. In the predicted distributions, all algorithms tended to reduce extreme values, shrinking predictions closer to the center. As a result, maximum predicted values were more consistent across datasets, unlike the larger differences seen in the observed values. Examples of predicted mass and nutritional composition for the different combinations of algorithms and available datasets were provided in **Figure C2 (Appendix C)** for selected dishes.

Table 6.2. Descriptive statistics on observed values for mass, energy, and macronutrients content for dishes included in the test set from Nutrition5k, before or after ingredient-mass correction and matching with Italian-FCDB-specific nutritional values. Nutrition5k test set (n = 676)

Single available datasets ¹					Merged dataset ¹
Target variable	US FCDB-no correction	US FCDB-correction	IT FCDB-no correction	IT FCDB-correction	
Mass (g)					
Median (Q1, Q3)	142.0 (70.5, 250.0)	142.0 (70.0, 249.0)	143.0 (70.5, 251.5)	142.0 (70.0, 249.0)	142.0 (70.0, 250.0)
Mean (SD)	189.1 (332.1)	177.3 (142.9)	205.9 (467.1)	177.4 (142.9)	187.4 (304)
Min, Max	1.0, 7974.0	1.0, 871.0	1.0, 8094.0	1.0, 871.0	1.0, 8094.0
Energy content (kcal)					
Median (Q1, Q3)	161.9 (61.5, 343.4)	160.0 (61.2, 339.7)	167.2 (60.6, 333.3)	165.6 (60.3, 329.8)	164.5 (60.8, 335.3)
Mean (SD)	252.1 (536.2)	224.0 (205.6)	264.7 (687.8)	227.5 (218.1)	242.1 (461.0)
Min, Max	0.0, 9485.8	0.0, 1050.5	0.0, 12376.1	0.0, 1332.6	0.0, 12376.1
Protein content (g)					
Median (Q1, Q3)	8.7 (1.6, 23.0)	8.5 (1.6, 22.7)	7.9 (1.6, 22.0)	7.9 (1.6, 21.8)	8.3 (1.6, 22.2)
Mean (SD)	15.7 (19.3)	15.4 (18.9)	15.2 (18.7)	14.9 (17.9)	15.3 (18.7)
Min, Max	0.0, 105.6	0.0, 105.6	0.0, 123.6	0.0, 89.8	0.0, 123.6
Fat content (g)					
Median (Q1, Q3)	6.6 (0.6, 17.6)	6.6 (0.6, 17.4)	7.5 (0.4, 17.4)	7.4 (0.4, 17.2)	6.9 (0.5, 17.4)
Mean (SD)	13.6 (48.3)	11.1 (13.5)	15.4 (66.8)	11.9 (15.1)	13.0 (42.4)
Min, Max	0.0, 875.5	0.0, 84.2	0.0, 1,221.8	0.0, 115.8	0.0, 1221.8
Carbohydrates content (g)					
Median (Q1, Q3)	13.1 (4.4, 25.7)	13.0 (4.4, 25.4)	9.1 (2.3, 20.5)	9.0 (2.2, 20.5)	11.3 (3.3, 23.5)
Mean (SD)	19.2 (31.5)	17.5 (16.4)	15.0 (17.9)	14.6 (16.9)	16.6 (21.7)
Min, Max	0.0, 506.1	0.0, 85.8	0.0, 138.6	0.0, 116.5	0.0, 506.1

¹ US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. The merged dataset contained all the dishes from the four available datasets and therefore showed repeated dish IDs. Abbreviations: FCDB, Food Composition Database

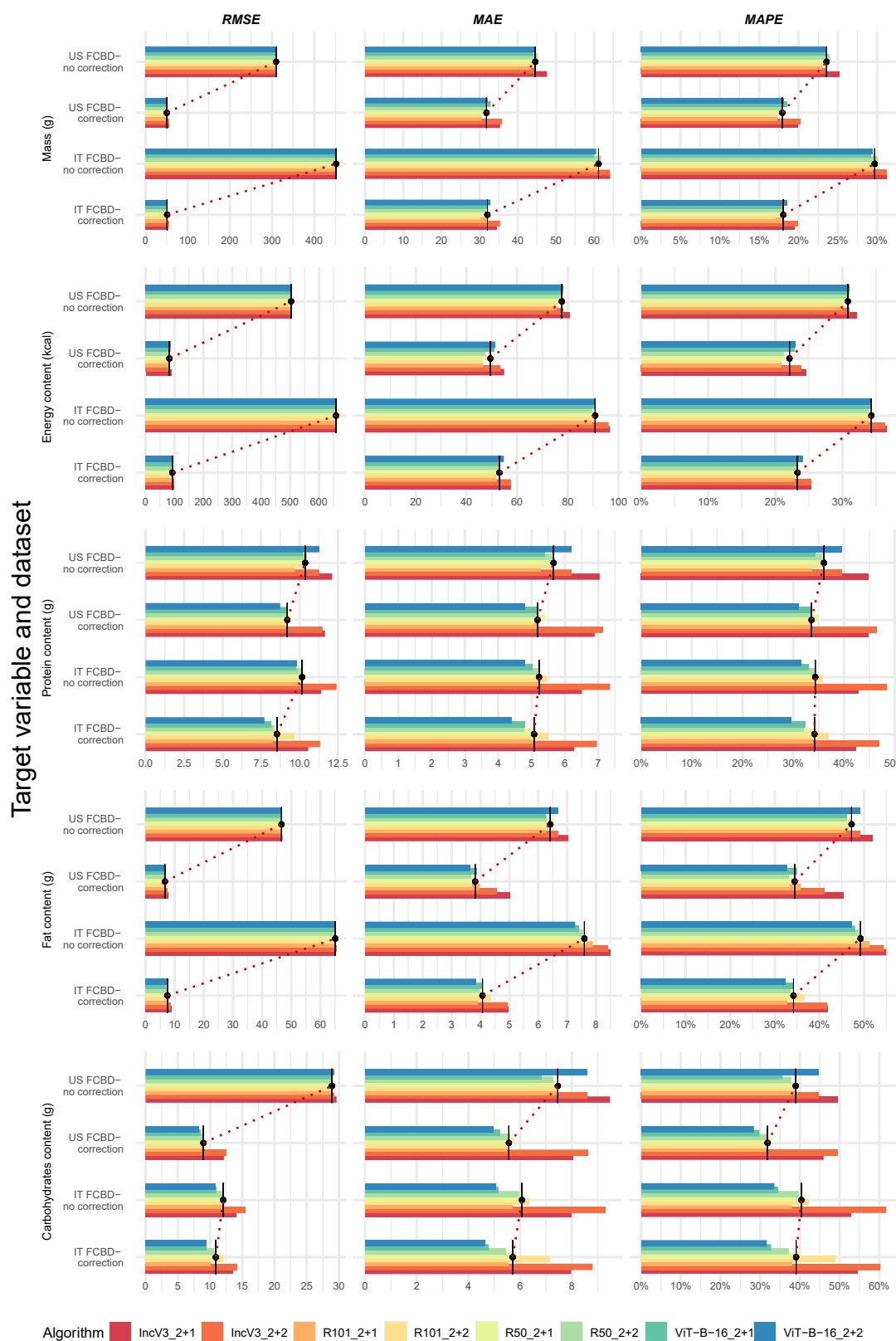
6.3.2 *Comparison between observed and predicted values from the test set with and without ingredient-mass correction and Italian nutritional value calculation*

Across all datasets and algorithms, perfect agreement between predicted and observed values was higher for mass (77–83%) and energy (76–82%) and lower for macronutrients: protein (62–78%), fat (65–78%), and carbohydrates (49–78%) (**Table C2, Appendix C**). Within each dataset, IncV3_2+2 and IncV3_2+1 consistently showed the lowest agreement across all target variables. For a given algorithm, agreement was generally higher in the corrected datasets, with the exception of protein. Cohen's kappa coefficients confirmed these trends: values ranged from 0.69 to 0.77 for mass, 0.67 to 0.76 for energy, 0.50 to 0.71 for protein, 0.53 to 0.71 for fat, and 0.32 to 0.71 for carbohydrates (**Table C3, Appendix C**). These results indicate weak to moderate agreement overall, with higher consistency for mass and energy. As seen with percentage agreement, kappa coefficients were typically higher in corrected datasets, again except for proteins, and lowest for the IncV3_2+2 and IncV3_2+1 algorithms.

Figures C3–C7 (Appendix C) display Bland-Altman plots for each target variable, comparing the differences between predicted and observed values against their mean, along with the 95% limits of agreement. Overall, the mean difference (i.e., the bias) ranged from –26.6 to –0.2 g for mass, –50.7 to –2.1 kcal for energy, –3.4 to –0.4 g for protein, –4.2 to 0 g for fat, and –3.5 to –0.6 g for carbohydrates. In all plots, the spread of the data increased with higher mean values on the x-axis, indicating heteroscedasticity (i.e., greater variability for dishes with larger quantities). When considering the same dataset, IncV3_2+2 and IncV3_2+1 generally provided wider limits of agreement across target variables (**Figures C3–C7, first row**). After ingredient-mass correction, the bias was closer to zero for mass, energy, and fat content, in both the US FCDB and IT FCDB datasets (**Figures C3, C4, and C6, second and fourth column from the left**). This correction also led to a substantial narrowing of the limits of agreement: up to 6–10 times for mass, energy, and fat (**Figures C3, C4, and C6, second and fourth column from the left**), and 1–4 times for protein and carbohydrates (**Figures C5, and C7, second and fourth column from the left**). Some architectures benefited more than others from this correction. R101 showed the strongest improvements for mass and energy (**Figures C3 and C4**), while ViT-B-16 performed better for protein and carbohydrates (**Figures C5 and C7**). Fat content showed no consistent pattern of change across models after correction (**Figure C6**). By contrast, IncV3_2+2 and IncV3_2+1 showed weaker improvements in agreement after correction (**Figures C3–C7**).

6.3.3 *Comparison between metrics with and without ingredient-mass correction and Italian nutritional value calculation*

Figure 6.1 shows the median performance metrics for each target variable, algorithm, and dataset (full details in **Table C4, Appendix C**). MAPE values allowed a fair comparison across target variables, ranging from 17.0–31.1% for mass, 20.7–36.5% for energy, 29.6–48.3% for protein, 32.4–55.0% for fat, and 28.4–61.7% for carbohydrates across all datasets and algorithms. When considering the same dataset, IncV3_2+2 and IncV3_2+1 generally showed the worst performance across all target variables and metrics, although differences in RMSE were less pronounced. When comparing corrected and uncorrected datasets for the same algorithm, performance metrics were generally better in the corrected versions, except for protein. In particular, MAPE improvements between corrected and uncorrected datasets (within the Italian FCDB) ranged from 5.6% for carbohydrates to 41.6% for mass. The strongest improvements were seen in RMSE values, likely due to their sensitivity to the extreme values found in the uncorrected datasets.

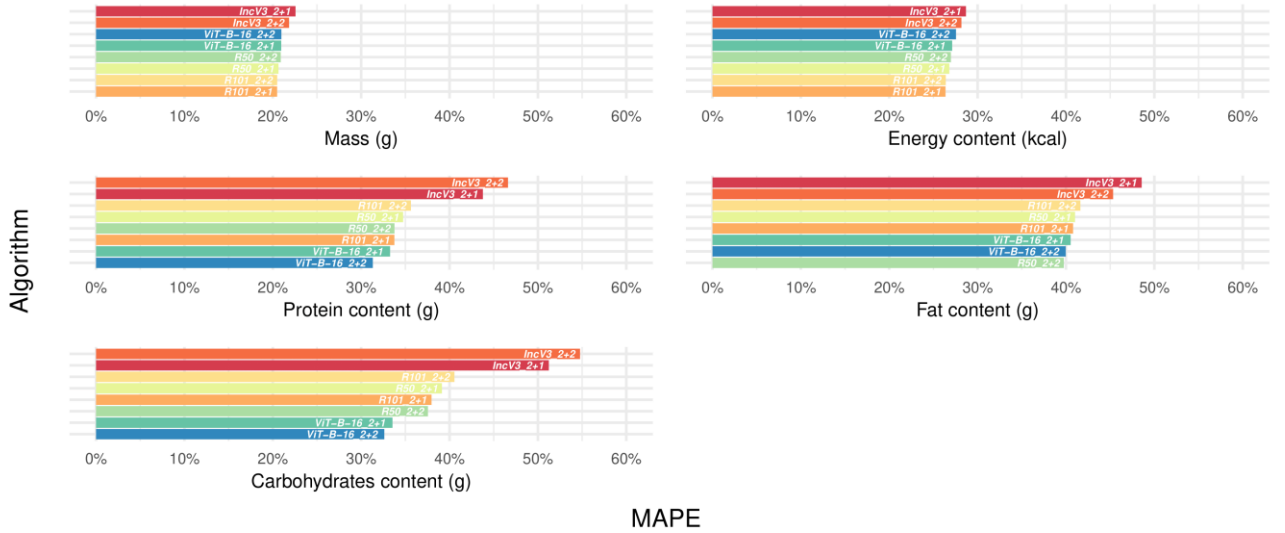
Figure 6.1. Performance metrics for single target variables, algorithms, and available datasets (104)¹

¹To improve readability, each subfigure displays performance metrics using its own scale, reflecting substantial variations in the metric's range. Abbreviations: FCDB, Food Composition Database; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; RMSE, Root Mean Squared Error (see **Table 6.1** for algorithm name abbreviations).

6.3.4 Selecting the best-performing deep learning algorithms

Figure 6.2 presents the median MAPE for single target variables and algorithms, calculated over available datasets. Overall, prediction errors were lower for mass (20.5–22.6%) and energy (26.4–28.7%) compared to macronutrients, with carbohydrates showing the highest variability (32.7–54.8%) and roughly doubling the maximum error observed for mass and energy (**Table C4, Appendix C**). Across all target variables and metrics, IncV3_2+1 and IncV3_2+2 algorithms consistently showed the poorest performance. Based on median MAPE and MAE, the top-performing algorithms were R101_2+1 for mass and energy, R50_2+2 for fats, and ViT-B-16_2+2 for protein and carbohydrates. Replacing the benchmark (IncV3_2+2) with these top algorithms led to notable reductions in MAPE: 6.2% for mass, 6.4% for energy, 12.3% for fat, and 33.1% and 40.2% for protein and carbohydrates, respectively. However, as the macronutrients were predicted in the same task, the final list of selected algorithms included R101_2+1 for mass and energy and ViT-B-16_2+2 for protein, fat, and carbohydrates content, together with the benchmark IncV3_2+2 (**Table C4, lower panel**).

Figure 6.2. Median error, as measured by mean absolute percentage error, for single target variables and algorithms across datasets, before frame filtering (104)



Abbreviations: MAPE, Mean Absolute Percentage Error (see **Table 6.1** for algorithm name abbreviations).

6.3.5 Incorrectly predicted dishes: a focus on nutritional characteristics of the ingredients after manual frame filtering

While looking for model-independent sources of error, we focused on 80 dishes that were consistently mispredicted by 7 or 8 DL algorithms (see **Section 6.2.10** for details). A manual frame-by-frame inspection of the images from the four revealed issues in 12 dishes:

- 7 dishes (*dish_1563566909*, *dish_1566414291*, *dish_1566501575*, *dish_1566501594*, *dish_1566589933*, *dish_1563566939*, and *dish_1563566965*) showed mismatches between visible ingredients and the (lower number of) ingredients listed in the metadata, mostly leading to overestimated predictions; except for carbohydrates, which sources were sometimes underrepresented in the images;
- 5 dishes (*dish_1558630325*, *dish_1558720236*, *dish_1562703447*, *dish_1563389626*, and *dish_1566838351*) suffered from poor image quality across all frames, including blurriness, bad framing, cropping, or the presence of distracting elements like hands, furniture, or cables.

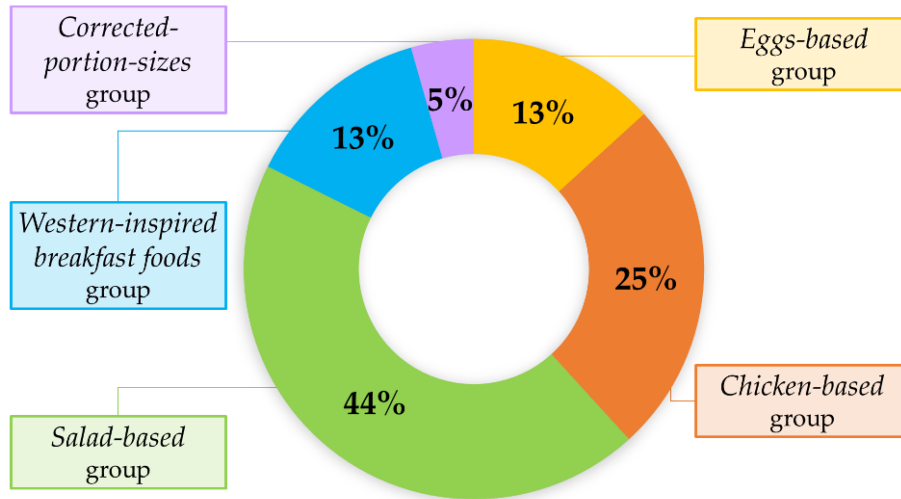
These 12 problematic dishes were excluded from further analysis, leaving a refined test set of 664 dishes, of which 68 remained consistently mispredicted (median: 32 frames per dish, IQR: 29–37; full range: 24–819). After manual frame filtering, a median of 39% (IQR: 24–50%) of the original frames was retained, resulting in a median of 12.5 frames per dish (IQR: 8.75–18.25) (**Table C5**, **Appendix C**).

Excluding the few dishes with corrected portion sizes (*Corrected-portion-size* group, 5%), the remaining mispredicted dishes were grouped based on ingredient characteristics (**Figure 6.3** and **Table C5**):

- *Salad-based* group (44%): typically complex dishes including at least two vegetables, two protein sources, cereals, herbs, and dressings (median: 16 ingredients per dish, IQR: 11.25–20.5);
- *Chicken-based* group (25%): simpler dishes, mostly centered on grilled or breaded chicken, sometimes visually ambiguous (median: 4 ingredients per dish, IQR: 3–5);
- *Eggs-based* group (13%): dishes featuring mainly scrambled eggs or boiled egg whites, often partially occluded (median: 5 ingredients per dish, IQR: 3–6);
- *Western-inspired breakfast foods* group (13%): hybrid category, blending elements of both sweet (e.g., fruit, almonds, or brownies) and savory (e.g., potatoes, sausages, or cheese) breakfasts with no dominant component (median: 2 ingredients per dish, IQR: 1–3).

Finally, the *Corrected-portion-size* group (median: 3 ingredients per dish, IQR: 2–3) included three dishes with known ingredient-mass corrections (as described in (103)). These dishes showed poor prediction performance in the uncorrected datasets only, either across all target variables (*dish_1551567508*) or for protein and carbohydrates only (*dish_1551382179*), depending on the corrected ingredient. Notably, reporting errors in Nutrition5k led to inconsistencies between listed ingredient masses and total dish mass for *dish_1551567573* and *dish_1551382179*, contributing to those dishes not being mispredicted in mass on the US FCDB-no correction dataset (**Table C5**).

Figure 6.3. Frequency distribution of incorrectly predicted dishes by groups based on similarity in ingredient content and the presence of ingredient-mass correction (104)



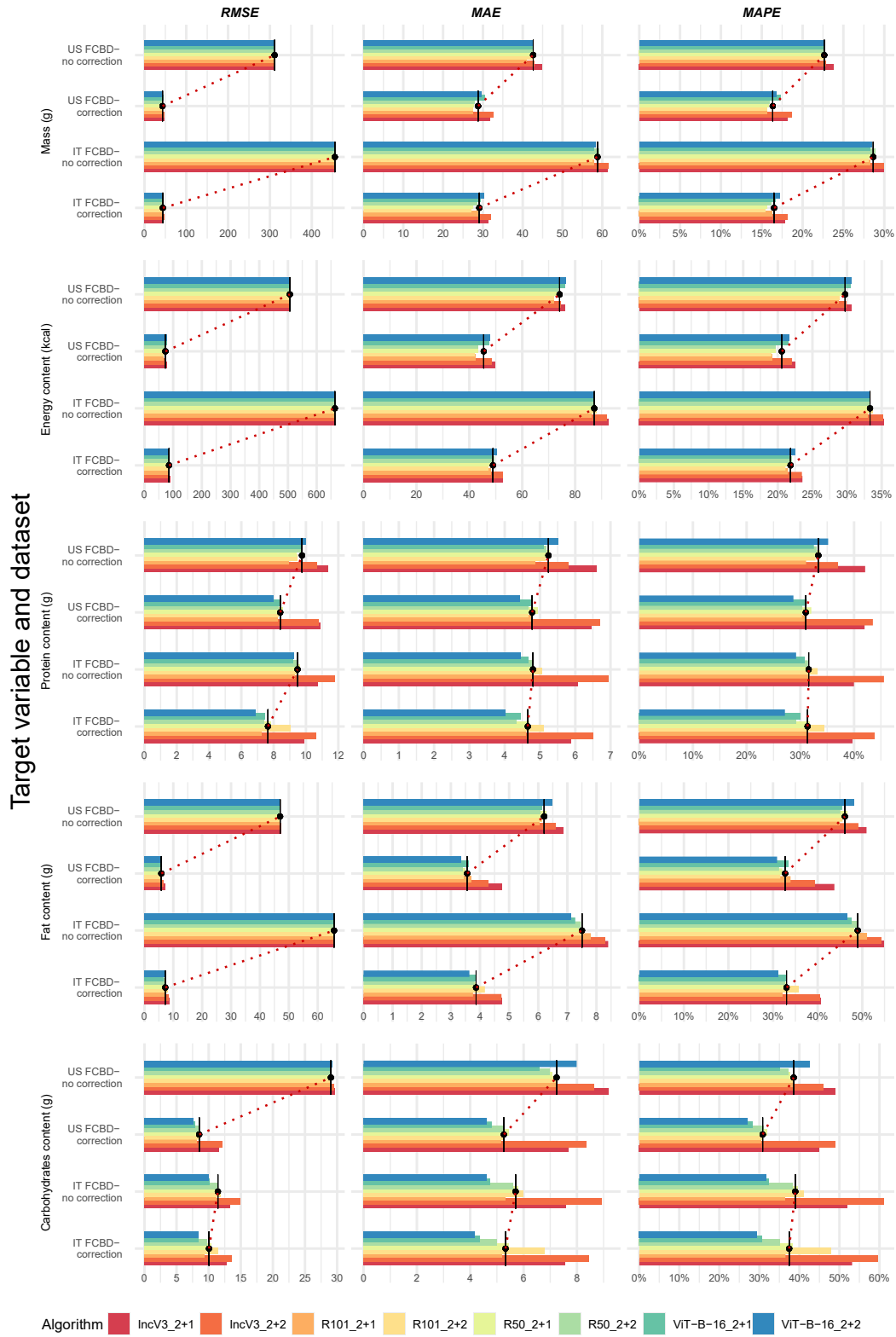
6.3.6 Confirming the best-performing deep learning algorithms after manual frame filtering

Figures 6.4 and 6.5 present the median performance metrics by target variable and algorithm, across individual datasets and overall, following manual frame filtering (details in Table C6, Appendix C).

We observed the following effect of manual frame filtering:

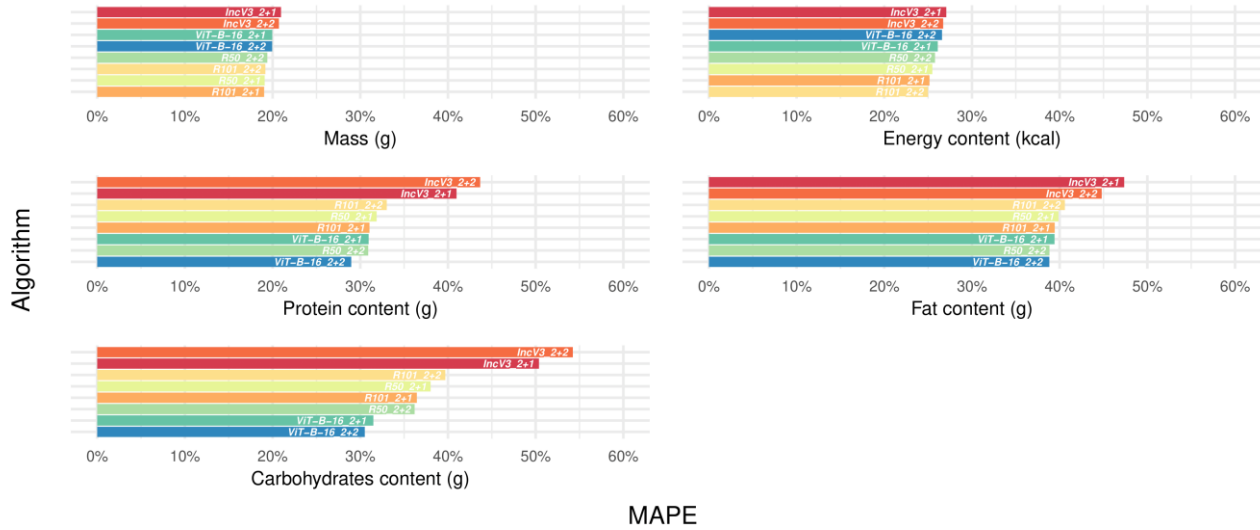
- 1) Reduced variation, minimal impact: frame filtering led to a slight reduction in the range of MAPE values across datasets and algorithms, but the improvements were modest, typically under 3%;
- 2) Correction still matters: for a given algorithm, performance was consistently better on corrected datasets than on uncorrected ones across all metrics, but especially for the RMSE;
- 3) Consistent underperformance of benchmark: within each dataset, IncV3_2+2 and IncV3_2+1 generally showed the worst metrics across target variables, except for RMSE;
- 4) Marginal overall gains: after merging the datasets, frame filtering led to slight reductions in median MAPE, with ranges: 19.0-21.0% for mass, 25.0-27.1% for energy, 29.0-43.7% for protein, 38.8-47.4% for fat, and 30.5-54.2% for carbohydrates;
- 5) Top performers confirmed: the top-one algorithms remained consistent with previous results, R101_2+1 for mass, R101_2+2 for energy content, and ViT-B-16_2+2 for proteins, fats, and carbohydrates. Overall, these results reinforced the superior performance of the R101_2+2 and ViT-B-16_2+2 architectures compared to the benchmark IncV3_2+2, even after accounting for image quality through manual frame filtering.

Figure 6.4. Performance metrics for single target variables, algorithms, and available datasets, after frame filtering (104)¹



¹To improve readability, each subfigure displays performance metrics using its own scale, reflecting substantial variations in the metric's range. Abbreviations: FCDB, Food Composition Database; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; RMSE, Root Mean Squared Error (see **Table 6.1** for algorithm name abbreviations).

Figure 6.5. Median error, as measured by mean absolute percentage error, for single target variables and algorithms across datasets, after frame filtering (104)



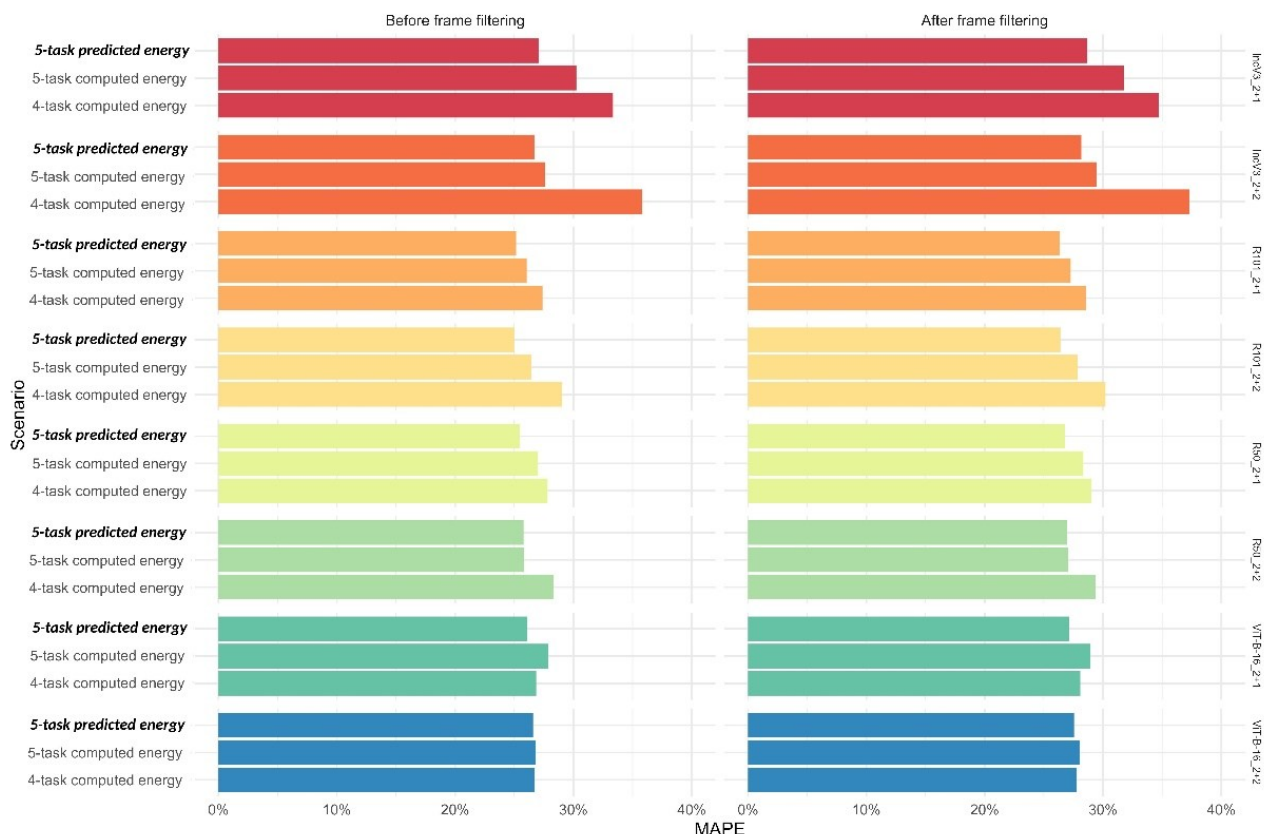
Abbreviations: MAPE, Mean Absolute Percentage Error (see **Table 6.1** for algorithm name abbreviations).

6.3.7 Sensitivity analysis: comparing predicted versus calculated energy content using the 4-task and 5-task deep learning algorithms

When comparing predicted and computed energy content from the 4-task and 5-task models, the highest agreement was found between the *5-task predicted* and *5-task computed* values. This pair consistently showed the best results across all datasets and algorithms, with 59–94% perfect agreement on uncorrected datasets and 71–92% on corrected ones, along with moderate-to-strong agreement based on unweighted Cohen’s kappa. The other two comparisons (*5-task vs. 4-task computed*, and *5-task predicted vs. 4-task computed*) showed lower but similar agreement, typically ranging from 60–80% perfect agreement and weaker kappa values. Across all datasets and comparisons, IncV3_2+1 or IncV3_2+2 generally showed the worst agreement, whereas ViT-B-16_2+1 and ViT-B-16_2+2 showed the best agreement according to both percentages of perfect agreement and Cohen’s kappa coefficients (**Tables C7 and C8, Appendix C**). These trends remained generally consistent in the subset of 664 dishes with reduced frame counts. Finally, compared to the *5-task predicted energy content* scenario (main analysis), performance metrics for the other two scenarios were generally worse across all algorithms, with the exception of ViT-B-16_2+1 and ViT-B-16_2+2, which showed minimal differences (<7%). Notably, the *4-task computed* scenario performed much worse than the *5-task computed*, with differences reaching up to 34%, compared to a maximum of 12% for the *5-task computed* scenario. In contrast, predictions for mass and macronutrients were more stable, showing <10% variation from the main analysis. The largest

differences were seen in fat prediction under the *4-task computed* energy scenario, with errors up to 28%, both before and after frame filtering (**Figure 6.6** and **Table C9, Appendix C**).

Figure 6.6. Sensitivity analysis: median error, as measured by mean absolute percentage error, of single algorithms for the predicted and computed energy content scenarios under the 4-task and 5-task deep learning algorithms across datasets, before and after frame filtering¹



¹The scenario presented in the main analysis is indicated in bold and italics typeface. Abbreviations: MAPE, Mean Absolute Percentage Error (see **Table 6.1** for algorithm name abbreviations).

6.4 DISCUSSION

This study explored the use of the Nutrition5k dataset (96) to directly predict dish mass and nutritional composition from 2D images. It addressed three main research questions: (1) whether selected DL models outperform the benchmark IncV3_2+2 when using the same task setup; (2) how manual data curation affects model performance; (3) and which types of dishes are consistently mispredicted, and the reasons why.

All selected DL algorithms outperformed the benchmark IncV3_2+2 and the related variant IncV3_2+1 both before and after applying ingredient-mass correction and manual frame filtering. The best-performing models varied by nutritional target, but R101 and ViT-B-16 consistently showed strong results and were prioritized for further analysis. This study (104) also confirmed a trend previously observed in Thames et al. (95), with prediction performance declining progressively from

mass and energy to protein, carbohydrates, and fat. This likely reflects the increasing difficulty of these tasks, with fat prediction being particularly challenging due to the often-subtle visual appearance of fat-rich components like dressings.

Manual data curation proved effective in improving performance. Ingredient-mass correction notably enhanced prediction accuracy, reflected in increased perfect agreement rates and higher Cohen’s kappa coefficients (especially for mass, fat, and carbohydrates) while protein prediction benefited less, likely because the corrected ingredients (i.e., olives and asparagus) are less relevant for protein (41,49). Manual frame filtering, though labor-intensive, had a more limited impact, as it was applied only to 80 mispredicted dishes in the test set. Nonetheless, the filtering procedure highlighted the substantial manual effort required (16 working hours for one researcher) and provides a benchmark for assessing the potential utility of automated filtering methods in future analyses.

The study also examined why certain dishes were consistently mispredicted across models and datasets. Through manual review and ingredient-based grouping, it was found that dishes with high visual complexity or ambiguous composition were particularly challenging. These dishes often included many ingredients (e.g., salads, with a median of 16), suffered from occlusion, or featured visually indistinct elements like boiled egg whites or grilled chicken blending into white plates. The placement and visibility of certain ingredients, such as almonds or dressings, also contributed to underestimation, suggesting that incorporating volume estimation into models could improve prediction accuracy.

In addition, the study investigated whether energy content should be directly predicted by DL models or calculated from predicted macronutrients, as is typically done in nutrition science. The sensitivity analysis comparing three scenarios (*5-task predicted* energy, *5-task computed* energy, and *4-task computed* energy) revealed that direct prediction yielded the best results. The 4-task computed scenario performed the worst, likely due to error propagation from macronutrient predictions, especially fat. The 5-task computed energy scenario, where energy prediction was included during training but excluded at inference, showed intermediate results, possibly due to stabilizing effects during learning. These findings suggest that direct energy prediction, as implemented in the main analysis, remains the most reliable approach.

The study’s strengths include its multidisciplinary team of informaticians, nutritionists, and medical statisticians, which enabled a comprehensive methodological framework. In addition to standard performance metrics, the team conducted dish-level analyses using outlier detection, agreement measures, and comparative evaluations across datasets. These analyses not only confirmed known data issues in the Nutrition5k dataset but also demonstrated the value of detailed manual curation

beyond standard nutritional database checks (190). The study also emphasized reproducibility by closely aligning its pipeline with that of the original Nutrition5k project (95), including the use of the same train/test split, task structure, loss functions, and performance metrics, while reporting benchmark comparisons whenever deviations occurred.

However, several limitations remain. Although Nutrition5k is well designed, it contains errors in images, nutritional data, and ingredient labels. Manual filtering revealed that only 39% of frames were retained per mispredicted dish on average, raising concerns about image quality. Whether similar filtering is needed in the training set remains to be explored with automated tools. The use of the Italian FCDB in place of USDA data also introduced uncertainty, due to lack of standardized food IDs and more challenging food-item matching. The fixed central cropping used in preprocessing may have systematically excluded relevant visual cues at the edges of images, although initial resizing likely reduced the extent of this issue. Finally, although results were consistent across scenarios, the comparison of results across so many algorithms, datasets, and target variables might be difficult to manage. Despite growing interest in using DL to predict nutrition from images, the lack of large, well-annotated datasets that provide both images and complete nutritional information (88,89,191,192) remains a major bottleneck.

6.5 CONCLUSION

In this work, we systematically benchmarked state-of-the-art DL architectures—including IncV3, R101, R50, and ViT-B-16—for nutrient prediction on the Nutrition5k dataset (95). Although all models outperformed the original IncV3 family, performance gains varied across nutrients and architectures. ViT-B-16 achieved the best results for macronutrient prediction, while R101 showed higher accuracy for mass and energy estimation, albeit with smaller differences for these targets. Our analyses also demonstrated that dataset curation, particularly ingredient–mass correction, substantially improved model performance, though the effect size differed across nutrients and models. These findings offer new insight into how architecture choice and data quality interact in complex nutritional estimation tasks. Building on this work, Project 4 adds ingredient recognition to the regression framework and systematically tests how architectures, cross-database harmonization, and complete preprocessing procedures jointly determine prediction performance, for the development of culturally adaptive, image-based dietary assessment tools.

7. INTEGRATING INGREDIENT RECOGNITION AND FULL NUTRITIONAL PROFILE IN THE 2D PREDICTION FROM NUTRITION5K IMAGES: DEEP LEARNING ALGORITHM SELECTION AND AUTOMATED FRAME FILTERING

Building on the benchmarking and harmonization work presented in the previous chapters 5 and 6, this study (Project 4) expands the analytical framework from nutrient estimation to ingredient-level analysis. This chapter explores how database harmonized US and Italian FCDBs, and preprocessing jointly influence prediction performance of selected model architectures. The study integrates regression and classification tasks to evaluate both ingredient and nutrient prediction. This transition advances toward automated dietary assessment pipelines that better capture mixed-dish complexity and cultural variation.

7.1 RATIONALE AND AIM

Recent advances in artificial intelligence AI and deep learning DL have opened new perspectives for automating dietary data collection and analysis (193), capable of overcoming limitations of traditional dietary assessment tools (1). Building on our previous work (104), where we benchmarked several DL architectures on the Nutrition5k dataset (96) and demonstrated the positive impact of ingredient-mass correction on nutrient prediction, the present study aims to integrate ingredient recognition into this framework. Specifically, we aim to: (1) evaluate whether automated frame filtering enhances prediction performance; (2) identify the most effective algorithms for ingredient and nutrient estimation; (3) characterize the features of misclassified ingredients and dishes; and (4) assess whether the prediction of nutritional values improves after integrating ingredient recognition into the pipeline.

7.2 MATERIALS AND METHODS

Details on DL algorithms, available datasets, variables and tasks, and the overall prediction pipeline are provided in **Table 7.1** and briefly discussed below.

7.2.1 Available datasets

Building on our previous work (104), we applied the top-performing DL architectures to food images linked to two reference datasets of ingredients and nutritional values previously introduced: the US FCDB-correction dataset, derived from the original Nutrition5k after ingredient-mass correction, and the IT FCDB-correction dataset, obtained by matching Nutrition5k ingredients with food items in the Italian BDA (41,103) (**Table 7.1**).

7.2.2 Variables and tasks

The predictive framework of DL algorithms was structured as a multi-task learning problem combining regression and classification. The regression part jointly predicted continuous variables including dish mass (grams), energy content (kcal), and three macronutrients content (i.e., protein, fat, and carbohydrates) (grams). In parallel, a multi-label classification task identified the presence of single ingredients in the available dishes, with each ingredient associated to a categorical variable. This setup allowed simultaneous prediction of quantitative and qualitative nutritional features from food images (**Table 7.1**).

7.2.3 Dish splitting and frame preprocessing

At the beginning of our pipeline, dishes from *dish_metadata_cafel.csv* file were split into training/validation (3930 dishes with available videos, 209 unique ingredients, and 228514 corresponding frames) and test (676 dishes with available videos, 167 unique ingredients, and 37597 corresponding frames) sets by following specific information provided in the Nutrition5k project (96). Corresponding frames were similarly sampled in line with the approach proposed in Nutrition5k (95). Remaining frames then underwent a preprocessing step tailored to the neural network architecture used (**Table 7.1**) and an additional automated frame filtering step fully described below.

7.2.4 Automated frame filtering

To improve the quality of the image dataset, all frames in the training, validation, and test sets were screened for artefacts likely to degrade model performance. The procedure was guided by our prior manual review of “problematic” test dishes (104) and followed a two-step workflow. First, we identified four recurrent visual anomalies through manual inspection: (1) visible hands, (2) legs or chairs in the background, (3) missing plate, and (4) multiple plates within a single frame, typically

due to recording errors. Second, we selected a small set of frames for each anomaly type to prototype automated filtering strategies. Based on these preliminary tests, the multimodal model GroundingDINO (194) was adopted for object detection. Unlike conventional, fixed-label detectors, GroundingDINO aligns free-form text prompts (e.g., “hand”, “person holding a plate”) to specific image regions by combining visual and linguistic information. Specifically, each frame was processed independently with the pre-specified prompts “hand”, “person”, “plates”, “chair”, “shoes”, and “floor”, concatenated via dot notation (e.g., “hand . person . plates . chair . shoes . floor”) and passed to the model. The output for each frame included a set of bounding boxes (i.e., 2D spatial coordinates of the boxes) and the associated textual labels. Labels allowed to exclude frames when: (1) any of the undesired elements were detected, (2) multiple plates were found within the same frame, and (3) no plates were found in the frame.

7.2.5 Feature extraction

The feature extraction part of the problem was carried out using three network architectures (i.e., IncV3, R101, and ViT-B-16) chosen based on our previous work in nutritional composition prediction (104). IncV3 remained the benchmark model, aligning with the approach by Thames et al. in Nutrition5k (95), though we used ImageNet for pretraining instead of the proprietary JFT-300M dataset. Pre-processed images were then encoded into fixed-size vector representations for downstream modeling.

7.2.6 Problem solving

Previous fixed-size vector representations were processed by a 2+2 multi-layer perceptron (MLP), where two fully connected layers were interleaved by a Rectified Linear Unit (ReLU) activation function. Specifically, four trainable functions were designed to predict mass, energy, the three macronutrients together, and the presence/absence of each of the 209 unique ingredients available in the training set (i.e., acting as a binary classifier on each of the ingredients).

7.2.7 Optimization of the loss function for feature extraction and problem solving

The loss function extends the one proposed in Nutrition5k by using the average of four components: the three single mean absolute errors (MAEs) for predicting mass, energy, and macronutrients (**Table 7.1**) and the ASymmetric Loss (ASL) function (195) (parameters empirically set to $\gamma_{\text{neg}}=5$ and $\gamma_{\text{pos}}=0$) for predicting ingredients. The MAE is defined as: $MAE = 1/N \sum_{i=1}^N |\hat{y}_i - y_i|$, where $\hat{y}_i$ and y_i

represent the predicted and the ground truth values, respectively. The ASL function addresses class imbalance in multi-label classification by down-weighting easy negatives and emphasizing hard positives and hard negatives, helping the model focus on informative, underrepresented examples rather than being biased by abundant negative labels. For each run, training followed the configuration in **Table 7.1** and the weights achieving the best performance on the validation set across all epochs were selected for calculating the predictions on the test set.

7.2.8 Performance metrics for problem solving

Consistent with our prior work (104), for each algorithm and run, performance on the regression tasks was assessed using three complementary metrics: the MAE, MAPE, and RMSE (see Chapter 6, section 6.2.7 for definition and further details). The MAPE was prioritized when comparing performance across different continuous variables, as it is scale-independent and facilitates interpretability (104). Performance on the multi-label classification task (i.e., ingredient recognition) was evaluated for each algorithm and run using the F1 score, defined as the harmonic mean of precision (or positive predictive value) and recall (or sensitivity):

$$F1 = 2 \times \frac{Precision \times Recall}{(Precision + Recall)}, \text{ with } Precision = \frac{TP}{TP + FP}, \text{ and } Recall = \frac{TP}{TP + FN},$$

with elements of the confusion matrix for each ingredient across dishes given by:

- TPs (True Positives): number of ingredients correctly predicted as present across dishes;
- FPs (False Positives): number of ingredients predicted as present but actually absent across dishes;
- TNs (True Negatives): number of ingredients correctly predicted as absent across dishes;
- FNs (False Negatives): number of ingredients predicted as absent but actually present across dishes.

Following the formula, the F1 score ranges from 0 to 1. It takes the value of 0 if either precision or recall is 0, and reaches its maximum value of 1 only when both precision and recall are equal to 1, thus rewarding models achieving both high recall and high precision simultaneously. The F1 score may also be indeterminate (e.g., Not a Number (NaN)) in three scenarios:

- both precision and recall are equal to 0,
- recall is indeterminate and precision is equal to 0,
- precision is indeterminate and recall is equal to 0,
- both precision and recall are equal to 0.

Of these, the first scenario was indicated as “Not a Number, but right prediction - NaN_R”, because an absent ingredient in the test set was correctly predicted to be “absent” by the specific algorithm in the specific dataset and frame filtering scenario. The remaining scenarios were indicated as “Not a Number, but wrong prediction - NaN_W” because the prediction was incorrect. Additional details on indeterminate F1 scores are outlined in **Figures D1-D2 (Appendix D)**. The F1 score is particularly appropriate for imbalanced datasets, as it considers the type of errors (i.e., FPs and FNs) rather than just the total number of incorrect predictions. This is especially relevant in applications like ours, where minority classes are often the most important to detect. In such cases, accuracy alone can be misleading, as it tends to favor the majority class.

7.2.9 Predicting mass, energy, and macronutrient content and classifying ingredients on available datasets

After standardizing file formats, column names, and frame folder structures, we applied the processing steps outlined in previous sections to each of the two ground truth datasets individually (US FCDB–correction, IT FCDB–correction). For each dataset, we generated dish-specific predictions for the five continuous variables (i.e., mass, energy, and macronutrients content) as well as ingredient-specific classifications (presence: yes vs. no) across all dishes in the test set, using the three DL algorithms: IncV3_2+2, R101_2+2, and ViT-B-16_2+2, where algorithm names were combined with the “2+2” structure (104). As for performance metrics, predictions and classification were averaged over the five available runs. This resulted in a total of 30 regression predictions per dish (5 continuous variables $\times$ 2 datasets $\times$ 3 algorithms), and 1045 ingredient classifications (209 unique ingredients $\times$ 2 datasets $\times$ 3 algorithms). Subsequent statistical analyses were conducted on both ground truth (indicated as observed from now onwards) and predicted values for all dishes ($n = 676$) and ingredients ($n = 209$) in the test set.

7.2.10 Statistical analysis

We explored the effect of automated frame filtering by summarizing, on the test set, the distributions of original, retained, and removed frames (in absolute value and as percentage) with the following statistics: minimum, 1st quartile, median, 3rd quartile, mean, standard deviation, and maximum values. We computed the same statistics for the dataset-specific distributions of the observed values, and predicted values of target variables (i.e., the continuous variables representing mass and nutritional profile and the categorical variables representing the ingredients) across all dishes in the

test set, before and after frame filtering. These statistics were also computed separately by algorithm and dataset for the predicted values.

Dish-specific (raw, absolute) differences between predicted and observed values of the variables were evaluated for both tasks (i.e., ingredient recognition and nutritional profile prediction) before and after frame filtering across datasets and algorithms. For the number of ingredients, we plotted the difference versus the observed number of ingredients. For the nutritional profile, we considered: (1) Bland–Altman plots and corresponding 95% limits of agreement; and (2) unweighted Cohen’s kappa statistics among quartile-based categories, to take into account the possibility of agreement occurring by chance (with rules in a recent article (172) as follows: 0.01–0.39 as none to slight, 0.40–0.59 as weak, 0.60–0.79 as moderate, 0.80–1.00 as strong to very strong agreement).

To identify top-performing algorithms for comparison with our benchmark (IncV3_2+2), we calculated the median metrics for each target variable across the available datasets before and after frame filtering. Specifically, we selected the algorithm with the best median MAPE for continuous variables and that with F1-score >0.8 for the categorical variables. Performance metrics after frame filtering were considered our reference for evaluating the best algorithm.

Furthermore, after frame filtering, we defined misclassified ingredients as those showing determinate F1 scores < 0.2 across all algorithms in at least one dataset; in addition, in presence of indeterminate F1 scores, we defined misclassified ingredients as those showing all NaN_W F1 scores across all algorithms in at least one dataset. Similarly, we defined mispredicted dishes across nutritional values and datasets as those that satisfied both the following conditions for all the three DL algorithms: (1) exceeded the limits of agreement in the Bland–Altman plots and (2) had the highest 5% of absolute differences (regardless of sign) between observed and predicted values. These dishes and ingredients were separately analyzed to provide an extra focus on nutritional or visual characteristics of dishes and ingredients.

To assess the effect of the automated frame filtering on prediction accuracy and performance, we calculated the percentage difference of single measures of accuracy and performance before and after frame filtering in the following way: $100 \times (\text{measure before frame filtering} - \text{measure after frame filtering}) / \text{measure before frame filtering}$. We applied this strategy to unweighted Cohen’s kappa, bias and limits of agreement from the Bland-Altman plots, and measures of performance including the MAPE and F1-score.

To evaluate whether integrating ingredient recognition improved nutrient predictions, we computed summary statistics and kernel density estimates of the paired differences between the performances in this application and those reported in Bianco et al. (104), stratified by algorithm, dataset, and

nutrient. Similarly, we compared the lists of mispredicted dishes across the current and previous publication (104). Analyses were limited to the three algorithms and two datasets featured here, and therefore previous analyses (104) were re-run for these specific settings. To facilitate cross-algorithm and cross-dataset comparisons while minimizing heterogeneity from frame filtering, we conducted these comparisons in the pre-filtering scenario.

Python (version 3.10) (174) was used for data structure management and prediction of target variables, the R statistical software (version 4.3.2) for the statistical analysis (112), with the corresponding packages (175,176,188,189,196).

Table 7.1. Prediction pipeline: available datasets, variables and tasks, and details on DL algorithms for feature extraction and problem solving

Bianco et al 2025 (104)		Current application
Available datasets		
Original Source files	<i>dish_metadata_cafe1.csv, dish_metadata_cafe2.csv, rgb_train_ids.txt, rgb_test_ids.txt</i>	Same as (104)
Final files used	US FCDB–no correction US FCDB–correction IT FCDB–no correction IT FCDB–correction	US FCDB–correction IT FCDB–correction
Variables and tasks		
Tasks	Regression tasks Prediction of mass, energy, and macronutrients (protein, fat, carbohydrates)	Regression tasks Prediction of mass, energy, and macronutrients (protein, fat, carbohydrates)
		Classification task Ingredient recognition
Final target variables	Mass Energy Macronutrients (protein, fat, carbohydrates)	Mass Energy Macronutrients (protein, fat, carbohydrates) 209 ingredients
Overall prediction pipeline		
Data splitting and preprocessing		
Training/test split	Same as Nutrition5k (96): <i>rgb_train_ids.txt</i> : n=4059, <i>rgb_test_ids.txt</i> : n=709; after exclusions due to lack of videos: n=3930 for training, n=676 for test sets	Same as (104)
Validation set	90% training, 10% validation within training set; k-repeated shuffled validation to reduce the impact of stochastic factors	Same as (104)
Frame sampling strategy	1st selection: 1 random frame every 5 for Training/Validation/Test set videos; 2nd selection: Training/Validation: 1 random frame for each dish at every iteration;	Same as (104)

	Test: all available frames used	
Frame preprocessing	Resize depending on the algorithm, central crop depending on the algorithm; scale [0,255] to MinMax [0,1] per channel; ImageNet mean/std normalization	Same as (104)
Frame filtering		
Type and extent	Manual on a subset of dishes of the test set	Automated on both training and test sets
Training settings		
Epoch	100 epochs per run	Same as (104)
Run	5	Same as (104)
Batch size	64 (ViT-B-16: 32 due to memory limits)	Same as (104)
Optimizer	Adam	Same as (104)
Learning rate	0.001	Same as (104)
Loss function details	Average MAE over 3 targets (mass, energy, and average of macronutrients)	sum of 3 MAEs targets (mass, energy, and average of macronutrients) and ASL, divided by 4
Feature extraction		
Architectures	IncV3, R101, R50, ViT-B-16, with benchmark algorithm: IncV3	IncV3, R101, ViT-B-16, with benchmark algorithm: IncV3
Pre-training dataset	ImageNet1K versus private JFT-300M used in Nutrition5k	Same as (104)
Freezing of backbone weights	ViT-B-16 only	Same as (104)
Feature vector size	2048 (ResNet, IncV3), 768 (ViT)	Same as (104)
Problem solving		
MLP details	“2+1”: 2 fully connected layers + 1 per task; “2+2”: 2 fully connected layers + 2 per task; interleaved by ReLU activations, inspired by the MLP architecture in Nutrition5k project	“2+2”: 2 fully connected layers + 2 per task, interleaved by ReLU activations, inspired by the MLP architecture in Nutrition5k project
Checkpointing strategy	Best weights on validation set across 100 epochs used for test predictions	
Performance metrics		
Type	MAE, MAPE, RMSE used for each algorithm and run	MAE, MAPE, RMSE used for each algorithm and run; F1 score

Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; MAE, mean absolute error; MAPE, mean absolute percentage error; MLP, multilayer perceptron; R101, Resnet101; R50, Resnet50; ReLU, Rectified Linear Unit; RMSE, root mean square error; ViT-B-16, Vision Transformer-B-16.

7.3 RESULTS

7.3.1 Datasets of images after automated frame filtering

Table 7.2 summarizes frame counts and percentages before/after automated filtering for training and test sets. The median percentage of removed frames per dish was equal to 26.5% (IQR: 16.7–38.9%) and 25.0% (IQR: 14.3–37.9%) in the training and test sets, respectively. This corresponded to 24 (IQR: 19–61) and 25 (IQR: 19–58) left frames per dish in the training and test sets, respectively,

versus the original 32 (IQR: 28–115) and 32 (IQR: 28–114). After accounting for two dishes (*dish_1550861074* and *dish_1567107049*) in the training set having all frames removed, the corresponding final number of dishes was 3928 in the training and 676 in the test set.

Table 7.2. Effect of automated frame filtering performed in both the training and test sets, as well as of manual frame filtering performed on the mispredicted dishes from the test set in Bianco et al., 2025 (104) for comparison: summary statistics of original, left and removed frames in absolute values or percentages

Dataset	Total frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames
<i>Training set (n = 3930)</i>	<i>N = 228514</i>	<i>N = 150967</i>	<i>N = 77547</i>		
Median	32	24	10	73.53	26.47
(IQR)	(28–115)	(19–61)	(5–23)	(61.11–83.33)	(16.67–38.89)
Mean (SD)	58 (128)	38 (31)	20 (116)	70.91 (18.25)	29.09 (18.25)
Min–Max	11–7475	0–521	0–7101	0.00–100.00	0.00–100.00
<i>Test set (n = 676)</i>	<i>N = 37597</i>	<i>N = 26109</i>	<i>N = 11488</i>		
Median	32	25	10	75.00	25.00
(IQR)	(28–114)	(19–58)	(5–21)	(62.07–85.71)	(14.29–37.93)
Mean (SD)	56 (51)	39 (32)	17 (25)	71.62 (18.20)	28.38 (18.20)
Min–Max	12–819	1–380	0–439	3.57–100.00	0.00–96.43
<i>Mispredicted dishes, test set from (104) (n = 68¹)</i>	<i>N = 4163</i>	<i>N = 1490</i>	<i>N = 2673</i>		
Median	32	12.5	23	39.00	61.00
(IQR)	(29–37)	(8.8–18.3)	(16–27)	(23.80–50.10)	(49.90–76.20)
Mean (SD)	61.2 (104.6)	21.9 (27.9)	39.3 (89.7)	38.9 (22.3)	61.1 (22.3)
Min–Max	24–819	1–127	0–692	0.00–100.00	0.00–96.90

¹The original number of mispredicted dishes from Bianco et al. (104) was 80; however, 12 dishes showed either mismatches between visible ingredients and the ingredients listed in the metadata or suffered from image quality problems in all frames, and were therefore removed, thus leaving a total of 68 mispredicted dishes from the test set. Abbreviations: n, number of dishes; N, number of frames.

7.3.2 Prediction accuracy of ingredients and nutritional values: descriptive statistics on observed and predicted values from the test set, before and after automated frame filtering

Based on the remaining frames on the test set, the observed dishes to be predicted had a median of 3 ingredients (IQR: 1–8); 38.3% were single-ingredient dishes, whereas 40.1% of dishes had 2–9 ingredients, and the 21.6% of dishes had 10–31 ingredients (**Table D1, Appendix D**). Median observed nutritional values generally differed between US and IT FCDBs, with the highest differences in absolute values for fats (12%) and carbohydrates (31%) content. Specifically, median observed values were: mass 142.0g for both US- and IT-FCDBs; energy 160.0 kcal (US-FCDB) vs 165.6 kcal (IT-FCDB); protein 8.5g (US-FCDB) and 7.9g (IT-FCDB); fat content 6.6g (US-FCDB)

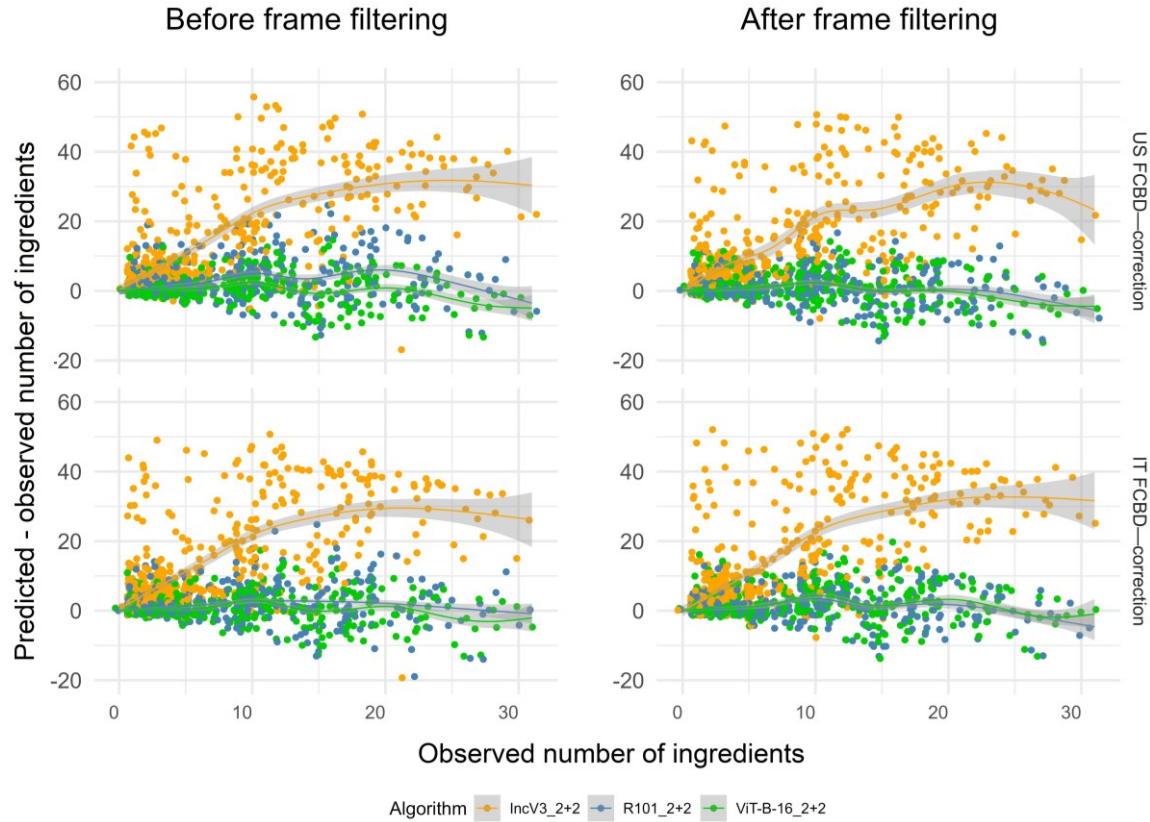
and 7.4g (IT-FCDB), and carbohydrates 13.0g (US-FCDB) and 9.0g (IT-FCDB) (**Table D2, Appendix D**).

Summary statistics of the number of predicted ingredients were reported in **Table D1**, and predicted nutritional values were reported in **Table D2**, both by dataset, algorithm, and before/after frame filtering. Before frame filtering, predictions were unbiased in median (i.e., number of observed ingredients was equal to number of predicted ingredients) across algorithms and datasets, except for IncV3_2+2, which showed an overestimate of 5 (median: 8, IQR: 2–24.25), or 6 ingredients (median: 9, IQR: 2–24) per dish in median. After frame filtering, the overestimate for IncV3_2+2 was slightly attenuated for IT-FCDB (4 median ingredients), but the potential shrinkage effect was unclear on the third quartile values across datasets and algorithm (**Table D1**).

Figure 7.1 displays the raw absolute difference between predicted and observed number of ingredients against the observed number of ingredients, before and after frame filtering and separately for IT-FCDB and US-FCDB. Before filtering, IncV3_2+2 showed a clear bias in both datasets (median absolute difference ~5 ingredients, versus 0 for the other models) and a pronounced nonlinear relationship with complexity: difference rose steeply from 0–10 observed ingredients (up to ~20), increased more gradually between 10–20 (up to ~25), and then reached a plateau beyond 20 (around ~30). After filtering, the trend was similar, but a more irregular nonlinearity was evident in the US-FCDB for 10–20 ingredients, and after 20 ingredients. For both datasets, before filtering, R101_2+2 and ViT-B-16_2+2 showed a similar trend: unbiased (i.e., around 0) between 0 and 10 ingredients, between 10 and 20 ingredients R101_2+2 overestimated in the order of 5 ingredients, while ViT-B-16_2+2 was still close to 0. After frame filtering, the R101_2+2 trajectory improved in accuracy getting differences closer to zero for 10 and 20 ingredients, especially for US-FCDB.

Figures D3-D7 (Appendix D) show the observed difference versus the observed values for each variable in the nutritional profile. Overall, the algorithms followed similar trajectories, remaining approximately unbiased (i.e., close to zero difference) up to the third quartile of observed values, and then leveling off in the region of underestimation beyond that point. Most underestimates were around 100g for mass, 200 kcal for energy, and 20g for all macronutrients content. These behaviors were consistent before and after frame filtering. Post-filtering, the algorithms diverged in the underestimation region, with R101_2+2 producing the most conservative underestimates.

Figure 7.1. Difference between predicted and observed number of ingredients per dish by dataset and algorithm, before and after frame filtering (n=676)



Abbreviations: IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Figures D8-D12 (Appendix D) show the Bland–Altman plots for each target variable, including 95% limits of agreement. These plots display the raw absolute difference between predicted and observed values on the test set against their mean, confirming the presence of heteroscedasticity (i.e., non-constant variance) for increasing mean values on the x-axis (104). Automated frame filtering had two main effects: (1) the mean difference (i.e., the bias) was closer to zero (median of percentage difference: -35.5% , IQR: -67.1 to -6.7%); and (2) limits of agreement became narrower (median of percentage difference: -3.8% , IQR: -7.0 to -1.8%). By algorithm, bias reductions were strongest for IncV3_2+2 (median: -65.4% , IQR: -83.7 to -48.6%) and R101_2+2 (median: -45.0% , IQR: -67.1 to -33.5%), while ViT-B-16_2+2 showed minimal change (median: -1.3% , IQR: -11.6 to 12.9%); limits of agreement width also decreased most for R101_2+2 (median: -7.0% , IQR: -8.6 to -6.5%), followed by IncV3_2+2 (median: -3.5% , IQR: -5.6 to -3.1%) and ViT-B-16_2+2 (median: -1.9% , IQR: -3.6 to -0.6%). By dataset, median bias reductions were -33.2% (IQR -72.9 to 2.7%) for US-FCDB and -46.1% (IQR -61.7 to -18.3%) for IT-FCDB, while the limits of agreement width decreased in median by -5.0% (IQR -7.4 to -2.9%) and -3.2% (IQR -5.5 to -1.2%) for US FCDB and IT FCDB, respectively, thus suggesting an improvement in the Bland–Altman plots for the IT-FCDB. After frame filtering, the median bias across datasets and algorithms was 0.5 g (IQR: -4.5 to

3.6g) for mass, −6.6 kcal (IQR: −11.7 to −2.7 kcal) for energy, −1.5g (IQR: −1.8 to −1.0g) for protein, −0.7g (IQR: −1.1 to −0.3g) for fat, −1.4 g (IQR: −2.0 to −1.3g) for carbohydrates. When comparing algorithms across datasets, the R101_2+2 provided the narrowest limits of agreement. When comparing datasets, limits of agreement were similar (US FCDB: 38.0, IQR: 31.4 to 204.0; IT FCDB: 37.1, IQR: 29.9 to 201.1).

Table D3 (Appendix D) reports unweighted Cohen’s kappa coefficients from cross-classification of dishes into quartiles of observed vs. predicted values, before and after frame filtering. Overall, the impact of filtering was minimal, with no change in kappa classification categories. Across datasets, algorithms, and nutrients, the median percentage difference was modest (0.74%, IQR −0.48 to 2.07%), indicating only slight improvements after filtering. Among algorithms, R101_2+2 achieved the largest gain (median 1.09%, IQR −0.27 to 2.05%), followed by IncV3_2+2 (0.70%, IQR −1.09 to 1.85%) and ViT-B-16_2+2 (0.14%, IQR −0.21 to 1.85%). By dataset, the improvement was slightly stronger for US-FCDB (median 1.15%, IQR 0.49–2.21%) than for IT-FCDB (−0.28%, IQR −2.04 to 1.53%). After filtering, kappa values indicated overall moderate agreement, highest for mass (0.72–0.78) and energy (0.71–0.77), intermediate for protein (0.62–0.73) and fat (0.63–0.74), and lowest for carbohydrates (0.44–0.69). Finally, R101_2+2 achieved the best agreement for mass, fat, and carbohydrates, while ViT-B-16_2+2 led for energy and protein.

7.3.3 *Performance metrics of ingredients detection and prediction of nutritional values, before and after automated frame filtering*

When evaluating performance for ingredients detection, the effect of frame filtering was modest. Indeed, the overall median of the percentage difference across datasets and algorithms was equal to 0 (IQR: −4.62 to 8.16%). In addition, when stratifying by dataset, the medians were still equal to 0 (IQR: −4.19 to 8.39% for the US FCDB–correction, and IQR: −4.76 to 7.69% for the IT FCDB–correction). When stratifying by algorithm, the median was equal to 0 (IQR: −4.41 to 8.32% for R101_2+2, and IQR: −4.85 to 3.53% for ViT-B16_2+2), but it was equal to 3.25% (IQR: −4.42 to 13.14%) for IncV3_2+2, thus suggesting frame filtering increased performances in median for IncV3_2+2. When stratifying by dataset and algorithm, the median effect around 3% was confirmed in both datasets for IncV3_2+2, although the quartiles suggested a stronger effect in the IT FCDB–correction (IQR: −6.95 to 10.24% for US FCDB–correction, and IQR: −1.04 to 16.83% for the IT FCDB–correction). For the remaining algorithms the median was still close to 0, except for R101_2+2 in the US FCDB–correction where the effect of frame filtering was stronger, and performance difference reached 1.65% (IQR: −2.32 to 14.35%) (**Table 7.3** as well as **Tables D4–D5** and **Figures**

D13–D14 for additional details on the single ingredients detected). After frame filtering, R101_2+2 and ViT-B-16_2+2 showed a better performance than IncV3_2+2. Specifically, in the US FCDB–correction dataset, the median F1 scores were around 0.61 vs. 0.37 of IncV3_2+2. Similarly, the number of ingredients with F1 score exceeding 0.8 was lower for IncV3_2+2 than for R101_2+2 and ViT-B-16_2+2: ~33 for both algorithms vs. 3 for IncV3_2+2. Accordingly, the number of ingredients with F1 score < 0.2 was lower for R101_2+2 and ViT-B-16_2+2 (12 and 8 ingredients, respectively, vs. 26 ingredients from IncV3_2+2); in addition, ViT-B-16_2+2 showed a lower number of ingredients with F1 < 0.2 compared to R101_2+2. Finally, the number of indeterminate F1 values linked to wrong predictions was lower for ViT-B-16_2+2 compared to R101_2+2 and especially to IncV3_2+2. Results were similar for IT FCDB–correction and US FCDB–correction datasets (**Table 7.4**).

Table 7.3. Distribution of percentage differences in F1-score (Δ F1-score) before and after frame filtering by algorithm and dataset

Dataset	Algorithm		
	<i>IncV3_2+2</i>	<i>R101_2+2</i>	<i>ViT-B-16_2+2</i>
<i>US FCDB—correction</i>			
Undeterminate F1			
“UP”, <i>n (%)</i>	8 (2.8)	6 (2.9)	5 (2.4)
“NO CHANGES”, <i>n (%)</i>	82 (39.3)	67 (31.9)	74 (35.4)
“DOWN”, <i>n (%)</i>	0	8 (3.8)	0
Determinate F1, <i>n (%)</i>	119 (56.9)	128 (61.4)	130 (62.2)
ΔF1 continuous			
<i>Median (IQR)</i>	3.11 (-6.95, 10.24)	1.65 (-2.32, 14.35)	0.00 (-4.50, 3.34)
<i>Min, Max</i>	-66.25, 320.00	-73.50, 150.00	-70.19, 153.85
<i>IT FCDB—correction</i>			
Undeterminate F1			
“UP”, <i>n (%)</i>	4 (2.0)	6 (2.9)	14 (6.7)
“NO CHANGES”, <i>n (%)</i>	82 (39.1)	70 (33.4)	64 (20.6)
“DOWN”, <i>n (%)</i>	7 (3.4)	7 (3.4)	4 (1.9)
Determinate F1, <i>n (%)</i>	116 (55.5)	126 (60.3)	127 (60.8)
ΔF1 continuous			
<i>Median (IQR)</i>	3.63 (-1.04, 16.83)	0.00 (-6.12, 4.90)	0.00 (-5.06, 3.69)
<i>Min, Max</i>	-77.01, 433.33	-40.00, 148.39	-58.62, 135.71

Abbreviations: IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

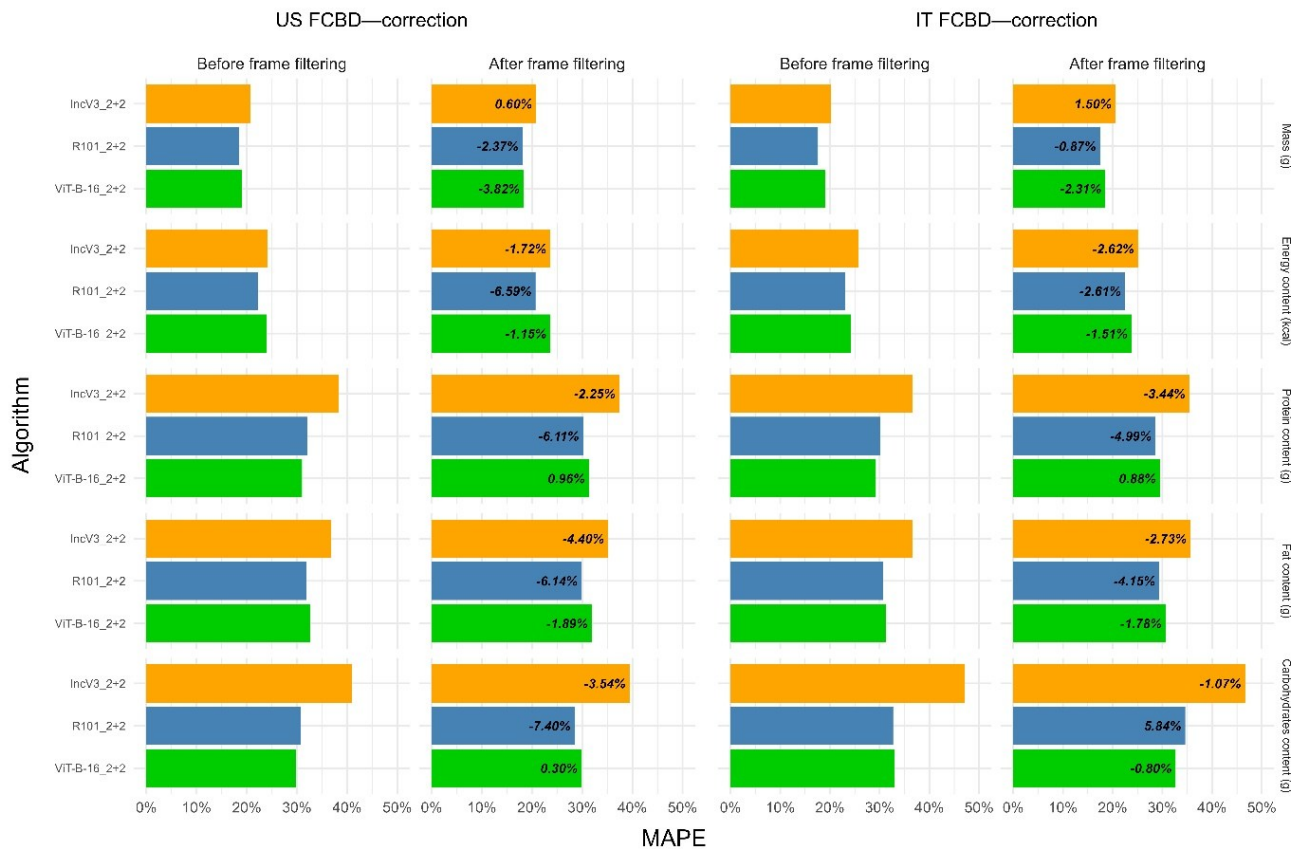
Table 7.4. Distribution of F1-score from ingredients prediction by algorithm and dataset, before and after frame filtering

Dataset	Algorithm					
	<i>IncV3_2+2</i>		<i>R101_2+2</i>		<i>ViT-B-16_2+2</i>	
	Before frame filtering	After frame filtering	Before frame filtering	After frame filtering	Before frame filtering	After frame filtering
US FCDB—correction						
Indeterminate F1 – right predictions, <i>n (%)</i>	36 (17.2)	39 (18.7)	38 (18.2)	36 (17.2)	37 (17.7)	38 (18.2)
Indeterminate F1 – wrong predictions, <i>n (%)</i>	54 (25.9)	46 (22.0)	38 (18.2)	40 (19.2)	42 (20.1)	37 (17.7)
Determinate F1, <i>n (%)</i>	119 (56.9)	124 (59.3)	133 (63.6)	133 (63.6)	130 (62.2)	134 (64.1)
F1 in categories						
<i>F1 < 0.2, n (%)</i>	30 (25.2)	26 (21.0)	12 (9.0)	12 (9.0)	6 (4.6)	8 (6.0)
<i>0.2 ≤ F1 ≤ 0.8, n (%)</i>	88 (74.0)	95 (76.6)	88 (66.2)	88 (66.2)	92 (70.8)	95 (70.9)
<i>F1 > 0.8, n (%)</i>	1 (0.8)	3 (2.4)	33 (24.8)	33 (24.8)	32 (24.6)	31 (23.1)
F1 continuous						
<i>Median</i>	0.34	0.37	0.58	0.61	0.63	0.63
<i>(IQR)</i>	(0.20, 0.48)	(0.24, 0.49)	(0.40, 0.80)	(0.40, 0.80)	(0.46, 0.80)	(0.43, 0.79)
<i>Min, Max</i>	0.05, 0.91	0.04, 0.49	0.10, 1.00	0.05, 1.00	0.09, 1.00	0.08, 1.00
IT FCDB—correction						
Indeterminate F1 – right predictions, <i>n (%)</i>	37 (17.7)	35 (16.8)	36 (17.2)	37 (17.7)	35 (16.8)	37 (17.7)
Indeterminate F1 – wrong predictions, <i>n (%)</i>	51 (24.4)	54 (25.8)	40 (19.2)	41 (19.6)	44 (21.0)	34 (16.3)
Determinate F1, <i>n (%)</i>	121 (57.9)	120 (57.4)	133 (63.6)	131 (62.7)	130 (62.2)	138 (66.0)
F1 in categories						
<i>F1 < 0.2, n (%)</i>	29 (24.0)	26 (21.7)	13 (9.8)	13 (9.9)	7 (5.3)	7 (8.0)
<i>0.2 ≤ F1 ≤ 0.8, n (%)</i>	89 (73.5)	91 (75.8)	87 (65.4)	85 (64.9)	90 (69.2)	95 (68.8)
<i>F1 > 0.8, n (%)</i>	3 (2.5)	3 (2.5)	33 (24.8)	33 (25.2)	33 (25.5)	32 (23.2)
F1 continuous						
<i>Median (IQR)</i>	0.35 (0.20, 0.46)	0.38 (0.22, 0.51)	0.60 (0.40, 0.80)	0.59 (0.41, 0.80)	0.66 (0.46, 0.82)	0.61 (0.42, 0.79)
<i>Min, Max</i>	0.06, 0.95	0.03, 0.91	0.09, 1.00	0.10, 1.00	0.13, 1.00	0.10, 1.00

Abbreviations: IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Figure 7.2 shows the median performance metrics assessed with the MAPE for each nutritional variable, algorithm, and dataset, before and after frame filtering, together with the percentage change (Δ MAPE) post-filtering. Filtering generally improved performance across datasets, nutritional values, and algorithms, although effects were modest overall: median Δ MAPE was -2.4% (IQR: -6.3% to -1.4%) for the US FCDB and -1.8% (IQR: -2.7% to -0.8%) for the IT FCDB, being more consistent for the US FCDB. After frame filtering, across datasets and algorithms MAPE values ranged from 17.5% to 20.8% for mass, from 20.7% to 25.1% for energy, from 28.6% to 37.4% for proteins, from 29.4% to 35.7% for fats, and from 28.5% to 46.6% for carbohydrates across all datasets and algorithms. In addition, R101_2+2 typically achieved the lowest median MAPE across nutritional values and datasets and also exhibited the largest error reduction attributable to filtering (**Figure 7.2** and **Table D6, Appendix D**).

Figure 7.2. Median performance metrics assessed with the MAPE for each nutritional variable, algorithm, and dataset, both before and after frame filtering, as well as the percentage increment (details on additional metrics provided in **Table D6** and **Figure D15**)



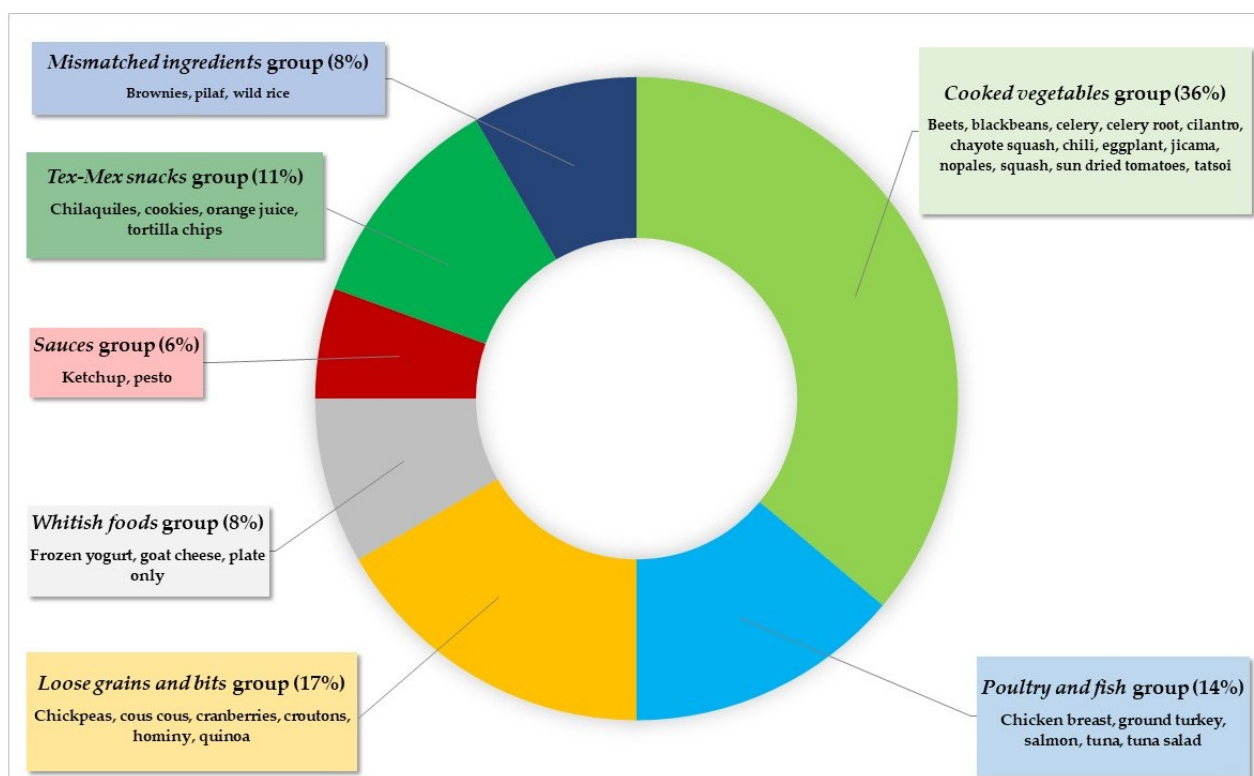
Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; MAPE, Mean Absolute Percentage Error; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

7.3.4 *Misclassified ingredients and mispredicted dishes after automated frame filtering*

After frame filtering, misclassified ingredients expressed as those showing in at least one dataset either: (1) F1 scores < 0.2 across all algorithms; or (2) NaN_W F1 scores across all algorithms, were extracted from **Tables D4-D5**. Specifically, 3 ingredients with determinate F1 (i.e., chili, cilantro, and quinoa) were consistently mispredicted across all datasets and algorithms. In addition, celery was identified to be misclassified in the US dataset and cranberries, eggplants, salmon, and squash in the Italian dataset. Except for celery, these ingredients showed low precisions, linked to a higher number of FPs, thus suggesting that all the selected algorithms tended to predict absent ingredients as present. IncV3_2+2 traded higher recall (more true positives) for lower precision, whereas R101_2+2 and ViT-B-16_2+2 exhibited similarly limited precision and recall. In addition, 28 ingredients were misclassified due to 3 NaN_W in at least one dataset, of which 22 were shared across US and IT FCDBs, 3 derived from the US FCDB-correction dataset and another 3 derived from the IT FCDB-correction dataset. **Figure 7.3** shows classes of misclassified ingredients by similarity in ingredient content and visual characteristics of the ingredients:

- *Cooked vegetables* group (36%): Mainly cooked vegetables, visually ambiguous due to being finely chopped, cooked, and often mixed with other ingredients, making them hard to identify individually;
- *Poultry and fish* group (14%): Cooked poultry and fish pieces, with or without skin, often fragmented and visually unclear in terms of cut;
- *Loose grains and bits* group (17%): Ingredients in grain form (e.g., cereals) or very small discrete units (e.g., croutons), typically dispersed over the dish and not constituting a clearly defined portion;
- *Whitish foods* group (8%): Pale or whitish foods that often blend into the background of the plate, reducing visual contrast;
- *Sauces* group (6%): Sauces and dressings that disperse and mix with other foods, lacking a clear portion boundary;
- *Tex-Mex snacks* group (11%): Sweet and savory items suitable for snacks or breakfast, with features blending Mexican- and U.S.-inspired characteristics;
- *Mismatched ingredients* group (8%): Ingredients whose label does not match the actual image, where the labeled ingredient appears together with other, unmentioned components.

Figure 7.3. Frequency distribution of misclassified ingredients by groups based on similarity in ingredient content and visual characteristics of the ingredients



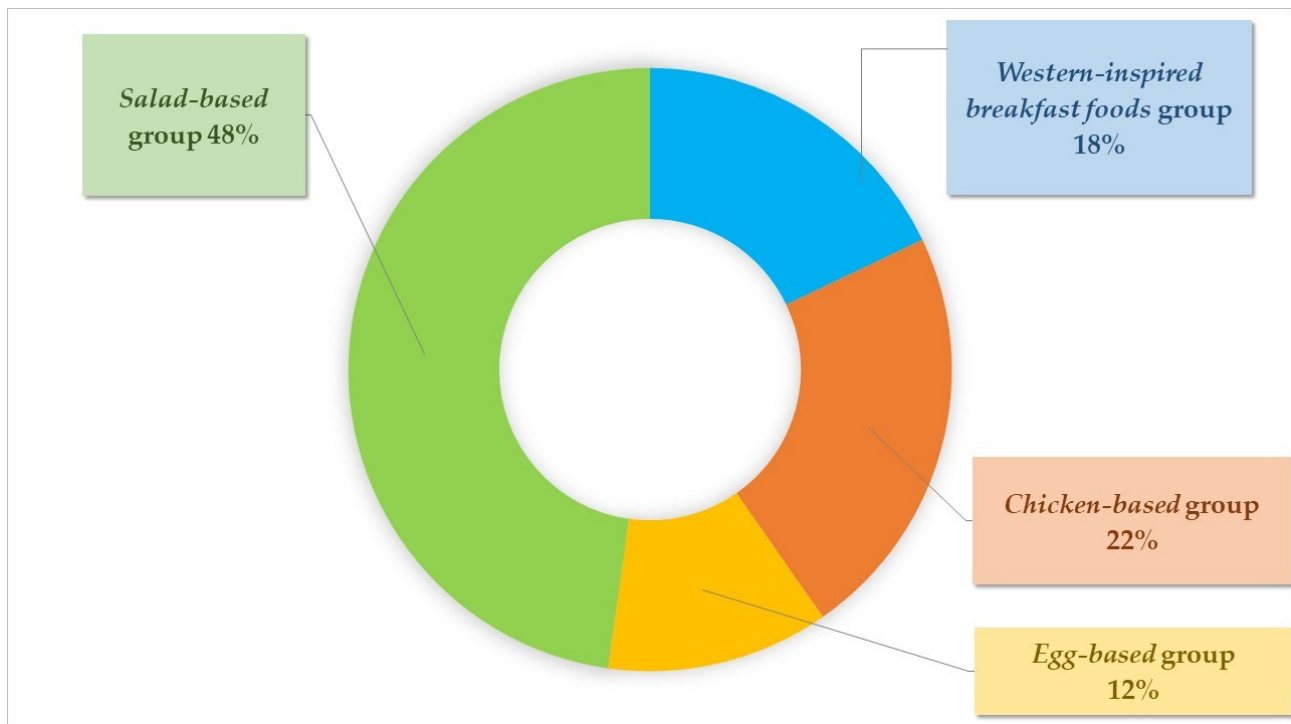
Similarly, after frame filtering, we identified 67 mispredicted dishes across nutritional values and datasets as those satisfying the following conditions for all the three DL algorithms: (1) exceeded the limits of agreement in the Bland–Altman plots and (2) had the highest 5% of absolute differences (regardless of sign) between observed and predicted values. Of them, 52 were in common with the post-filtering list of mispredicted dishes introduced in Bianco et al. (104). Given the very good overlapping between the two sets, we kept the same classes of mispredicted dishes by similarity in ingredient content (**Figure 7.4** and **Table D7, Appendix D**) introduced in Bianco et al. (104):

- *Salad-based* group (48%): Complex dishes, with at least two vegetables (e.g., raw and/or cooked), two protein sources (e.g., fish and/or meat), two cereal types, herbs, and dressings (median number of ingredients per dish: 15, IQR: 10.75–19);
- *Chicken-based* group (22%): Dishes primarily composed of chicken (grilled, breaded, or sliced in a cold salad), simpler in composition, but sometimes visually ambiguous (median number of ingredients per dish: 4, IQR: 2.5–5.5);
- *Eggs-based* group (12%): Dishes featuring mainly scrambled eggs or boiled egg whites, with few ingredients, but often showing partial occlusion (median number of ingredients per dish: 5, IQR: 3.5–6.25);

- *Western-inspired breakfast foods* group (18%): Hybrid category featuring dishes with a limited number of ingredients, blending elements of both sweet (e.g., fruit, almonds, or brownies) and savory (e.g., potatoes, sausages, or cheese) breakfasts without a single dominant component (median number of ingredients per dish: 1, IQR: 1–3).

Differently from Bianco et al. (104), the *Corrected-portion-size* group (5%) was not identified anymore as it originally included dishes with poor prediction performance in the uncorrected datasets only (104), but, in the current publication, we referred to corrected datasets only (**Table D7**). In addition, two groups, *Salad-based* and *Western-inspired breakfast foods* groups, showed an increasing sharing of 4 and 5%, respectively, vs. the remaining groups, which showed slightly decreasing sharing percentages (**Figure 7.4**). The corresponding medians and IQR were similar for all the groups except for the *Western-inspired breakfast foods* (median of 1 ingredient vs. the original 2 in Bianco et al. (104)), suggesting the strengthen of 1-ingredient dishes in this class.

Figure 7.4. Frequency distribution of incorrectly predicted dishes by groups based on similarity in ingredient content



Of the 15 dishes highlighted as mispredicted in the current publication only, 5 (*dish_1558630325*, *dish_1558720236*, *dish_1562703447*, *dish_1563389626*, and *dish_1566838351*) had been previously identified in Bianco et al (104) as having various image quality issues in all frames including, but not limited to, blurriness and cropping. Another additional 5 dishes had been previously identified in

Bianco et al (104) as having mismatches between visible ingredients and the (lower number of) ingredients listed in the metadata, mostly leading to overestimated predictions (*dish_1563566909*, *dish_1566501575*, *dish_1566501594*, *dish_1563566939*, and *dish_1563566965*). On the other hand, while correctly predicted in Bianco et al (104), the last 5 currently incorrectly predicted dishes (*dish_1563551194*, *dish_1563898084*, *dish_1566316757*, *dish_1566849987*, and *dish_1568146942*) showed underestimates for mass, energy, and most nutritional values, likely due to cropping, occlusion, and whitish colors; overestimates were however identified for fats in particular for *dish_1568146942* (median predicted values across datasets and algorithms given by 23.4g vs. median observed values across datasets of 9.3g), likely due to the similar appearance with Caesar dressing ingredient. Additional details on prediction of ingredients and nutritional values for the last group are provided in **Table D8, Appendix D**.

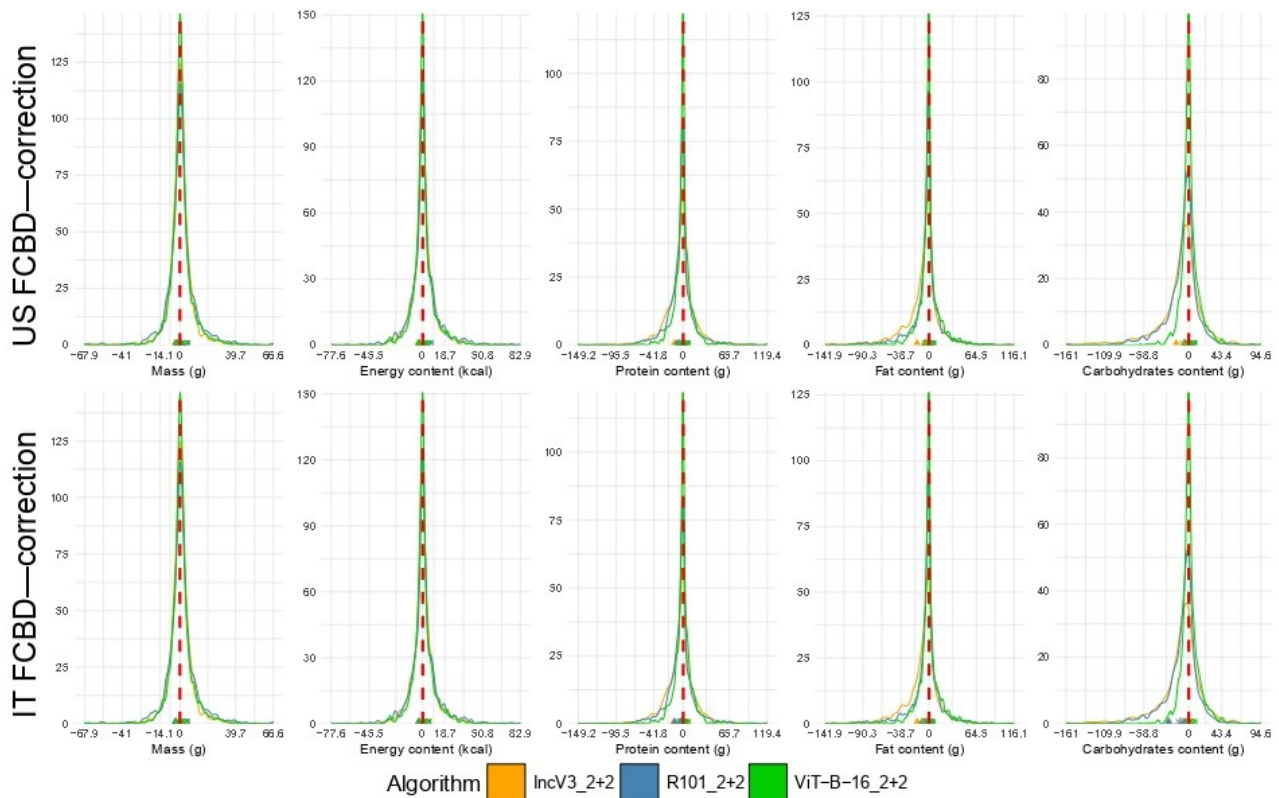
7.3.5 *Prediction performances, and mispredicted dishes before frame filtering: a comparison with Bianco et al 2025*

Figure 7.5 and **Figures D16-D18** shows kernel densities estimation plots of the raw absolute differences in prediction errors (MAPE, %) between the current application and Bianco et al. (104). Detailed information on median values and IQRs of the difference distribution for mass, energy and the macronutrients content are provided in **Table D9, Appendix D**. Overall, the five distributions were centered around zero, although densities privileged negative values, especially for the three macronutrients. This suggested that the current application provided slightly better prediction performances across nutrients, compared to Bianco et al (104) (**Figure D16**). This pattern was confirmed across datasets: while energy and mass remained symmetric with respect to zero, the three macronutrients showed negative median values and distributions slightly skewed toward negative differences, indicating lower MAPEs in the current application than in Bianco et al (104). The effect was more pronounced in the Italian dataset, particularly for carbohydrates, suggesting a slightly greater improvement in macronutrient prediction (**Figure D17**). Distributions for mass and energy were also symmetric and comparable across algorithms. For macronutrients, both IncV3_2+2 and R101_2+2 showed a consistent shift toward negative values, with broader distributions suggesting improved but more variable prediction performance in the current application. By contrast, ViT-B-16_2+2 displayed more symmetric and narrower distributions (**Figure D18**). Finally, the overall pattern was confirmed when the analysis was conducted by combining dataset and algorithm. For macronutrients, both IncV3_2+2 and R101_2+2 confirmed the tendency toward negative median values in both datasets, with the effect more pronounced in the Italian FCDB–correction dataset. In

contrast, ViT-B-16_2+2 exhibited smaller differences across datasets, with nearly symmetric distributions and narrower interquartile ranges for all nutrients (**Figure 7.5**).

Integrating ingredient recognition with prediction of nutritional values had a modest impact on the number of mispredicted dishes. Specifically, before frame filtering, the number of 71 mispredicted dishes identified in Bianco et al (104) became 73 in the current application. Sixty-five mispredicted were shared between the two analyses, of which 9 were suffering either from image quality issues or label mismatches. In addition, six dishes (*dish_1560203424*, *dish_1563984140*, *dish_1565894910*, *dish_1566246513*, *dish_1566316681*, and *dish_1566328724*) which used to be mispredicted in the re-run of Bianco et al (104) were well predicted in the current application. Briefly, across dishes, whitish items (e.g., chicken, egg whites) and very dark items (e.g., brownies, cookies) reduced discriminative visual features, hindering nutrient estimation. In one case, an improper incremental scan introduced a temporal mismatch (the “egg whites” were added while recording), degrading frame consistency. In another, pervasive occlusion concealed key components; without explicit volume cues, this impaired both mass inference and downstream nutrient estimates.

Figure 7.5. Kernel density estimation plots of the raw absolute difference in prediction errors (MAPE, %) between the current application and Bianco et al (104), stratified by algorithm and dataset before frame filtering



Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

7.4 DISCUSSION

This paper evaluates whether incorporating explicit ingredient recognition into an image-based pipeline improves prediction of energy, mass, and macronutrient content. Although modest, improvements in algorithm performance were present. Secondary objectives were to: (1) quantify the impact of automated frame filtering; (2) identify the best-performing algorithm; and (3) characterize misclassified ingredients and mispredicted dishes. While the effect of automated frame filtering was modest, we confirmed that IncV3_2+2 was outperformed by R101_2+2 and ViT-B-16_2+2 in several respects. While ViT-B-16_2+2 outperformed R101_2+2 in ingredient recognition, and R101_2+2 outperformed ViT-B-16_2+2 in nutrient content prediction, our preference was for ViT-B-16_2+2, given its more consistent behavior for increasing number of ingredients. Misclassified ingredients and mispredicted dishes largely suffered from cropping, occlusion, and visual ambiguity, and mismatches between visible and labeled items, all of which limited accurate ingredient detection and, consequently, reliable nutrient estimation.

Automated frame filtering was applied to both training and test sets using GroundingDINO, which pairs pre-selected, concatenated natural-language prompts with 2D frames and excludes images with multiple/no plates or extraneous elements (e.g., hands, feet). The results of automated frame filtering were modest, although in the expected direction (i.e., (1) improved prediction accuracy and precision, (2) improved performances, and (3) reduced number of misclassified ingredients and mispredicted dishes). Specifically, differences were smaller than 10%, and more pronounced for the Italian dataset and the worst algorithm (IncV3_2+2). The lack of full control on image selection suggested however to adopt a more conservative approach than in Bianco et al (104): this ended up into 25% removed frames versus 61% in Bianco et al (104). We also carefully chose the prompts to manage only trivially affected frames (e.g., presence of hands/feet, chairs, floor, etc.). Cropping and occlusion have not been tackled by GroundingDINO due to the risk of discarding too many acceptable frames. On the other hand, it is reassuring that a clear improvement was observed in the weakest-performing algorithm.

In the choice of the best-performing algorithm, R101_2+2 and ViT-B-16_2+2 clearly outperform IncV3_2+2 (our benchmark algorithm) in both ingredients classification and nutritional values prediction, in line with previous evidence emerged in Bianco et al (104). In addition, while R101_2+2 and ViT-B-16_2+2 showed mostly aligned performances, ViT-B-16_2+2 exhibited a lower number of ingredients with either indeterminate or negligible F1 scores. On the other end, R101_2+2 appeared to achieve the lowest median MAPE across nutritional values and datasets, although differences with ViT-B-16_2+2 were at most in the order of 3%. A plausible explanation is related to architectural

inductive characteristics: the convolutional model (R101_2+2) may better exploit local, texture- and intensity-based cues that correlate with continuous nutrient estimates, whereas the transformer (ViT-B-16_2+2), with stronger global context modeling, is comparatively more effective at ingredient classification (fewer items with $F1 < 0.2$).

After frame filtering, we identified 67 mispredicted dishes across nutritional values and datasets. Of them, 52 were in common with the post-filtering list of mispredicted dishes introduced in Bianco et al (104), and 15 dishes were mispredicted in the current publication only. However, 10 of these 15 had already been flagged as problematic in Bianco et al (104), although they were not classified as mispredicted. These 10 dishes suffered from either: (1) occlusion and cropping in all frames, thus showing underestimated nutritional values as GroundingDINO did not tackle these issues; (2) mismatches between visible and reported ingredients, thus showing overestimated nutritional values, because the images contained more ingredients than those specified in the dish label. In addition, a few of the remaining 5 currently mispredicted dishes (not previously identified in Bianco et al (104)) may provide insights into the relationship between ingredient recognition and nutritional values prediction and were discussed later. In the *dish_1568146942* (including chicken and mixed greens), fats were overestimated in the order of 138.8%. Not surprisingly, among FP ingredients, the *Caesar dressing* and olive oil were identified (both by IncV3_2+2). Similarly, the 185.8% overestimate of carbohydrates (corresponding to median 6.6g predicted vs median 2.5g observed) can be traced back by considering all the vegetable sources cross-classified as FPs. In addition, for *dish_1563551194*, the models missed 4 out of 8 ingredients, effectively reducing the predicted composition to sweet potato and oil. This led to consistent underestimation of mass (−32.2%) and nutrients: −28.7% energy, −15.4% protein (largely due to the unrecognized Greek yogurt and egg whites), −31.9% fat (largely due to the unrecognized chia seeds), and −38.4% carbohydrates (largely due to the unrecognized bagel). Notably, all unrecognized ingredients share a pale or whitish appearance, which likely contributed to their misclassification. Although *dish_1566316757* and *dish_1563551194* share a similar core composition (sweet potato, olive oil, egg whites), their results differed: *dish_1566316757* correctly retrieved all 4 ground-truth ingredients but added 7 spurious ones, while *dish_1563551194* missed several true ingredients and produced 45 FPs. Despite its better ingredient recognition, *dish_1566316757* showed a larger protein underestimation (−19.6%). Two mechanisms may explain this bias: (1) a high FP rate can distort totals, either offsetting or amplifying underestimation depending on the nutrient profiles of the spurious items (as observed in *dish_1563551194*); (2) even with fewer FPs, incomplete detection of key protein sources (e.g., egg whites), compounded by the absence of depth/volume cues in 2D imagery, propagates into larger nutrient (e.g., protein) bias. Similarly, misclassified ingredients were mostly affected by: (1) whitish, low-contrast appearances

that blended into the plate background; (2) fine chopping/cooking and mixing with other items; (3) fragmented poultry/fish pieces with ambiguous cuts (with/without skin); (4) loose grains or very small discrete units dispersed across the dish, preventing portion-like regions; (5) sauces/dressings that occluded boundaries and altered surface texture; (6) hybrid snack items with overlapping visual cues across different ingredients; and (7) label–image mismatches, where the ground-truth label omitted co-present ingredients. These examples illustrate that both excessive noise and incomplete detection can bias results in opposite directions. In conclusion, there might be a trade-off between ingredient precision/recall and downstream nutrient accuracy: noisy recognition may mask deficits, whereas precise but incomplete recognition can still yield substantial nutrient error when quantity information or volume is weak.

More generally, we acknowledge that integrating ingredient recognition to nutritional values prediction yielded a modest effect on performance metrics and the list of mispredicted dishes, in the before frame filtering comparison. This is in line with recent studies showing that integrating ingredient- or segmentation-based information can enhance nutrient prediction, although the extent of improvement was generally modest and largely depends on dataset quality, label consistency, and visual complexity. For instance, Zhao et al (197) reported performance gains in the order of at most 4% after integrating segmentation features. Similarly, integrating ingredient features into different layers (198) improved performance at most by 10%. Additionally in our case, although modest, improvements in performance metrics were more evident for macronutrients than for mass and energy, especially when comparing IncV3_2+2 and R101_2+2 against ViT-B-16_2+2, and when using the Italian FCDB–corrected dataset. This similarly happened in Zhao et al (197), where differences in percentage across investigated scenarios ranged from 2.84% to 3.34% for energy and mass, and from 4.43% to 7.09% for protein, fat, and carbohydrates. Possible mechanisms behind the improved performance after ingredient recognition include: (1) Improved semantic grounding of the plate content: explicit ingredient recognition provides a more faithful representation of the dish, thereby reducing classification ambiguity (e.g., differentiating plain potato from sweet potato paired with cream cheese); (2) Reduced propagation of error: explicit ingredients recognition reduces the likelihood of mis-recognized or missing key ingredients, thereby reducing error accumulation; (3) Improved handling of mixed or complex dishes: explicit ingredients recognition allows the model to detect minor yet nutritionally significant components, which purely dish-classification models often omit, and thereby improving prediction of nutritional values; (4) Improved generalization: explicit ingredient identification reduces vulnerability to unexpected combinations or recipe variations, preventing large errors in macronutrient estimates by detecting additional components; and (5) Reduced reliance on portion/volume heuristics: explicit ingredient identification allows the model to

allocate nutrients at the ingredient level and then adjust by estimated size/volume, yielding more robust totals and reducing dependence on error-prone visual cues. Finally, in our comparison, ViT-B-16_2+2 exhibited smaller differences across datasets, with nearly symmetric distributions and narrower interquartile ranges for all nutrients. This further supports previous findings on the consistence of behavior of ViT-B-16_2+2 across scenarios.

To further provide insights into the relationship between ingredient recognition and nutritional values prediction, we could investigate the role of ingredient recognition in the six dishes which used to be mispredicted in the re-run of Bianco et al (104) and were well predicted in the current application. We hypothesize that, in all these cases, integrating the ingredient recognition task with the prediction of the full nutritional profile can help disentangle visual issues and improve the nutritional accuracy of predictions. This is true because all of these dishes exhibited whitish (e.g., chicken and egg whites) or blackish (e.g., brownies and cookies) ingredients, a limited number of ingredients. Additional issues include occlusion, thus limiting the ability to capture appropriate mass and nutritional values in the absence of volume estimation. As a matter of example, *dish_1566316681* improved its prediction of mass and protein content in the current application. Specifically, this dish, labeled sweet potato and olive oil, contained occasional visual contamination from egg whites in about 33% of the frames. In the model predicting nutrients directly from images (without ingredient recognition), this visual cue likely misled the network toward protein-rich patterns, yielding a large overestimation of protein content (median 15 g vs. 1.4 g ground truth). When ingredient recognition was integrated, the network could instead rely on the explicit identification of the correct components (sweet potato and olive oil), and down-weight the spurious egg white signal, reducing the predicted mass and protein content to a more realistic value (median 3.4 g). This similarly happened with mass (median 243g from Bianco et al (104) vs. median 128 from the current application vs. 122 g ground truth).

An additional analysis examines prediction accuracy and precision in terms of the number of observed ingredients. IncV3_2+2 systematically overestimated counts (median $\sim +5$ ingredients) with a non-linear error profile: the slope was steep up to ~ 10 ingredients (difference $\sim +20$ at 10), then flattened, reaching a plateau beyond ~ 20 . On the other hand, the other algorithms were median-unbiased, with ViT-B-16_2+2 the most accurate and stable across the full range, datasets, and filtering procedures. The overestimate effect detected by IncV3_2+2 is amplified by the Nutrition5k test set (96) including 38.3% dishes with 1 observed ingredient and 3 ingredients per dish in median. For those dishes, the error is 5 times higher with 1 observed ingredient, going down to twice for 5 observed ingredients. This is also evident when looking at the number of FPs produced by IncV3_2+2 in the misclassified ingredients showing determinate F1 scores < 0.2 . Furthermore, in our data, the discrepancy between observed and predicted counts depend on the number of ingredients in a non-linear pattern. This non-

linear discrepancy aligns with prior evidence (199,200) that recognition degrades disproportionately as scenes include more, smaller, occluded, or mixed components, increasing multi-label FP/FN rates. Comparatively, the stability of the estimates over the entire range of observed ingredients for ViT-B-16_2+2 provide additionally support for choosing this algorithm compared to R101_2+2.

The current application has several strengths and limitations, besides those previously described in (103,104). First, we acknowledge that this analysis builds on results from previous work (104), and can tackle research questions within a more simplified context including only datasets with corrected annotations and a few selected algorithms. In addition, we critically explored Grounding DINO for automated frame-filtering in food image-based nutrient-prediction pipelines, in the attempt to extend the previously performed manual frame filtering (104). While related work has employed it for object-based filtering and frame-selection in large-scale generic image/video pipelines (201,202), or for food-item detection and annotation (203), our approach first extends its use to selectively exclude frames with poor visual quality or irrelevant content. Finally, our multidisciplinary team still integrates nutritional evaluation of ingredients and dishes within a standard ML pipeline to investigate shared characteristics of mispredicted dishes and misclassified ingredients, and to deepen our understanding of the relationship between ingredient recognition and nutritional value prediction. Among limitations, we acknowledge that we did not fully understand the mechanisms behind the relationship between ingredient recognition and nutritional values prediction: all the algorithms allowed to jointly predict these tasks, thus providing interconnection between regression and classification tasks. The propagation of errors should be therefore limited during prediction. Other potential mechanisms earlier discussed may be relevant, although their applicability to our setting is uncertain. As an initial step, we examined dishes that were mispredicted in Bianco et al (104) but correctly predicted in the current application; this is only one of several viable approaches to assess this point. Second, differences in median observed values between US and IT FCDBs, especially for fats and carbohydrates necessitated conducting separate analyses for the two datasets, thereby increasing the complexity of result reporting. In the context of developing a DL-based dietary assessment tool, this detailed information nevertheless provides a valuable national benchmark for future analyses. Third, analyses of mispredicted dishes indicate that a non-negligible fraction of test set images exhibits mismatches between ingredient labels and observed ingredients, as well as visual issues affecting ingredient recognition (e.g., lighting variability, color ambiguity, cropping, and occlusion). This observation aligns with known methodological issues in Nutrition5k’s data creation pipeline (95,103,104): when automation is used for label assignment and image acquisition, post-hoc quality checks are essential to verify label–image consistency, ensure camera synchronization, and validate portion sizes. Building on these lessons, we created a pilot dataset of Italian composite

recipes, with complete ingredient and nutritional annotation and synchronized RGB-Depth videos, which prioritizes rigorous quality assessment (e.g., cross-checks of ingredient labels against frame content, automated sync diagnostics, and standardized portion verification). Although smaller and still being expanded, it offers safer annotations and imaging, thereby reducing label noise and acquisition artifacts that can confound ingredient recognition and downstream nutrient prediction.

7.5 CONCLUSION

In conclusion, integrating ingredient recognition into the nutrient-prediction pipeline confirms that R101_2+2 and ViT-B-16_2+2 outperform the IncV3_2+2 benchmark; among them, ViT-B-16_2+2 shows the most consistent performance as the number of ingredients increases across datasets and frame filtering scenarios. Analysis of mispredicted dishes further reveals visual artefacts (especially cropping and occlusion) that likely constrain recognition, motivating the addition of volume estimation and standardized portion sizing to inform both ingredient recognition and nutrient prediction. This may help in better understanding the mechanisms behind a fruitful interconnection between ingredient recognition, prediction of nutritional values, and volume estimation.

8. STANDARDIZED MULTIMODAL DATASET OF ITALIAN DISHES: FROM KITCHEN PREPARATION TO RGB-DEPTH IMAGING FOR DIETARY ASSESSMENT

8.1 RATIONALE AND AIM

As part of WP7 (Objective 3) of the INDACO Study, this work focuses on developing a pilot dataset to support the validation of deep learning models for food recognition and nutrient estimation within the Italian context. Specifically, we created a standardized multimodal dataset of approximately 50 traditional and complex Italian dishes, combining RGB and depth imaging with detailed recipe, ingredient, portion, and nutrient annotations based on the BDA database. This work is intended to serve as an external validation set for assessing model performance on Italian specific foods and to provide high-quality reference data for future image-based dietary assessment research in Italy.

8.2 MATERIALS AND METHODS

8.2.1 *Recipe compilation and nutritional annotation*

Composite Italian recipes were selected and prepared under standardized conditions. For each recipe, three portion sizes (i.e., small, medium, large) were created. The average portion size was anchored to the recipe's main ingredient, applying LARN quantitative standards (18) whenever possible; the remaining ingredients were then scaled according to the recipe's proportions (e.g., for the pasta with tomato sauce, pasta was the main ingredient and was fixed at 80g according to LARN, with the sauce and dressing components adjusted proportionally).

However, for composite recipes with multiple co-primary components (e.g., more than one protein source such as ham and cheese, several vegetables, or concurrent carbohydrate sources such as potatoes and bread), LARN single-item standards were not directly applicable. In these cases, we preserved the recipe's internal ratios and derived per-serving amounts from the stated yield (e.g., dividing quantities by four when the recipe served four), taking also into account the dish's role within the meal (e.g., a nutritionally substantial one-dish main may warrant portions exceeding LARN single-item values). Where needed, quantities were refined using dietetic judgement to reflect typical consumption. In addition, we defined portion-size variants as follows: small portions were defined as one third below the average portion; large portions were defined as one third above the average, with all ingredients scaled proportionally.

Each dish was documented with an Excel-based record including dish ID and names, ingredient ID and names, raw and cooked weights (grams), yield factors, and calculated energy (kcal) as well as macro- and micronutrient contents expressed in grams, milligrams, or micrograms, according to the Italian Food Composition Database (BDA) (41). Nutritional values were computed per-portion and per-ingredient for each size variant (**Figure 8.1**).

8.2.2 *Image acquisition protocol*

To ensure visual consistency and replicability, each plated dish was scanned using a custom robotic setup assembled in the LABAS facility (University of Udine). In line with the Nutrition5k protocol (95), we used the same camera model (i.e., Intel RealSense D435i) mounted on a fixed-90°-support placed above a 360° motorized turntable (**Figures E1–E2, Appendix E**). The RGB stream was recorded at 1920×1080 for approximately 8 seconds, and overhead depth data were captured with depth units of 1e-4. The camera–plane distance was ~36 cm, measured from the lens to the capture plane (95).

The turntable was a commercially available, pre-automated unit. The robotic arm motion was programmed in-house using Arduino (204). Pressing the activation button triggered the movement of the arm: the camera, set at 90° relative to the plate, performed a single 8-second sweep along the y-axis, following an arc from 30° to 150°. The 30°–150° span was chosen (instead of 0°–180°) to avoid near-frontal viewpoints with limited lateral information and, in some cases, frames that excluded the dish. A second button signal ended the sequence and returned the arm to 90° relative to the plate.

Data collection was operator-assisted: one nutritionist managed start/stop triggers and timing, while a second nutritionist handled acquisition on the workstation using Depth Quality Tool for Intel RealSense Cameras and Intel RealSense Viewer (205). For each sample, we recorded an 8-second RGB video and acquired top-down RGB and depth images.

8.2.3 *Statistical analyses*

After assigning total nutritional composition (i.e., 86 nutritional components) to each ingredient according to the Italian FCDB (BDA) (41), we computed the following summary statistics to describe the Italian pilot dataset at the dish and ingredient levels: minimum, 1st quartile, median, 3rd quartile, mean, standard deviation, and maximum. For comparability with the Nutrition5k project (95), statistics were reported for mass (g), total energy (kcal), and macronutrient content (grams of protein, fat, and carbohydrates).

In addition, frequency distributions and corresponding percentages were calculated for the total number of ingredients, ingredient frequency of use, and total ingredient mass across all recipes and portion sizes. To visualize differences between the most frequently used ingredients and those contributing the greatest total mass, ingredients were ranked separately by occurrence and cumulative weight. Data were processed and summarized R statistical software (version 4.3.2) for the statistical analysis (112), with the corresponding package (188).

Figure 8.1. Workflow of the calculation of portion weights¹ and nutritional values² for standardized dish sizes (i.e., small, medium and large) within a given recipe**A**

Recipe	Ingredients	Raw ingredient weight (weighed)	Total raw ingredients (sum)	Total cooked recipe weight (weighed)	YF	Cooked portion (S) weighed	Cooked portion (M) weighed	Cooked portion (L) weighed	Raw portion (S) (calculated)	Raw ingredients per portion (S)	Raw portion (M) (calculated)	Raw ingredients per portion (M)	Raw portion (L) (calculated)	Raw ingredients per portion (L)
Spaghetti with tomato sauce	Pasta, white, dried, raw	240.0								60.13		79.72		100.14
	Tomatoes, canned, whole contents	313.9								78.65		104.27		130.98
	Vegetable oil, olive, extravirgin	21.8	583.7	977.8	1.68	245.0	324.8	408.0	146.25	5.46	193.89	7.24	243.56	9.10
	Salt	3.0								0.75		1.00		1.25
	Basil, fresh	5.0								1.25		1.66		2.09

B

Dish ID	Dish name	Ingredient ID	Ingredient name	Ingredient mass	Nutritional values for 100g of ingredient				Nutritional values for ingredient portion				Total mass of the dish	Total nutritional values of the dish			
					Energy kcal	Protein g	Fat g	Carbohydrates g	Energy kcal	Protein g	Fat g	Carbohydrates g		Energy kcal	Protein g	Fat g	Carbohydrates g
dish_0019 SPA_POM_S		ingr_0060	Pasta, white, dried, raw	60.13	341	13.5	1.2	72.7	205.1	8.1	0.7	43.7	146.3	272.1	9.1	6.6	46.1
		ingr_0075	Tomatoes, canned, whole contents	78.65	22	1.2	0.5	3.0	17.3	0.9	0.4	2.4					
		ingr_0048	Vegetable oil, olive, extravirgin	5.46	899	0.0	99.9	0.0	49.1	0.0	5.5	0.0					
		ingr_0084	Salt	0.75	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0					
		ingr_0006	Basil, fresh	1.25	49	3.1	0.8	5.1	0.6	0.0	0.0	0.1					
dish_0020 SPA_POM_M		ingr_0060	Pasta, white, dried, raw	79.72	341	13.5	1.2	72.7	271.9	10.8	1.0	58.0	193.9	360.7	12.1	8.7	61.2
		ingr_0075	Tomatoes, canned, whole contents	104.27	22	1.2	0.5	3.0	22.9	1.3	0.5	3.1					
		ingr_0048	Vegetable oil, olive, extravirgin	7.24	899	0.0	99.9	0.0	65.1	0.0	7.2	0.0					
		ingr_0084	Salt	1.00	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0					
		ingr_0006	Basil, fresh	1.66	49	3.1	0.8	5.1	0.8	0.1	0.0	0.1					
dish_0021 SPA_POM_L		ingr_0060	Pasta, white, dried, raw	100.14	341	13.5	1.2	72.7	341.5	13.5	1.2	72.8	243.6	453.1	15.2	11.0	76.8
		ingr_0075	Tomatoes, canned, whole contents	130.98	22	1.2	0.5	3.0	28.8	1.6	0.7	3.9					
		ingr_0048	Vegetable oil, olive, extravirgin	9.10	899	0.0	99.9	0.0	81.8	0.0	9.1	0.0					
		ingr_0084	Salt	1.25	0	0.0	0.0	0.0	0.0	0.0	0.0	0.0					
		ingr_0006	Basil, fresh	2.09	49	3.1	0.8	5.1	1.0	0.1	0.0	0.1					

¹Panel A shows the computation of raw and cooked serving weights for small, medium, and large sizes based on ingredient weights and yield factors. Each ingredient was weighed with a precision digital scale (third column). The column “Total raw ingredients (sum)” reports the sum of single ingredients raw weights. The yield factor was computed as total cooked recipe weight ÷ total raw ingredients. Cooked portions (S/M/L) were derived by first setting the medium portion to total cooked weight ÷ 3; the small and large portions were then defined as one third below and one third above the medium portion, respectively. Raw portions (S/M/L) were obtained by dividing the corresponding cooked portions by yield factor. Finally, “Raw ingredients per portion” was calculated by applying each ingredient’s raw-weight proportion in the recipe to the raw portion weight for S, M, and L.

²Panel B shows the computation of the nutritional values for the small, medium, and large portions derived from ingredient-level data. Columns in yellow indicate the nutrient composition per 100 g of each ingredient, columns in green indicate the corresponding nutrient values per portion, and columns in blue indicate the total nutritional values of the dish. For clarity of illustration, only energy and macronutrients are shown in this example, however, the full set of 86 nutritional components from the BDA (41) was calculated for every recipe. Abbreviations: L, large; M, medium; S, small; YF, yield factor.

8.3 RESULTS

8.3.1 Distribution of mass, energy, and macronutrient content across dishes in the Italian pilot dataset

A total of 162 dishes were prepared from 54 unique Italian composite recipes, each in three standardized portion sizes (small, medium, large). The recipes used 106 distinct ingredients, yielding 1,071 ingredient instances across dishes. **Table 8.1** reports descriptive statistics for dish mass, energy, and macronutrient content, calculated by assigning nutrient values from the Italian FCDB (41) to each ingredient in the Italian pilot dataset. The lowest values were observed in *dish_0106* (bruschetta with tomatoes, oil, and basil, small portion), which provided the minimum mass (67.3 g), energy content (114.8 kcal), and fat content (3.1 g). The lowest protein content (2.5 g) was observed in *dish_0052* (*Eggplant caponata*, small portion), a vegetable-based side dish, while the lowest carbohydrate content was recorded in *dish_0112* (*Vitello tonnato*, small portion), a cold main course based on veal and tuna sauce. The distributions of mass and nutrient values were slightly right-skewed. The highest energy (1385.0 kcal), protein (56.4 g), and fat content (104.7 g) were found in *dish_0069* (*cotechino sausage with lentils*, large portion). The maximum dish weight (770.4 g) was observed in *dish_0063* (soup with rice and vegetables, large portion), whereas *dish_0084* (jam tart, large portion) provided the highest carbohydrate content (147.8 g).

Table 8.1. Descriptive statistics for mass, energy and macronutrients content of dishes after attributing Italian FCDB nutritional values to ingredient in the pilot dataset

	Mass (g)	Energy (kcal)	Proteins (g)	Fats (g)	Carbohydrates (g)
Minimum	67.3	114.8	2.5	3.1	0.1
1st quartile	185.9	320.6	12.4	12.3	22.3
Median	262.0	450.8	21.6	19.3	43.4
3rd quartile	379.0	590.7	30.4	28.5	62.4
Maximum	770.4	1385.0	56.4	104.7	147.8
Mean	302.8	475.7	22.7	22.6	45.2
SD	156.4	215.5	12.4	14.8	29.9

8.3.2 Distribution of dish ingredients by frequency of use and mass

Dish complexity ranged from single-ingredient preparations to recipes containing up to 14 ingredients, with a median of 6 ingredients per dish (IQR: 4.25–8). The most frequently used ingredients were olive oil, water, salt, Grana Padano cheese, onions, and pasta, with a cumulative

frequency of ~31% (333 out of 1,071). In addition to these core ingredients, other common items included canned tomatoes, butter, bouillon cube, white flour, potatoes, and eggs, accounting for an additional ~14% (153 out of 1,071) (**Figure 8.2**). A comparison between the 30 most frequently used ingredients and those ranked by total mass (**Figure 8.3**) revealed marked differences in their functional roles within Italian composite dishes. Ingredients such as extra-virgin olive oil, salt, Grana Padano, and bouillon cubes were among the most frequently used, reflecting their role as condiments or flavor enhancers. However, they contributed little by weight and therefore ranked low, or not at all, in the mass-based list. By contrast, bulk components (water, potatoes, pasta, tomato products, and meat cuts such as veal and beef) dominated the mass-based ranking (cumulative ~41%). These ingredients are the principal contributors to mass and nutrients in many dishes, significantly influencing overall portion size. Notably, water ranked second by frequency and first by total mass due to its ubiquitous use in cooking processes such as boiling, simmering, and blending. Only a limited number of ingredients, including pasta, onions, canned tomatoes, eggs, potatoes, and mozzarella, appeared consistently in both rankings. Details on individual dishes, portion sizes, cooked portion weights (in grams), and associated ingredients are provided in **Table 8.2**, while **Figure E3 (Appendix E)** shows examples of recipes (two main courses and one dessert) presented in all three portion sizes, with details of nutritional composition and portion weights.

Figure 8.2. Top 30 ingredients by frequency of use in the pilot dataset of Italian recipes

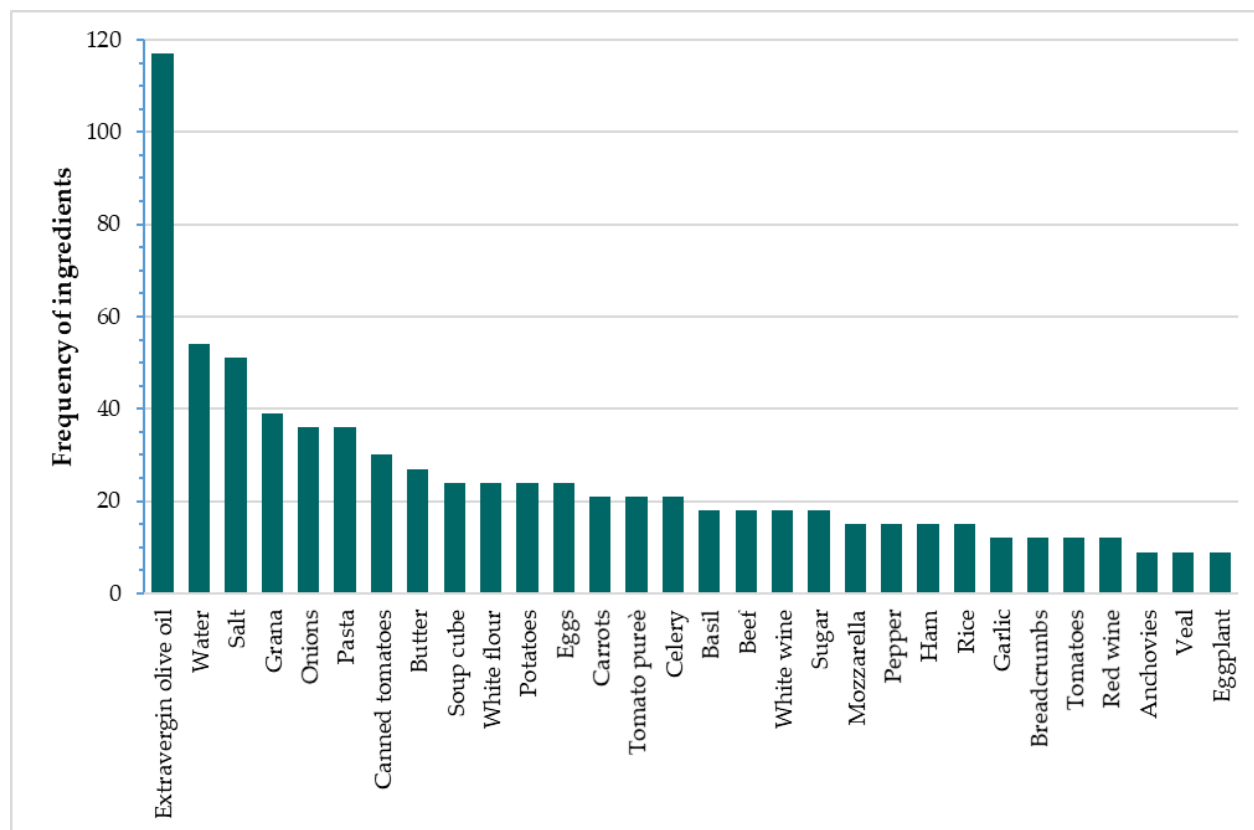
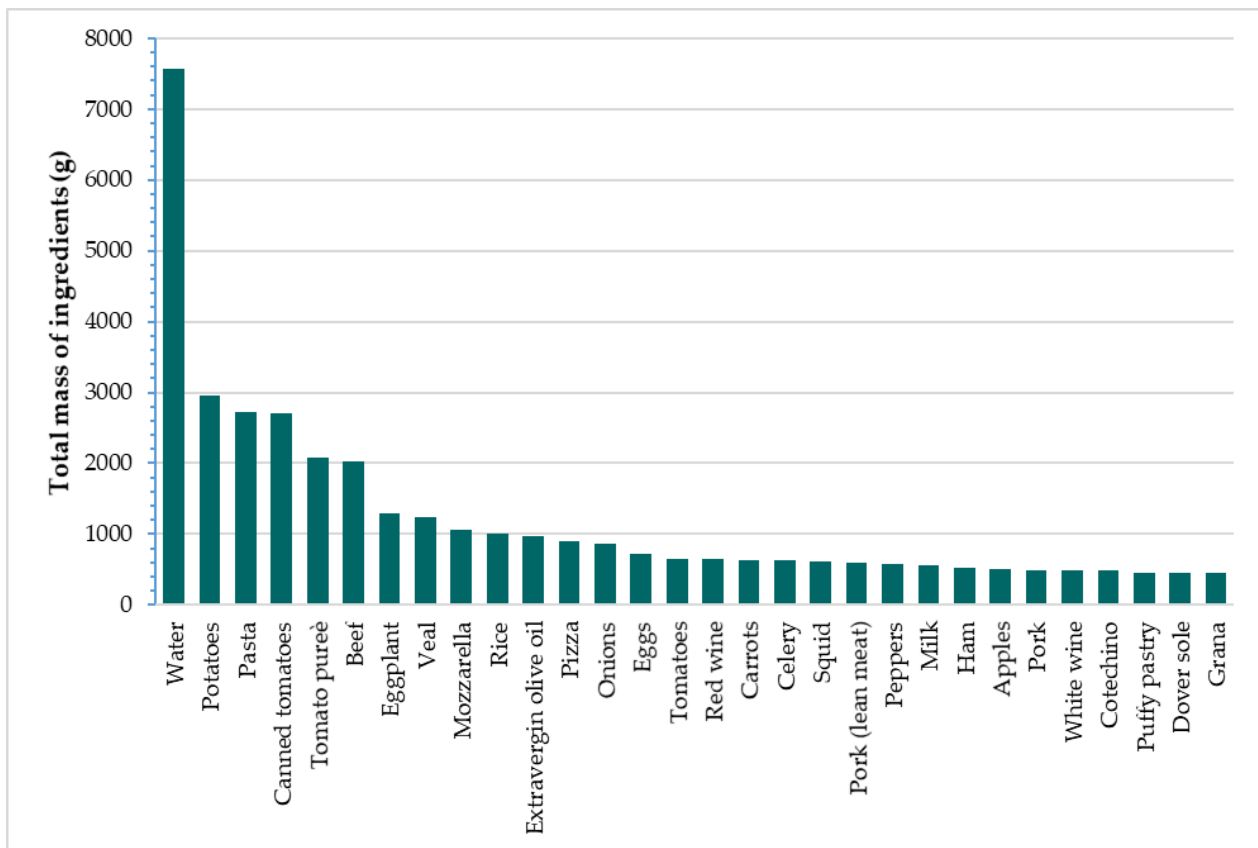


Figure 8.3. Top 30 ingredients by total mass (g) across dishes in the pilot dataset of Italian recipes**Table 8.2.** Composition of Italian dishes across portion sizes, cooked weights and ingredient list

Dish ID	Recipe	Portion size	Cooked weight	Ingredient names
dish_0001	Rice salad	Small	212.0	Rice, Eggs, Frankfurters, Emmenthal, Ham, Peppers, Canned peas, Canned tuna, Black olives, Extravirgin olive oil
dish_0002		Medium	305.5	
dish_0003		Large	382.8	
dish_0004	Risotto with saffron	Small	190.8	Rice, Onions, Extravirgin olive oil, Grana Padano cheese, Butter, Saffron, Water, Soup cube
dish_0005		Medium	254.3	
dish_0006		Large	317.6	
dish_0007	Risotto with mushrooms	Small	258.1	Rice, Onions, Mushrooms, Extravirgin olive oil, Butter, Grana Padano cheese, Water, Soup cube
dish_0008		Medium	361.5	
dish_0009		Large	450.0	
dish_0010	Risotto with sausage and red-leaf chicory	Small	264.3	Rice, Sausage, Onions, Red-leaf chicory, Butter, Extravirgin olive oil, Grana Padano cheese, Water, Soup cube
dish_0011		Medium	371.2	
dish_0012		Large	461.4	
dish_0013	Gnocchi with Bolognese sauce	Small	287.7	Potatoes, White flour, Beef, Onions, Carrots, Celery, Canned tomatoes, Salt, Red wine, Sugar, Water, Extravirgin olive oil
dish_0014		Medium	412.0	
dish_0015		Large	487.6	
dish_0016	Gnocchi with tomato sauce	Small	204.0	Potatoes, White flour, Canned tomatoes, Extravirgin olive oil, Salt, Basil
dish_0017		Medium	249.0	
dish_0018		Large	345.0	
dish_0019	Spaghetti with tomato sauce	Small	245.0	Pasta, Canned tomatoes, Extravirgin olive oil, Salt, Basil
dish_0020		Medium	324.8	
dish_0021		Large	408.0	
dish_0022	Tagliatelle with Bolognese sauce	Small	299.0	Egg pasta, Beef, Onions, Carrots, Celery, Canned tomatoes, Red wine, Sugar, Salt, Water, Extravirgin olive oil
dish_0023		Medium	398.0	
dish_0024		Large	500.0	
dish_0025	Lasagna	Small	307.3	

dish_0026		Medium	403.7	Egg pasta, Beef, Onions, Carrots, Celery, Canned tomatoes, Extravirgin olive oil, Red wine, Salt, Sugar, Grana Padano cheese, Milk, Butter, White flour
dish_0027		Large	515.1	
dish_0028	Orecchiette with broccoli	Small	227.0	Pasta, Broccoli, Anchovies, Extravirgin olive oil, Salt
dish_0029		Medium	328.6	
dish_0030		Large	408.0	
dish_0031	Mashed potato bake	Small	381.9	Potatoes, Grana Padano cheese, Mozzarella cheese, Eggs, Ham, Bacon, Extravirgin olive oil
dish_0032		Medium	492.0	
dish_0033		Large	644.6	
dish_0034	Chickpea flatbread	Small	131.4	Chickpea flour, Extravirgin olive oil, Herbs, Salt, Water
dish_0035		Medium	171.4	
dish_0036		Large	225.7	
dish_0037	Frico (Montasio cheese and potato fritter)	Small	109.0	Potatoes, Montasio cheese, Extravirgin olive oil, Salt
dish_0038		Medium	142.5	
dish_0039		Large	190.1	
dish_0040	Crepes with ham and mozzarella	Small	193.0	Milk, White flour, Eggs, Butter, Ricotta cheese, Ham, Salt, Mozzarella cheese, Grana Padano cheese
dish_0041		Medium	234.0	
dish_0042		Large	270.0	
dish_0043	Linguine with pesto	Small	198.8	Pasta, Basil, Extravirgin olive oil, Grana Padano cheese, Pine nuts, Garlic
dish_0044		Medium	263.5	
dish_0045		Large	320.0	
dish_0046	Valtellina-style pizzoccheri (Buckwheat pasta)	Small	349.8	Buckwheat pasta, Asiago cheese, Potatoes, Cabbage, Butter, Pepper
dish_0047		Medium	450.0	
dish_0048		Large	564.0	
dish_0049	Eggplant “parmigiana”	Small	217.7	Eggplant, Canned tomatoes, Extravirgin olive oil, Mozzarella cheese, Parmigiano cheese, Basil
dish_0050		Medium	300.2	
dish_0051		Large	369.2	
dish_0052	Eggplant “caponata”	Small	174.0	Eggplant, Onions, Green olives, Tomato pureè, Celery, Tomatoes, Extravirgin olive oil, Basil, Salt, Water
dish_0053		Medium	234.0	
dish_0054		Large	290.8	
dish_0055	Meatballs in tomato sauce	Small	160.0	Beef, Eggs, Breadcrumbs, Grana Padano cheese, Garlic, Parsley, Extravirgin olive oil, Tomato pureè
dish_0056		Medium	215.0	
dish_0057		Large	268.0	
dish_0058	Pasta salad	Small	259.8	Pasta, Tomatoes, Mozzarella cheese, Canned tuna, Green olives, Zucchini, Extravirgin olive oil
dish_0059		Medium	347.5	
dish_0060		Large	438.0	
dish_0061	Soup with rice and vegetables	Small	363.6	Rice, Onions, Potatoes, Tomato pureè, Zucchini, Carrots, Celery, Beans, Canned peas, Extravirgin olive oil, Grana Padano cheese, Water, Soup cube
dish_0062		Medium	505.9	
dish_0063		Large	619.5	
dish_0064	Pasta and bean soup	Small	149.0	Pasta, Beans, Canned tomatoes, Extravirgin olive oil, Water, Soup cube
dish_0065		Medium	199.3	
dish_0066		Large	250.0	
dish_0067	Cotechino sausage with lentils	Small	157.1	Cotechino, Lentils, Onions, Extravirgin olive oil, Tomato pureè, Water, Soup cube
dish_0068		Medium	212.5	
dish_0069		Large	265.6	
dish_0070	Russian salad	Small	95.1	Carrots, Peas, Potatoes, Mayonnaise
dish_0071		Medium	128.0	
dish_0072		Large	159.2	
dish_0073	Stuffed bell peppers	Small	230.8	Peppers, Extravirgin olive oil, Grana Padano cheese, Breadcrumbs, Eggs, Beef, Salt
dish_0074		Medium	326.1	
dish_0075		Large	402.1	
dish_0076	Savory pie with ricotta cheese and spinach	Small	169.3	Puffy pastry, Spinach, Ricotta cheese, Extravirgin olive oil, Grana Padano cheese
dish_0077		Medium	226.0	
dish_0078		Large	260.7	
dish_0079	Apple strudel	Small	108.1	Puffy pastry, Apples, Raisins, Lemon juice, Breadcrumbs, Butter, Cinnamon, Sugar, Powdered sugar
dish_0080		Medium	147.3	
dish_0081		Large	185.8	
dish_0082	Jam tart	Small	68.3	Shortcrust pastry, Jam
dish_0083		Medium	92.2	

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dish_0084		Large	108.0	
dish_0085	Tortellini with cream and ham	Small	200.1	Tortellini, Cream, Ham
dish_0086		Medium	261.5	
dish_0087		Large	329.0	
dish_0088	Pennette with cream and salmon	Small	165.0	Pasta, Salmon, Cream, Pepper
dish_0089		Medium	231.5	
dish_0090		Large	283.0	
dish_0091	Pennette with butter and sage	Small	110.6	Pasta, Butter, Sage
dish_0092		Medium	149.6	
dish_0093		Large	184.7	
dish_0094	Fusilli with mixed vegetables	Small	232.9	Pasta, Canned tomatoes, Zucchini, Eggplant, Extravirgin olive oil, Water
dish_0095		Medium	312.0	
dish_0096		Large	384.5	
dish_0097	Fusilli with Puttanesca sauce	Small	180.2	Pasta, Canned tomatoes, Anchovies, Green olives, Black olives, Extravirgin olive oil, Water
dish_0098		Medium	244.4	
dish_0099		Large	304.0	
dish_0100	Tomato and mozzarella sandwich	Small	198.7	White bread, Tomatoes, Lettuce, Mozzarella cheese
dish_0101		Medium	261.8	
dish_0102		Large	329.2	
dish_0103	Flatbread with ham and stracchino cheese	Small	117.5	Flatbread, Ham, Stracchino cheese
dish_0104		Medium	155.0	
dish_0105		Large	193.5	
dish_0106	Tomato “bruschetta”	Small	67.0	White bread, Tomatoes, Extravirgin olive oil, Oregano
dish_0107		Medium	84.5	
dish_0108		Large	114.0	
dish_0109	Roasted pork	Small	136.0	Pork, Extravirgin olive oil, Water, Soup cube, Salt, Herbs
dish_0110		Medium	194.0	
dish_0111		Large	228.0	
dish_0112	Veal with tuna-caper sauce	Small	132.3	Veal, Extravirgin olive oil, Eggs, Anchovies, Canned tuna, Broth, Capers
dish_0113		Medium	174.5	
dish_0114		Large	216.7	
dish_0115	Sole <i>meunière</i>	Small	99.6	Dover sole, White flour, Extravirgin olive oil, Salt, Parsley
dish_0116		Medium	136.3	
dish_0117		Large	169.5	
dish_0118	Seafood salad	Small	120.7	Prawns, Octopus, Extravirgin olive oil, Salt, Squid, Lemons, Peppers
dish_0119		Medium	160.5	
dish_0120		Large	203.4	
dish_0121	Spaghetti with mixed seafood	Small	216.5	Pasta, Prawns, Octopus, Mussels, Clams, Extravirgin olive oil, White wine, Garlic, Parsley, Water
dish_0122		Medium	290.7	
dish_0123		Large	364.3	
dish_0124	Stuffed “focaccia”	Small	124.7	Focaccia bread, Ham, Fontina cheese
dish_0125		Medium	160.9	
dish_0126		Large	195.2	
dish_0127	Bucatini with Amatriciana sauce	Small	209.0	Pasta, Bacon, Canned tomatoes, Pecorino cheese, Extravirgin olive oil, White wine
dish_0128		Medium	272.0	
dish_0129		Large	342.0	
dish_0130	Spaghetti with Carbonara sauce	Small	189.1	Pasta, Bacon, Pecorino cheese, Egg yolk, Pepper, Water
dish_0131		Medium	250.9	
dish_0132		Large	310.0	
dish_0133	Braised beef	Small	183.0	Beef, Onions, Carrots, Celery, Red wine, Extravirgin olive oil, White flour, Garlic, Salt, Rosemary, Pepper
dish_0134		Medium	244.6	
dish_0135		Large	299.1	
dish_0136	Veal stew	Small	298.8	Veal, Onions, Carrots, Celery, Tomato pureè, Extravirgin olive oil, Potatoes, White wine, Salt, Pepper, Water
dish_0137		Medium	395.6	
dish_0138		Large	495.4	
dish_0139	Tortellini in broth	Small	316.2	Dried tortellini, Grana, Soup cube, Water
dish_0140		Medium	416.6	
dish_0141		Large	523.9	

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dish_0142	Breaded pork cutlet	Small	112.2	Pork (lean meat), Breadcrumbs, Eggs, Extravirgin olive oil
dish_0143		Medium	151.0	
dish_0144		Large	189.8	
dish_0145	Veal scaloppini with white wine	Small	66.1	Pork (lean meat), Extravirgin olive oil, White flour, White wine
dish_0146		Medium	86.0	
dish_0147		Large	111.9	
dish_0148	Margherita pizza	Small	222.8	Pizza with Mozzarella cheese
dish_0149		Medium	297.8	
dish_0150		Large	376.8	
dish_0151	Roman-style veal with ham and sage	Small	76.3	Veal, White flour, Ham, Butter, Extravirgin olive oil, White wine, Sage
dish_0152		Medium	108.8	
dish_0153		Large	130.2	
dish_0154	Tiramisù	Small	87.0	Savoardi biscuits, Mascarpone cheese, Eggs, Sugar, Coffee, Cocoa
dish_0155		Medium	116.8	
dish_0156		Large	146.9	
dish_0157	Seafood stew	Small	191.3	Shrimps, Cuttlefish, Squid, Hake, Tomato pureè, White wine, Water, Extravirgin olive oil
dish_0158		Medium	255.5	
dish_0159		Large	305.0	
dish_0160	Frattau bread	Small	350.3	Carasau bread, Tomato pureè, Onions, Basil, Salt, Sugar, Extravirgin olive oil, Grana Padano cheese
dish_0161	(Sardinian flatbread	Medium	465.6	
dish_0162	layered with tomato sauce)	Large	588.0	

8.4 DISCUSSION

The present work was developed within the framework of WP7 of the INDACO Study, and Objective 3 of this thesis, with the goal of developing a pilot dataset to validate DL models for food recognition and nutrient estimation in the Italian setting. While traditional dietary assessment methods are prone to recall bias and cultural variability in portion reporting (1,27), image-based approaches supported by AI can automate and standardize nutrient estimation. However, their performance depends heavily on the availability of high-quality, culturally representative data (55,206). We therefore designed a pilot multimodal dataset of Italian recipes for external validation of prediction performance of DL models previously trained using the Nutrition5k dataset (95), yet representative of real-world Italian food culture.

The development of the current dataset closely followed the conceptual and technical framework of the Nutrition5k project (95) which provided RGB and depth imaging of complex dishes annotated for ingredient composition and nutrient content. In line with Nutrition5k approach (95), each Italian dish was recorded under standardized conditions using an Intel RealSense D435i RGB-Depth camera, and ensuring reproducible lighting, perspective, and geometry. Notably, the acquisition parameters (e.g., 8-second sweep, 1920×1080 RGB resolution, and 1e-4 depth units) mirrored those in Nutrition5k (95), and the experimental setup was custom built, with the robotic arm motion programmed in Arduino (204) to reproduce controlled camera movement along a defined arc. In addition, the dataset integrates multimodal input data, including RGB and depth recordings for ingredient recognition and portion-size estimation, complemented by detailed nutritional annotations to support nutrient content prediction. Similarly, the choice to record one video and complementary static images per dish ensures a consistent visual reference that can later support algorithm benchmarking under controlled conditions.

Despite these similarities, several key aspects differentiate the current Italian pilot dataset from the original Nutrition5k dataset (95). First, Nutrition5k was based on incremental plate-weighing in a cafeteria setting, where dishes could combine multiple recipes (e.g., pizza and brownies) or single ingredients (e.g., eggs, fruit, or nuts) within the same plate. By contrast, the Italian pilot dataset was manually curated and included composite recipes. No single-ingredient preparations were included, and each dish corresponded to a single, self-contained recipe. Second, while Nutrition5k relied on semi-automated annotation derived from real-time ingredient recognition and incremental mass logging, the present dataset was manually annotated by trained nutritionists. Each recipe was reconstructed step by step, with precise weighing of raw and cooked ingredients, yield-factor calculation, and attribution of nutrient values from the Italian Food Composition Database (BDA)

(41). Portions were standardized across three serving sizes (i.e., small, medium, and large) rather than resulting from incremental weighing. This manual approach, although more labor-intensive, ensured high-quality annotations that accurately represent Italian cooking practices and portion standards, as defined by the LARN guidelines (18). Finally, the choice of the BDA (41) as the reference database, rather than the USDA SR Legacy database (49), allowed alignment with local food codes and preparation methods, ensuring cultural and compositional specificity. This was particularly relevant for composite dishes where ingredient formulations and nutrient profiles differ substantially between countries (e.g., cured meats, cheeses, and oils).

Descriptive analyses indicate that dishes in the Italian pilot are both more energy-dense and more complex than those in Nutrition5k. Whereas Nutrition5k (95) reported averages of 255 kcal, 215g mass, 12.7g fat, 19.4g carbohydrates, and 18.0g protein content per dish, the Italian pilot showed higher means of 475.7 kcal, 302.8g mass, 22.6g fat, 45.2 g carbohydrates, and 22.7g protein content per dish. These differences reflect the nature of the recipes, including complete, composite recipes rather than isolated or simple items, and resulting in larger portions and higher nutrient density overall. Similarly, the median number of ingredients per dish was higher in the Italian pilot (6; IQR 4.25–8) than in Nutrition5k dataset (3; IQR 1–9), consistent with the inclusion of complete, multi-component dishes (e.g., pasta with elaborate sauces, soups, or stews) rather than simpler single-item plates. The distribution of ingredients usage showed a pattern comparable to that observed in Nutrition5k (95), although with clear context-specific differences. In both datasets, frequently used ingredients were predominantly condiments and aromatic bases. In Nutrition5k, olive oil, salt, garlic, vinegar, pepper, onions, and lemon juice accounted for about one quarter of all ingredient occurrences, while in the Italian pilot, olive oil, water, salt, Grana Padano cheese, onions, and pasta represented approximately 31% of total ingredient frequency. However, as in Nutrition5k, the ingredients most frequent by count did not necessarily correspond to those contributing most by total mass. Nutrition5k is headed by protein-rich items (eggs, meat, fish, and tofu; ~25%), followed by fruits, starchy foods (e.g., potatoes, corn, pizza), and some vegetables (carrots, broccoli). By contrast, the Italian pilot shows highest total mass for core components typical of composite cooked dishes, such as potatoes, pasta, tomato products, and meat cuts (veal/beef), with water at the top due to its extensive use in boiling, simmering, and blending. Overall, both datasets share a similar structure (condiments are frequent but contribute little by weights, and bulk foods occur less often yet account for most of the mass), although they differ in which bulk items predominate, thus reflecting diverse culinary contexts and recipe construction.

The principal strength of the current work lies in the precision and transparency of its methodological process. Each phase, from recipe selection to ingredient weighing, portioning, and nutrient

calculation, was executed manually by trained nutritionists under standardized laboratory conditions, ensuring traceability of all quantitative and qualitative aspects. The dataset also provides harmonized multimodal data (i.e., RGB, Depth, and nutrient annotation), and the design is fully reproducible and can be easily extended using the same pipeline to include new recipes or regional specialties. The main limitation is the size of the dataset, with 54 recipes in three portion sizes (162 dishes total). This is adequate for validation and proof-of-concept analyses but limits representativeness of Italy's culinary diversity. Accordingly, the dataset should be considered a structured pilot for external validation, not a comprehensive reference. Its internal consistency and detailed documentation nonetheless support future expansion and assessments of cross-cultural model generalization.

8.5 CONCLUSION

Future work will focus on extending this pilot dataset to include a broader range of Italian dishes (both widely consumed and region-specific) to increase diversity in ingredient composition, preparation methods, and visual appearance. Once scaled, this resource could support not only external validation but also model training tailored to the Italian dietary context, improving accuracy in food recognition and nutrient estimation tasks. In the longer term, the integration of such curated data into digital dietary assessment platforms will enable users to capture food images and obtain real-time, nutrient-specific feedback on portion size and composition. In conclusion, culturally grounded data combined with deep learning can connect traditional assessment with AI-based monitoring and enhance nutritional epidemiology.

9. DEVELOPMENT AND APPLICATION OF A WEB-BASED FFQ FOR RECRUITMENT AND DIETARY ASSESSMENT IN THE INDACO STUDY

9.1 RATIONALE AND AIM

To address Objective 4 (i.e., supporting cancer risk prediction with improved dietary data), this project was conducted as part of WP3 of the INDACO Study, combining platform development with cohort enrollment. We implemented the Web Assessment on Lifestyle and NUTrition–BDA (WALNUT-BDA), a privacy-compliant web platform enabling standardized administration of digital FFQs and automated energy/nutrient estimation through the Italian BDA database. Building on this tool, we focused on recruiting healthy, middle-aged university employees through structured interviews and standardized assessments of lifestyle, anthropometry, body composition, and diet. The resulting dataset is designed to serve as the external validation cohort for WP1 and WP2 of the INDACO Study, while the platform provides a scalable framework for high-quality dietary data collection.

9.2 MATERIALS AND METHODS

9.2.1 *Study design and participant recruitment*

Between February and July 2025, university employees from the University of Udine and the University of Milan were recruited via institutional mailing lists. Eligibility criteria included being Italian citizens aged >45 years and free from major neoplastic conditions (with the exception of melanoma). After candidates voluntarily expressed interest, eligibility was verified by telephone against inclusion/exclusion criteria, and interviews were scheduled accordingly. All procedures were approved by the relevant Ethics Committees, and informed consent was obtained from all participants prior to data collection.

9.2.2 *WALNUT-BDA: development and implementation*

The WALNUT-BDA web application was developed by our research team at the University of Udine, composed by academic nutritionists and supervised by senior investigators, in collaboration with the software company Eye-Tech S.r.l. The tool was designed to enable the creation, administration, and management of different types of questionnaires and supporting the standardized administration of a validated, reproducible FFQ (207). The FFQ captures habitual frequency and portion size for 78

foods, beverages, and recipes over the year preceding the interview; items are subsequently aggregated into food groups based on similarity in consumption and nutrient profile. User-reported consumption frequencies (daily, weekly, monthly, seasonal) and portion sizes (open or predefined) are algorithmically linked to the Italian FCDB (BDA) (17,41) to generate automated estimates of energy and 156 macro- and micro-nutrients, including vitamins, minerals, and anti-oxidant components. The system is extensible in real time (adding foods or nutrients), offers modular, section-based layouts with nested/branched logic, performs plausibility checks (e.g., missing portion sizes, implausible frequencies) to support data quality, and exports clean datasets to Excel for analysis.

9.2.3 Questionnaire administration and data collection

Interviewers were trained by a dietitian to administer the FFQ and to perform bioelectrical impedance analysis (BIA) using standard procedures. Each visit (90–120 minutes) followed a standardized protocol including: (1) written informed consent and assignment of a unique study ID; (2) anthropometric assessment in which waist and hip circumferences were measured with a non-elastic tape, body weight was recorded using a calibrated analog scale, and height was self-reported. Body composition was then assessed by bioelectrical impedance analysis (BIA) using the Nutrilab™ device (Akern S.r.l.). For BIA, participants were examined in the supine position, and disposable AKERN Biatrodes were placed at the wrist and ankle according to the standard protocol. Raw resistance and reactance, together with age, sex, weight, and height, were processed with Bodygram PLUS to estimate total body water (TBW), fat-free mass (FFM), fat mass (FM), body cell mass (BCM), and intra-/extracellular water (ICW, ECW). Results were reviewed with the participant and scheduled for delivery by email the following day.

Dietary data were collected and processed with WALNUT-BDA. The questionnaire (207) included three main parts: (1) sociodemographics; (2) lifestyle (smoking status, duration, and intensity; occupational and leisure-time physical activity, current and past) and anthropometrics (current and past); and diet. In detail, the questionnaire first addressed general dietary practices (e.g., use of condiments, number of daily meals, dietary restrictions), then food-group-specific sections (dairy, cereals, fruit and vegetables, fish/meat/eggs, legumes, sweets, and alcoholic beverages) with weekly frequency and usual portion size. Open-ended fields allowed additional foods to be recorded when consumed ≥ 24 times per year. During the dietary interview, a food atlas (20) was used as a visual aid to refine portion-size estimation and enhance comparability with reference values.

According to protocol, at the end of the interview, participants received a printed summary of their anthropometric and BIA results, along with brief nutritional counselling and recommendations from the Cancer Research Fund (WCRF), as illustrated in **Figures 9.1** and **9.2**.

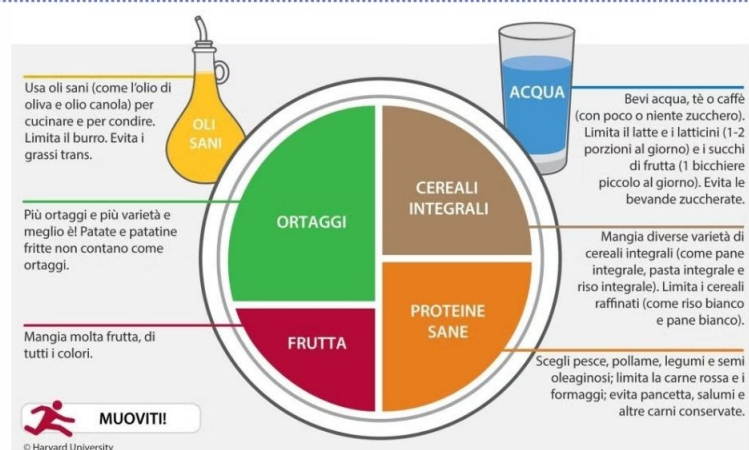
Figure 9.1. Counselling material for INDACO Study: the Healthy Eating Plate and ten nutritional advice



INDACO



CONSIGLI ALIMENTARI: IL PIATTO DEL MANGIARE SANO



OLI SANI
Usa oli sani (come l'olio di oliva e olio canola) per cucinare e per condire. Limita il burro. Evita i grassi trans.

Più ortaggi e più varietà e meglio è! Patate e patatine fritte non contano come ortaggi.

Mangia molta frutta, di tutti i colori.

ACQUA
Bevi acqua, tè o caffè (con poco o niente zucchero). Limita il latte e i latticini (1-2 porzioni al giorno) e i succhi di frutta (1 bicchiere piccolo al giorno). Evita le bevande zuccherate.

Mangia diverse varietà di cereali integrali (come pane integrale, pasta integrale e riso integrale). Limita i cereali raffinati (come riso bianco e pane bianco).

Scegli pesce, pollame, legumi e semi oleaginosi; limita la carne rossa e i formaggi; evita pancetta, salumi e altre carni conservate.

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The Nutrition Source
www.hsph.harvard.edu/nutritionsource

Harvard Medical School
Harvard Health Publications
www.health.harvard.edu

Fai una colazione completa
Scegli una fonte di proteine come latte o yogurt (anche vegetali); una fonte di carboidrati come pane, biscotti secchi, cereali o fette biscottate (meglio se integrali); frutta fresca e/o secca per gli zuccheri semplici e i grassi sani. Una colazione così impostata migliora il **senso di sazietà** e aiuta a regolare l'appetito durante la giornata.

Il pranzo e la cena
Abbinare: una fonte di carboidrati come cereali integrali (pasta, riso, orzo, farro, pane) o patate; una fonte di proteine all'interno di un **piatto unico** (es: pizza margherita, pasta al ragù) o come "secondo piatto"; verdura di stagione, cotta o cruda. Puoi concludere il pasto con un frutto, per raggiungere le 2-3 porzioni di frutta al giorno.

Varia i "secondi piatti"
Ci sono **14** pasti in una settimana:

CARNE	3 vv/settimana (max 1 carne rossa)
PESCE	2-3 vv/settimana
FORMAGGI	2-3 vv/settimana
AFFETTATI	<1 vv/settimana
UOVA	n. 2-4/settimana
LEGUMI	3-4 vv/settimana

Modera i condimenti
Usa **olio extravergine di oliva**, meglio se a crudo. Limita burro, panna, margarine e salse. Riduci il consumo di sale (max 5 g/giorno, compreso quello già presente negli alimenti) e insaporisci i piatti con **spezie ed erbe aromatiche**.

Leggi le etichette!
Imparare a leggere le etichette dei prodotti confezionati è fondamentale per fare **scelte più consapevoli**. Confronta sempre il contenuto di grassi, zuccheri, fibra e sale: preferisci alimenti con meno sale, meno zuccheri, meno grassi saturi e più fibra.

Che carne scegliere?
Preferisci la **carne bianca** a quella rossa e le bistecche alle polpette/cotolette già pronte. Anche il ragù è considerato carne rossa. Limita salsiccia, wurstel, insaccati e affettati. Tra gli affettati prediligi prosciutto crudo, bresaola e fesa di tacchino.

Gli spuntini
Opta per yogurt con frutta fresca, una manciata di frutta secca (noci, mandorle, etc) o pane e olio. **Evita snack confezionati**, dolci industriali, salatini, patatine e merendine. Limita anche crackers, grissini e taralli, contengono più grassi e più sale del pane. Evita o consuma saltuariamente le bevande zuccherate e l'alcol.

Alimenti vegetali
Includi ogni giorno **frutta e verdura di stagione**, cruda o cotta (NB: le patate non sono verdura): aumenta il senso di sazietà a breve e lungo termine, inoltre la fibra facilita il transito intestinale e l'evacuazione. Ricordati di bere a sufficienza però, ogni giorno 1,5-2 L di acqua! I **legumi** sono una fonte proteica: abbinali ai cereali per un pasto vegetale completo.

Che formaggi scegliere?
Preferisci **formaggi freschi** come ricotta o mozzarella (100 g/porzione) rispetto a quelli (semi-)stagionati (50 g/porzione).

Che pesce scegliere?
Prediligi quelli di **piccola taglia**, anche congelati. Modera il consumo di pesce in scatola o affumicato (max 1 vv/settimana).

progettoindaco2025@gmail.com

Figure 9.2. Counselling material for INDACO Study: recommendations from WCRF



**UNIVERSITÀ
DEGLI STUDI
DI UDINE**

UNIVERSITÀ
DEGLI STUDI
DI MILANO

INDACO



**UNIVERSITÀ
DEGLI STUDI
DI TRIESTE**

WALNUT
BDA

IL DECALOGO DELLA SALUTE WCRF

Il Fondo Mondiale per la Ricerca sul Cancro (WCRF), che da anni si occupa del rapporto tra cancro e alimentazione, dopo un lavoro di revisione di migliaia di studi, ha sintetizzato in dieci raccomandazioni le evidenze scientifiche più importanti.



MANTIENI IL PESO PIÙ SALUTARE IN OGNI FASE DELLA VITA

Evita di mettere su chili nell'età adulta, e fai attenzione ai piccoli: chi è sovrappeso o obeso nell'infanzia ha un'elevata probabilità di esserlo anche da adulto. **L'eccesso di peso e l'obesità** sono all'origine di 12 tumori diversi.



LIMITA IL CONSUMO DI FAST FOOD E DI CIBI CONFEZIONATI, RICCHI IN GRASSI, AMIDI E ZUCCHERI

Attenzione ai cosiddetti **cibi spazzatura**, ma anche a **cibi trasformati** e confezionati e a **bevande come milk-shake e cole**, alimenti ricchi di grassi, zuccheri e amidi che contengono molte calorie.



SEGUI UNA DIETA RICCA DI CEREALI INTEGRALI, VERDURA, FRUTTA E LEGUMI

Mangiare **cereali integrali, cibi che contengono fibre e vegetali** protegge contro diversi tipi di cancro. La raccomandazione è di mangiare ogni giorno almeno **30 g di fibre e 400 g di frutta e verdura**.



FAI ATTIVITÀ FISICA

L'**attività fisica** protegge contro diversi tipi di tumore. L'Organizzazione Mondiale della Sanità consiglia agli adulti di muoversi ogni giorno e di fare ogni settimana almeno tra i 150 e i 300 minuti di attività fisica moderata oppure tra i 75 e i 150 minuti di attività ad alta intensità.



LIMITA IL CONSUMO DI CARNI ROSSE ED EVITA QUELLE LAVORATE

Il suggerimento è di consumare al **massimo tre porzioni di carne rossa alla settimana** (equivalenti a circa 350 – 500 grammi di carne cotta) e di non consumare, o limitare al massimo, la carne rossa processata, ovvero i prosciutti, gli insaccati ecc.



LIMITA IL CONSUMO DI BEVANDE ZUCCHERATE

Non esistono evidenze scientifiche che colleghino il consumo di **bevande zuccherate** allo sviluppo di neoplasie, mentre è chiaro che contribuiscono al sovrappeso e all'obesità, che sono correlati a 12 tipi diversi di tumore.



LIMITA IL CONSUMO DI ALCOL

Sono molti i dati che mostrano il legame tra consumo di **bevande alcoliche** e sviluppo di tumori. Non esiste una soglia al di sotto della quale il rischio non aumenta: **è meglio non bere alcolici**.



NON UTILIZZARE INTEGRATORI PER PREVENIRE IL CANCRO

Una **dieta varia ed equilibrata** basta a soddisfare i fabbisogni di micronutrienti e a proteggere da molti tipi di tumori.



ALLATTA AL SENO I TUOI BAMBINI

L'**allattamento al seno** fa bene sia alla mamma, perché la protegge dal cancro al seno, sia al bambino, per una crescita con minor rischio di sovrappeso e obesità.

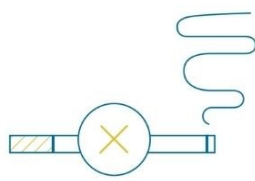


DOPO UNA DIAGNOSI DI CANCRO SEGUI SE POSSIBILE LE NOSTRE RACCOMANDAZIONI

Molte ricerche si concentrano sugli effetti di alimentazione e attività fisica sul rischio di recidive e nuovi tumori. Chi ha già affrontato il cancro, una volta terminate le cure può ottenere benefici seguendo queste raccomandazioni. Tuttavia è opportuno concordare con il proprio medico la dieta individuale più adatta a ciascun singolo caso.

SÌ A UNA DIETA SANA, NO AL TABACCO

Il decalogo del WCRF si riferisce a studi sul rapporto tra alimentazione e tumori. È comunque bene ricordare che il tabacco è la principale causa evitabile di malattia e morte nel mondo ed è anche la principale causa dello sviluppo di cancro.



Fonte: www.airc.com

progettoindaco2025@gmail.com

9.2.4 *Data management and compliance*

To protect participant privacy, two distinct datasets were created: one containing identifiable and health-related data, and the other dietary data anonymized through unique random codes. All data were stored on secure cloud servers managed by UNIUD, with data protection procedures aligned with the EU General Data Protection Regulation (GDPR), the Oviedo Convention on Human Rights and Biomedicine, EU Regulation 536/2014, and national legislation.

9.2.5 *Statistical analyses*

Descriptive tables are presented overall and stratified by center and by sex. Continuous variables are generally reported as mean (SD), median (IQR), and range (min–max); for weekly food-group intakes, only median (IQR) and range are reported. Categorical variables are presented as counts (percentages). Differences in weekly intake of individual food groups between strata were tested with the Wilcoxon rank-sum (Mann–Whitney) test, while differences in the distribution of categories of adherence to the recommended food group consumption cut-off (208,209) were evaluated with Pearson’s chi-square test of independence. To account for multiple comparisons, the Benjamini–Hochberg procedure was applied to control the false discovery rate (FDR). Adjusted associations were estimated with separate logistic regression models for each food group, using categories of adherence (yes/no) as the outcome. Covariates included center (Milan/Udine), age, sex, education, BMI, and cardiovascular risk factors (yes/no). To follow guideline conventions and improve interpretability, descriptive tables use sometimes a different categorization. Specifically, in descriptive tables, full WHO BMI classes (i.e., <18.5, 18.5–24.9, 25–29.9, >30 kg/m²) (210) and binary split for education (≤ 13 years and >13 years) were used, whereas the regression models rely on pre-specified, harmonized categories selected for statistical stability and comparability (BMI: <25.0, 25.0–29.9, ≥ 30.0 kg/m²; education: 11–15, 15–17, 17–27 years). All inferential statements refer to the model specification. Interval bounds shown in tables (e.g., 17.4–<25) reflect the observed range in this cohort. Model estimates are presented as adjusted odds ratios (OR) with 95% confidence intervals; coefficient significance was assessed using Wald z-tests. Missing values were handled via regression-based single imputation (linear models). All tests were two-sided with $\alpha = 0.05$. The R statistical software (version 4.3.2) was used for the statistical analysis (112).

9.3 RESULTS

9.3.1 Sociodemographic profile

A total of 345 subjects were enrolled (Udine: N=216, Milan: N=129), including 208 (60%) women (Udine: N= 131, 61%; Milan: N= 77, 60%) and 137 (40%) men (Udine: N= 85, 39%; Milan: N= 52, 40%). In the Udine site the overall age distribution showed a median of 56 years (IQR 51–60; range 45–70 years); in addition, age was comparable by sex: both men and women were in median 56 years (IQR 51–61; range 45–70 years) and 56 (IQR 51–59.5; range 45–69 years), respectively. Regarding education, 22% had completed secondary schooling (≤ 13 years of education), whereas 78% held a university degree or higher (>13 years of education). Occupationally, the cohort included 34% faculty members, 4% researchers, 44% administrative staff, 11% technical staff, and 7% in other roles. Similarly, in the Milan site, overall age was in median 54.0 years (IQR 49.0–58.0; range 44.0–68.0 years), with men showing in median 52.5 years (IQR 49.8–57.3; range 44–68 years) and women showing in median 54 years (IQR 49–59; range 44–66 years). Education level showed a more pronounced difference compared with the sample from Udine, with only 7% having secondary schooling (≤ 13 years) and 93% holding a university degree or higher (>13 years). The occupational distribution included 38% faculty members, 5% researchers, 28% administrative staff, 12% technical staff, and 16% other roles (**Table 9.1**).

Table 9.1. Baseline demographic and occupational characteristics by site and sex

	Udine			Milan		
	Overall (N=216)	Males (N=85)	Females (N=131)	Overall (N=129)	Males (N=52)	Females (N=77)
Age (years)						
<i>Min, Max</i>	45.0, 70.0	45.0, 70.0	45.0, 69.0	44.0, 68.0	44.0, 68.0	44.0, 66.0
<i>Median</i>	56.0	56.0	56.0	54.0	52.5	54.0
<i>(IQR)</i>	(51.0–60.0)	(51.0–61.0)	(51–59.5)	(49.0–58.0)	(49.8–57.3)	(49.0–59.0)
<i>Mean (SD)</i>	56.0 (5.9)	56.0 (5.9)	56.0 (5.9)	54.0 (5.8)	53.8 (5.8)	54.1 (5.9)
Years of education (n, %)						
≤ 13 years	47 (22%)	18 (21%)	29 (22%)	9 (7%)	2 (4%)	7 (9%)
>13 years	169 (78%)	67 (79%)	102 (78%)	129 (93%)	50 (96%)	70 (91%)
Occupation (n, %)						
<i>Faculty</i>	74 (34%)	41 (48%)	33 (25%)	49 (38%)	18 (35%)	31 (40%)
<i>Research</i>	9 (4%)	5 (6%)	4 (3%)	7 (5%)	2 (4%)	5 (6%)
<i>Administrative staff</i>	95 (44%)	20 (24%)	75 (57%)	36 (28%)	14 (27%)	22 (29%)
<i>Technical staff</i>	23 (11%)	13 (15%)	10 (8%)	16 (12%)	8 (15%)	8 (10%)
<i>Other</i>	15 (7%)	6 (7%)	9 (7%)	21 (16%)	10 (19%)	11 (14%)

9.3.2 Anthropometry and adiposity

Anthropometric profiles were broadly similar across sites: median BMI was 24.1 kg/m² at both, with median weight 70.0 kg in Udine and 69.0 kg in Milan, and median height 170.0 cm and 169.5 cm, respectively. Across both sites, men were heavier, taller, and had higher BMI than women (median BMI: Udine 25.2 vs 23.0 kg/m²; Milan 24.6 vs 23.1 kg/m²). BMI categories aligned with this pattern: the combined prevalence of overweight/obesity was 38% in each cohort. Distributions varied by sex and site: among men, overweight was more frequent in Udine than in Milan (36% vs 31%); among women, it was more common in Milan than in Udine (26% vs 21%). Milan also showed a slightly higher prevalence of underweight among women (5% vs 2%) (**Table 9.2**, middle panels). Central adiposity (waist-to-hip ratio, WHR) met or exceeded the male risk threshold at both sites (medians: 0.90 in Udine; 0.92 in Milan; threshold ≥ 0.90). Among women, median WHR was below the threshold (0.80 in Udine; 0.84 in Milan; threshold ≥ 0.85), although the upper quartile in Milan exceeded the cut-off (**Table 9.2**, lower panels). Notably, severe obesity appeared only in Milan (maximum BMI 44.4 kg/m²).

Table 9.2. Distribution of anthropometric measures and BMI categories by site and sex

	Udine			Milan		
	Overall (N=216)	Males (N=85)	Females (N=131)	Overall (N=129)	Males (N=52)	Females (N=77)
Weight						
<i>Min, Max</i>	43.0, 133.0	60.0, 133.0	43.0, 107.0	47.0, 126.0	61.0, 113.5	47.0, 126.0
<i>Median</i>	70.0	81.0	63.0	69.0	78.2	63.7
<i>(IQR)</i>	(60.0–79.0)	(74.0–89.0)	(55.5–70.5)	(61.0–79.0)	(71.9–88.0)	(58.2–71.0)
<i>Mean (SD)</i>	71.7 (15.8)	83.5 (14.4)	64.0 (11.3)	71.0 (14.3)	80.1 (12.5)	64.9 (12.1)
Height						
<i>Min, Max</i>	150.0, 202.0	168.0, 202.0	150.0, 178.0	148.0, 191.0	165.0, 191.0	148.0, 178.0
<i>Median</i>	170.0	179.0	165.0	169.5	177.8	164.5
<i>(IQR)</i>	(163.0– 176.0)	(174.0– 183.0)	(160.0– 169.5)	(164.0– 176.0)	(174.0– 181.1)	(161.0– 168.5)
<i>Mean (SD)</i>	170.6 (9.3)	179.2 (6.7)	165.0 (5.8)	169.7 (8.7)	177.4 (5.9)	164.5 (6.1)
BMI¹						
<i>Min, Max</i>	17.4, 37.0	19.9, 35.8	17.4, 37.0	18.1, 44.4	19.6, 34.5	18.1, 44.4
<i>Median</i>	24.1	25.2	23.0	24.1	24.6	23.1
<i>(IQR)</i>	(21.5–26.6)	(23.4–27.6)	(20.5–25.6)	(21.9–26.1)	(22.5–27.7)	(21.2–25.5)
<i>Mean (SD)</i>	24.5 (4.0)	25.9 (3.5)	23.5 (4.0)	24.6 (4.3)	25.4 (3.9)	24.0 (4.4)
<i>Underweight</i>	1%	0%	2%	3%	0%	5%
<i>Normal weight</i>	61%	48%	69%	59%	54%	62%
<i>Overweight</i>	27%	36%	21%	28%	31%	26%
<i>Obesity</i>	11%	15%	8%	10%	15%	6%
WHR²						
<i>Min, Max</i>	0.4	0.7	0.4	0.7	0.8	0.7

<i>Maximum</i>	1.2	1.2	1.0	1.1	1.1	1.0
<i>Median</i>	0.8	0.9	0.8	0.9	0.9	0.8
<i>(IQR)</i>	(0.8–0.9)	(0.9–1.0)	(0.8–0.8)	(0.8–0.9)	(0.9–1.0)	(0.8–0.9)
<i>Mean (SD)</i>	0.9 (0.1)	0.9 (0.1)	0.8 (0.1)	0.9 (0.1)	0.9 (0.1)	0.8 (0.1)

¹WHR in the Milan dataset was computed after imputing three missing waist/hip circumferences via linear regression using center, sex, age, years of education (continuous), and BMI (continuous) as predictors. Model fit: adjusted $R^2 = 0.80$ for waist and 0.60 for hip. ²BMI categories were defined according to the World Health Organization adult classification (210): $<18.5 \text{ kg/m}^2$ = underweight; $18.5\text{--}24.9 \text{ kg/m}^2$ = normal weight; $25.0\text{--}29.9 \text{ kg/m}^2$ = overweight; $\geq 30.0 \text{ kg/m}^2$ = obesity. Abbreviations: BMI, Body Mass Index; WHR, waist-to-hip ratio

9.3.3 Medical history and comorbidities

Tables 9.3 and **9.4** summarize baseline medical history. **Table 9.3** reports the prevalence of pre-specified conditions by site and sex, whereas **Table 9.4** groups additional diagnoses captured outside the standard panel by organ-system category (see below for details on the open-ended item). Metabolic conditions showed similar patterns but different magnitudes: the prevalence of dyslipidaemia was higher in Milan than Udine (47% vs 24%), and hypertension under treatment was also more frequent in Milan (22% vs 17%), while obesity reached 10% in Milan and 6% in Udine and diabetes mellitus remained uncommon (1 vs 2%). Within each site, men consistently exhibited higher prevalence than women for obesity, hypertension, and dyslipidemia (**Table 9.3**). For gastrointestinal conditions, esophagitis was more prevalent in Milan (12% vs 6%), whereas gallbladder stones were more common in Udine (7% vs 3%); peptic ulcer was infrequent in both settings (~2%), intestinal polyps were comparable (8–9%) with a male predominance within each site, and celiac disease appeared only in Milan (2%). Thyroid disorders displayed site- and sex-specific profiles: thyroid nodules were more prevalent in Milan than Udine (9% vs 5%), with a clear female excess (e.g., 12% vs 4% in Milan), hyperthyroidism was higher in Milan (3% overall, 5% in women), whereas hypothyroidism was more frequent in Udine (9% overall; 12% in women). The prevalence of malignant neoplasms was low in both cohorts: 1% in Udine (two melanomas, and one basal cell carcinoma) and 2% in Milan (two basal cell carcinomas, and one melanoma) (**Table 9.3**). Finally, the item ‘other major diseases’ was reported by 15% of participants in Udine (33/216) and 13% in Milan (17/129). Because several respondents listed more than one condition, **Table 9.4** summarizes diagnoses by organ system rather than by individuals. In Udine, entries were led by gastroenterological/hepatobiliary conditions (13/40; 32.5%; listing gastritis, peritonitis, and ulcerative colitis/Crohn’s), followed by cardiovascular (8/40; 20.0%; including atrial fibrillation, coronary disease, pulmonary embolism), then neurologic (4/40; 10.0%; including multiple sclerosis, epilepsy, Chiari malformation) and infectious (3/40; 7.5%; including hepatitis B, malaria, meningitis), with smaller contributions from sleep, renal/urologic, ENT/ophthalmic, and rheumatologic/autoimmune categories (each 2/40; 5.0%) and isolated endocrine/metabolic,

psychiatric, respiratory, and trauma diagnoses (each 1/40; 2.5%). In Milan, the distribution was headed by respiratory conditions (4/18; 22.2%; mainly asthma), followed by endocrine/thyroid and rheumatologic/autoimmune disorders (each 3/18; 16.7%; e.g., Hashimoto thyroiditis or treated hyper/hypothyroidism; rheumatoid arthritis, dermatomyositis), and then gastroenterological/hepatobiliary, cardiovascular, and gynecologic entries (each 2/18; 11.1%; e.g., reflux; Wolff–Parkinson–White; endometriosis), with a smaller ENT/ophthalmic component (1/18; 5.6%; congenital glaucoma). Procedures (n=3, i.e., corneal and heart transplants, and cholecystectomy) were reported only in Udine and were excluded from these percentages.

Table 9.3. Prevalence of pre-specified clinical conditions by site and sex.

Condition	Udine			Milan		
	Overall (N=216)	Males (N=85)	Females (N=131)	Overall (N=129)	Males (N=52)	Females (N=77)
Diabetes mellitus	4 (2%)	2 (2%)	2 (2%)	1 (1%)	1 (2%)	0 (0%)
Obesity	12 (6%)	7 (8%)	5 (4%)	13 (10%)	8 (15%)	5 (6%)
Hypertension (on medication)	37 (17%)	21 (25%)	16 (12%)	29 (22%)	14 (27%)	15 (19%)
High cholesterol/triglycerides	52 (24%)	24 (28%)	28 (21%)	60 (47%)	27 (52%)	33 (43%)
Gallbladder stones	16 (7%)	9 (11%)	7 (5%)	4 (3%)	3 (6%)	1 (1%)
Esophagitis	12 (6%)	9 (11%)	3 (2%)	15 (12%)	7 (13%)	8 (10%)
Peptic ulcer	4 (2%)	2 (2%)	2 (2%)	2 (2%)	1 (2%)	1 (1%)
Intestinal polyps	17 (8%)	10 (12%)	7 (5%)	11 (9%)	8 (15%)	3 (4%)
Malignant neoplasms	3 (1%)	1 (1%)	2 (2%)	3 (2%)	1 (2%)	2 (3%)
Other major diseases	33 (15%)	20 (24%)	13 (10%)	17 (13%)	5 (10%)	12 (16%)
Unspecified thyroid disease	7 (3%)	2 (2%)	5 (4%)	1 (1%)	0 (0%)	1 (1%)
Thyroid nodules (adenomas)	11 (5%)	1 (1%)	10 (8%)	11 (9%)	2 (4%)	9 (12%)
Hyperthyroidism	5 (2%)	2 (2%)	3 (2%)	4 (3%)	0 (0%)	4 (5%)
Hypothyroidism	19 (9%)	3 (4%)	16 (12%)	8 (6%)	3 (6%)	5 (6%)
Goiter	4 (2%)	0 (0%)	4 (3%)	2 (2%)	0 (0%)	2 (3%)
Celiac disease	0 (0%)	0 (0%)	0 (0%)	2 (2%)	0 (0%)	2 (3%)

Table 9.4. Frequency distribution of ‘other major diseases’ by organ or system across sites^{1,2}.

Organ or system category	Udine (N=33)	Milan (N=17)
Gastroenterological/Hepatobiliary	13 (32.5%)	2 (11.1%)
Cardiovascular	8 (20.0%)	2 (11.1%)
Neurologic	4 (10.0%)	0 (0.0%)
Infectious	3 (7.5%)	0 (0.0%)
Rheumatologic/Autoimmune	2 (5.0%)	3 (16.7%)
ENT/Ophthalmic	2 (5.0%)	1 (5.6%)

Sleep Disorders	2 (5.0%)	0 (0.0%)
Renal/Urologic	2 (5.0%)	0 (0.0%)
Respiratory	1 (2.5%)	4 (22.2%)
Endocrine/Metabolic	1 (2.5%)	3 (16.7%)
Trauma	1 (2.5%)	1 (5.6%)
Psychiatric	1 (2.5%)	0 (0.0%)
Gynecologic	0 (0.0%)	2 (11.1%)

¹Diagnosis counts are presented by organ system rather than subject-level prevalence as the same participant could report multiple diagnoses. ²Procedures are excluded from the count. Abbreviations: ENT, Ear-Nose-and-Throat

9.3.4 Lifestyle behaviors

Lifestyle behaviors, including tobacco use, alcohol consumption, and physical activity, are summarized in **Table 9.5**. Never-smokers were more frequent in Udine than Milan (71% vs 62%). Current smoking was uncommon overall (Udine 5%, Milan 9%), and more frequent among men in Milan (13% vs 5% in women); in Udine, men were more often former smokers than women (31% vs 19%). Among ever-smokers, intensity was generally low-to-moderate: the median was 6 cigarettes/day overall, whereas across centers, men reported higher intensity than women; the separation was wider in Udine (men: median =10, IQR 3.5–17.5 vs woman: median = 5, IQR 3.0–10.0 cigarettes/day) than in Milan (men: median =7.5, IQR 3.0–15.0 vs woman: median =6, IQR 4.0–10.0 cigarettes /day). The upper quartile reached ~15–18 cigarettes/day in men, with occasional extremes up to 40/day. Smoking histories were long-standing, with median durations of 15 years in Udine (IQR 8–27 years) and 18 years in Milan (IQR 8–27 years); the longest histories were observed in Milan (men: median 19.5, IQR 8–32 years), with maxima up to 47 years (**Table 9.5**, middle panel). Daily alcohol intake was modest overall but higher in Udine than Milan (median 0.4 vs 0.3 units/day; mean 0.7 vs 0.5), a pattern seen in both men (0.7 vs 0.3) and women (0.3 vs 0.2). Notably, the highest recorded daily alcohol intake was observed among women at both sites (Udine: 5.9 units/day; Milan: 6.0 units/day), exceeding the male maxima (Udine: 4.4; Milan: 4.3) (**Table 9.5**, upper panel). Occupational physical activity was predominantly sedentary, especially in Udine (81% vs 62% in Milan); men were less sedentary than women within each site (Udine 68% vs 89%; Milan 63% vs 61%) and more often reported standing or moderate/heavy work. Leisure-time activity was higher in Milan, where 40% reported ≥ 5 h/week (men 54%, women 29%) versus 29% in Udine (men 32%, women 27%); conversely, <2 h/week was more frequent in Udine (37% vs 22%) (**Table 9.5**, lower panel). Compared with Udine, Milan shows a less favorable smoking profile (particularly among men) but a more active leisure-time pattern, whereas Udine has higher alcohol intake and a more sedentary occupational profile.

Table 9.5. Distribution of lifestyle behaviors and levels of physical activity across sites, by sex.

	Udine			Milan		
	Overall (N=216)	Males (N=85)	Females (N=131)	Overall (N=129)	Males (N=52)	Females (N=77)
Alcohol consumption (unit/day)						
<i>Min, Max</i>	0.0	0.0	0.0	0.0	0.0	0.0
<i>Maximum</i>	5.9	4.4	5.9	6.0	4.3	6.0
<i>Median</i>	0.4	0.7	0.3	0.3	0.4	0.2
<i>(IQR)</i>	(0.1–1.0)	(0.2–1.4)	(0.1–0.8)	(0.1–0.6)	(0.1–0.9)	(0.0–0.5)
<i>Mean (SD)</i>	0.7 (0.9)	1.0 (1.0)	0.5 (0.7)	0.5 (0.8)	0.7 (0.8)	0.4 (0.8)
Smoking attitude						
<i>Never</i>	154 (71%)	56 (66%)	98 (75%)	80 (62%)	32 (62%)	48 (62%)
<i>Former</i>	51 (24%)	26 (31%)	25 (19%)	38 (29%)	13 (25%)	25 (32%)
<i>Current</i>	11 (5%)	3 (4%)	8 (6%)	11 (9%)	7 (13%)	4 (5%)
Intensity (cigarettes/die)¹						
<i>Min, Max</i>	0.5, 30.0	0.5, 30.0	1.0, 20.0	0.5, 40.0	2.0, 30.0	0.5, 40.0
<i>Median</i>	6.0	10.0	5.0	6.0	7.5	6.0
<i>(IQR)</i>	(3.0–15.0)	(3.5–17.5)	(3.0–10.0)	(3.0–12.0)	(3.0–15.0)	(4.0–10.0)
<i>Mean (SD)</i>	9.1 (7.3)	10.3 (8.0)	8.2 (6.6)	9.9 (9.6)	9.7 (8.0)	10.1 (10.8)
Duration (years)¹						
<i>Min, Max</i>	1.0, 40.0	1.0, 40.0	2.0, 40.0	2.0, 47.0	3.0, 47.0	2.0, 43.0
<i>Median</i>	15.0	15.0	18.0	18.0	19.5	16.0
<i>(IQR)</i>	(8.8–27.3)	(8.0–26.5)	(9.0–28.0)	(8.0–27.0)	(8.0–32.3)	(9.0–22.0)
<i>Mean (SD)</i>	17.7 (11.9)	16.3 (11.6)	18.9 (12.2)	18.5 (12.1)	21.1 (13.9)	16.8 (10.7)
Occupational physical activity						
<i>Very heavy</i>	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
<i>Heavy</i>	1 (0%)	1 (1%)	0 (0%)	2 (2%)	2 (4%)	0 (0%)
<i>Moderate</i>	2 (1%)	2 (2%)	0 (0%)	10 (8%)	5 (10%)	5 (6%)
<i>Mostly standing</i>	39 (18%)	24 (28%)	15 (11%)	37 (29%)	12 (23%)	25 (32%)
<i>Sedentary</i>	174 (81%)	58 (68%)	116 (89%)	80 (62%)	33 (63%)	47 (61%)
Leisure-time physical activity (hours/week)						
<i>>7</i>	13 (6%)	9 (11%)	4 (3%)	19 (15%)	11 (21%)	8 (10%)
<i>5–7</i>	50 (23%)	18 (21%)	32 (24%)	32 (25%)	17 (33%)	15 (19%)
<i>2–4</i>	73 (34%)	31 (36%)	42 (32%)	50 (39%)	18 (35%)	32 (42%)
<i><2</i>	80 (37%)	27 (32%)	53 (40%)	28 (22%)	6 (12%)	22 (29%)

¹Intensity and duration were calculated only among ever-smokers only (former and current); for former smokers, intensity refers to typical consumption before cessation; duration is total years smoked

9.3.5 Dietary intake

Descriptive statistics of food group consumption

Descriptive statistics of weekly food group consumption are presented overall, and stratified by recruitment center and sex (**Table 9.6**). The median weekly frequency of consumption varied across food groups. Vegetable intake was higher in Udine compared with Milan ($p < 0.001$), while fruit consumption was relatively similar across strata. Among starchy foods, bread and cereals were

consumed more frequently by males than females ($p < 0.001$), whereas bakery products and potatoes were more frequently consumed in Udine (<0.001), but no sex-related differences were observed. Conversely, milk and yogurt were more common in Udine ($p < 0.001$), whereas no center- or sex-related differences were observed for other dairy products. Among protein-rich foods, legumes were consumed slightly more often in Milan ($p = 0.033$), while fish, eggs, and white meat showed relatively homogeneous consumption across strata. In contrast, red and processed meats displayed more relevant differences: men reported more frequent consumption of both, with statistical significance observed for red meat by sex ($p = 0.011$) and processed meat by center ($p = 0.001$). Finally, sweets were more frequently consumed in Udine ($p = 0.012$) and among men ($p = 0.043$). Overall, these findings highlight center-specific consumption patterns—with Udine participants tending toward higher vegetable, milk/yogurt, potato, bakery products, processed meat, and sweets intakes—and sex-specific differences, particularly for cereal, red meat and sweets.

Adherence to food group recommendations: preliminary results from distribution of categories and logistic regression findings

Table 9.7 reports categorical adherence to the optimal cut-off of consumption for each food group. Overall, most food groups showed a favorable adherence profile, with more than 40% of participants falling within the 75–100% adherence range. Exceptions were observed for legumes (~20% in the 75–100% range), red meat (~35%), processed meat (~25%), and sweets (~30%). Notably, about half of the participants for sweets and red meat, and nearly 60% for processed meat, exceeded the recommended cut-off by more than two-fold ($>100\%$ non-adherence). Significant differences between centers were observed for vegetables (higher adherence in Udine: 40% vs. 26%, $p = 0.03$), milk and yogurt (higher adherence in Milan: 94% vs. 80%, $p = 0.05$), bakery products (Milan: 72% vs. 53%, $p = 0.03$), potatoes (Milan: 98% vs. 89%, $p = 0.05$), processed meat (Milan: 23% vs. 11%, $p = 0.03$), and sweets (Milan: 27% vs. 13%, $p = 0.05$). Stratification by sex indicated that men were more adherent to bread, pasta, and rice consumption compared with women (57% vs. 35%, $p < 0.01$). Results from logistic regression (**Tables F1-F14, Appendix F**) are overall consistent with the univariate analyses. Participants from Udine had higher odds of being adherent to the vegetables cut-off than those from Milan (OR = 1.76, 95% CI 1.04–3.02, $p = 0.03$). For fruit, although category-specific comparisons did not reach statistical significance, the covariate as a whole contributed significantly to the model (Wald $p = 0.02$); in particular, the highest education tertile showed roughly twofold higher odds ratios of adherence versus the lowest tertile (OR = 1.94, 95%CI 0.92–4.43). For bread and cereals, men were more than twice as likely to be adherent as women (OR = 2.18, 95%CI 1.34–3.57, $p < 0.01$), and higher education was also associated with greater adherence (OR = 2.01,

95%CI 1.06–3.92, $p = 0.03$ for third vs first tertile). Compared to Milan, lower odds ratios of adherence were observed in Udine participants for milk and yogurt (OR = 0.23, 95%CI 0.09–0.53, $p < 0.001$), bakery products (OR = 0.32, 95%CI 0.18–0.55), potatoes (OR = 0.14, 95%CI 0.02–0.50, $p = 0.001$), and processed meat (OR = 0.27, 95%CI 0.13–0.54) food groups. For legumes, there was a weak, borderline indication of lower odds ratios of adherence in Udine (OR = 0.58, 95%CI 0.32–1.06, $p = 0.08$). Additional for bakery products, age was positively associated with adherence: approximately 33% higher odds per 5-year increase (OR = 1.33, 95%CI 1.08–1.66, $p < 0.01$). For fish and eggs, the presence of ≥ 1 cardiovascular risk factor was directly associated with adherence (fish: OR = 1.90, 95%CI 1.10–3.31, $p = 0.02$; eggs: OR = 2.52, 95%CI 1.04–6.80, $p = 0.04$). No covariates were significantly associated with adherence to cheese, and to white- or red-meat cut-offs. Finally, for sweets, adherence was associated with center (in Udine lower than Milan: OR = 0.37, 95%CI 0.19–0.70, $p < 0.01$), sex (men less adherent than women: OR = 0.60, 95%CI 0.19–0.80, $p < 0.01$), and education (highest vs high-school level: OR = 3.20, 95% CI 1.14–11.50, $p = 0.02$).

Table 9.6. Descriptive statistics of food group consumption (times per week), overall and stratified by center and sex

Raw frequency	N = 345	Overall		q-value ¹	Stratified by center		Stratified by sex	
		Milan N = 129 (37.4%)	Udine N = 216 (62.6%)		Females N = 208 (60.3%)	Males N = 137 (39.7%)	q-value ¹	
Vegetables²				<0.001			0.3	
Median (Q1, Q3)	11.0 (8.3, 15.9)	9.6 (7.7, 14.5)	12.0 (9.2, 17.5)		11.4 (8.7, 16.4)	10.7 (7.9, 15.5)		
Min, Max	0.3, 54.3	1.8, 29.5	0.3, 54.3		0.3, 36.4	1.0, 54.3		
Fruit				0.5			0.7	
Median (Q1, Q3)	10.4 (6.4, 13.9)	10.0 (5.8, 14.4)	10.7 (6.8, 13.8)		10.5 (6.4, 14.1)	10.3 (6.5, 13.9)		
Min, Max	0.0, 31.0	0.0, 31.0	0.1, 28.5		0.0, 31.0	0.1, 27.9		
Bread and cereals				0.3			<0.001	
Median (Q1, Q3)	12.8 (8.5, 18.1)	12.0 (8.0, 17.5)	13.0 (8.5, 18.5)		11.3 (8.0, 16.2)	15.0 (9.5, 21.0)		
Min, Max	1.0, 55.0	1.0, 55.0	1.8, 46.0		1.8, 35.5	1.0, 55.0		
Milk and yogurt				<0.001			0.6	
Median (Q1, Q3)	6.7 (2.0, 11.3)	5.0 (1.0, 7.9)	7.0 (2.9, 12.6)		5.9 (2.0, 11.7)	7.0 (2.3, 11.3)		
Min, Max	0.0, 54.6	0.0, 23.0	0.0, 54.6		0.0, 38.6	0.0, 54.6		
Dairy				0.8			0.3	
Median (Q1, Q3)	3.0 (2.0, 4.6)	3.5 (1.8, 5.0)	3.0 (2.0, 4.6)		3.0 (2.0, 4.9)	2.8 (1.6, 4.5)		
Min, Max	0.0, 17.4	0.0, 14.8	0.0, 17.4		0.0, 14.0	0.0, 17.4		
Bakery products				<0.001			0.090	
Median (Q1, Q3)	3.0 (0.5, 5.0)	1.0 (0.0, 4.0)	3.0 (1.0, 6.5)		3.0 (0.5, 6.0)	2.0 (0.5, 5.0)		
Min, Max	0.0, 26.5	0.0, 26.5	0.0, 25.0		0.0, 26.5	0.0, 25.0		
Legumes				0.033			0.3	
Median (Q1, Q3)	1.0 (0.5, 2.0)	2.0 (0.6, 3.0)	1.0 (0.5, 2.0)		1.0 (0.5, 2.0)	1.0 (0.5, 2.5)		
Min, Max	0.0, 14.0	0.0, 14.0	0.0, 12.0		0.0, 9.0	0.0, 14.0		
Potatoes				<0.001			0.3	
Median (Q1, Q3)	1.0 (0.5, 2.0)	0.8 (0.5, 1.3)	1.5 (1.0, 2.3)		1.0 (0.5, 1.5)	1.0 (0.5, 2.0)		
Min, Max	0.0, 8.0	0.0, 5.0	0.0, 8.0		0.0, 8.0	0.0, 8.0		
Fish				0.7			0.4	
Median (Q1, Q3)	2.0 (1.5, 3.0)	2.0 (1.5, 3.0)	2.0 (1.5, 2.5)		2.0 (1.5, 2.5)	2.0 (1.5, 3.0)		
Min, Max	0.0, 14.0	0.0, 14.0	0.0, 7.5		0.0, 6.0	0.0, 14.0		
Eggs				0.002			0.3	
Median (Q1, Q3)	2.0 (1.5, 3.0)	2.0 (1.0, 3.0)	2.0 (2.0, 4.0)		2.0 (1.5, 3.0)	2.0 (1.5, 4.0)		

		Overall		Stratified by center		Stratified by sex	
Raw frequency	N = 345	Milan N = 129 (37.4%)	Udine N = 216 (62.6%)	q-value ¹	Females N = 208 (60.3%)	Males N = 137 (39.7%)	q-value ¹
Min, Max	0.0, 14.0	0.0, 7.0	0.0, 14.0		0.0, 8.0	0.0, 14.0	
White meat				0.8			0.5
Median (Q1, Q3)	1.5 (1.0, 2.0)	1.0 (0.5, 2.0)	1.5 (1.0, 2.0)		1.5 (1.0, 2.0)	1.5 (1.0, 2.0)	
Min, Max	0.0, 7.0	0.0, 5.0	0.0, 7.0		0.0, 5.0	0.0, 7.0	
Red meat				0.050			0.011
Median (Q1, Q3)	1.5 (1.0, 2.5)	1.5 (1.0, 2.5)	2.0 (1.0, 2.5)		1.5 (1.0, 2.5)	2.0 (1.0, 3.0)	
Min, Max	0.0, 7.5	0.0, 6.0	0.0, 7.5		0.0, 4.5	0.0, 7.5	
Processed meat				0.001			0.090
Median (Q1, Q3)	2.0 (1.0, 3.5)	2.0 (1.0, 3.0)	2.5 (1.5, 3.5)		2.0 (1.0, 3.0)	2.5 (1.5, 4.0)	
Min, Max	0.0, 10.0	0.0, 8.0	0.0, 10.0		0.0, 10.0	0.0, 10.0	
Sweets				0.012			0.043
Median (Q1, Q3)	4.2 (2.2, 7.5)	3.8 (1.8, 6.2)	4.5 (2.5, 7.9)		3.8 (2.0, 7.0)	4.7 (2.5, 8.2)	
Min, Max	0.0, 70.0	0.0, 70.0	0.5, 23.2		0.0, 26.5	0.0, 70.0	

¹Wilcoxon-rank-sum test for group mean differences with Benjamini & Hochberg correction for multiple testing; ²Values are expressed as portions per week of consumption for each food group (1 portion = 1 time of consumption); *non included in the multiple testing correction.

Table 9.7. Categories of adherence to the optimal cut-off of consumption (times per week) for each food group according to recommendations (208,209), overall and stratified by center and sex

Categories of adherence	Overall	Stratified by center		q-value ¹	Stratified by sex		q-value ¹
	N = 345	Milan N = 129 (37.4%)	Udine N = 216 (62.6%)		Females N = 208 (60.3%)	Males N = 137 (39.7%)	
Vegetables²				0.025			0.5
>100% no adherence	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
0-25% adherence	8 (2.3%)	1 (0.8%)	7 (3.2%)		4 (1.9%)	4 (2.9%)	
25-50% adherence	39 (11.3%)	21 (16.3%)	18 (8.3%)		17 (8.2%)	22 (16.1%)	
50-75% adherence	109 (31.6%)	52 (40.3%)	57 (26.4%)		69 (33.2%)	40 (29.2%)	
75-100% adherence	69 (20.0%)	21 (16.3%)	48 (22.2%)		45 (21.6%)	24 (17.5%)	
100% adherence ³	120 (34.8%)	34 (26.4%)	86 (39.8%)		73 (35.1%)	47 (34.3%)	
Fruit				0.3			0.9
>100% no adherence	2 (0.6%)	2 (1.6%)	0 (0.0%)		2 (1.0%)	0 (0.0%)	
0-25% adherence	34 (9.9%)	14 (10.9%)	20 (9.3%)		22 (10.6%)	12 (8.8%)	
25-50% adherence	67 (19.4%)	27 (20.9%)	40 (18.5%)		38 (18.3%)	29 (21.2%)	
50-75% adherence	71 (20.6%)	28 (21.7%)	43 (19.9%)		42 (20.2%)	29 (21.2%)	
75-100% adherence	86 (24.9%)	24 (18.6%)	62 (28.7%)		51 (24.5%)	35 (25.5%)	
100% adherence	85 (24.6%)	34 (26.4%)	51 (23.6%)		53 (25.5%)	32 (23.4%)	
Bread and cereals				0.7			0.009
>100% no adherence	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
0-25% adherence	11 (3.2%)	5 (3.9%)	6 (2.8%)		9 (4.3%)	2 (1.5%)	
25-50% adherence	40 (11.6%)	18 (14.0%)	22 (10.2%)		24 (11.5%)	16 (11.7%)	
50-75% adherence	76 (22.0%)	30 (23.3%)	46 (21.3%)		56 (26.9%)	20 (14.6%)	
75-100% adherence	68 (19.7%)	26 (20.2%)	42 (19.4%)		47 (22.6%)	21 (15.3%)	
100% adherence	150 (43.5%)	50 (38.8%)	100 (46.3%)		72 (34.6%)	78 (56.9%)	
Milk and yogurt				0.049			0.9
>100% no adherence	5 (1.4%)	0 (0.0%)	5 (2.3%)		2 (1.0%)	3 (2.2%)	
0-25% adherence	3 (0.9%)	0 (0.0%)	3 (1.4%)		1 (0.5%)	2 (1.5%)	
25-50% adherence	5 (1.4%)	1 (0.8%)	4 (1.9%)		3 (1.4%)	2 (1.5%)	
50-75% adherence	17 (4.9%)	3 (2.3%)	14 (6.5%)		10 (4.8%)	7 (5.1%)	

Categories of adherence	Overall	Stratified by center		q-value ¹	Stratified by sex		q-value ¹
	N = 345	Milan N = 129 (37.4%)	Udine N = 216 (62.6%)		Females N = 208 (60.3%)	Males N = 137 (39.7%)	
<i>75-100% adherence</i>	22 (6.4%)	4 (3.1%)	18 (8.3%)	0.7	12 (5.8%)	10 (7.3%)	0.8
<i>100% adherence</i>	293 (84.9%)	121 (93.8%)	172 (79.6%)		180 (86.5%)	113 (82.5%)	
Dairy							
<i>>100% no adherence</i>	50 (14.5%)	20 (15.5%)	30 (13.9%)		31 (14.9%)	19 (13.9%)	
<i>0-25% adherence</i>	21 (6.1%)	10 (7.8%)	11 (5.1%)		13 (6.3%)	8 (5.8%)	
<i>25-50% adherence</i>	23 (6.7%)	7 (5.4%)	16 (7.4%)		18 (8.7%)	5 (3.6%)	
<i>50-75% adherence</i>	43 (12.5%)	18 (14.0%)	25 (11.6%)	0.029	25 (12.0%)	18 (13.1%)	0.3
<i>75-100% adherence</i>	41 (11.9%)	12 (9.3%)	29 (13.4%)		25 (12.0%)	16 (11.7%)	
<i>100% adherence</i>	167 (48.4%)	62 (48.1%)	105 (48.6%)		96 (46.2%)	71 (51.8%)	
Bakery products							
<i>>100% no adherence</i>	84 (24.3%)	23 (17.8%)	61 (28.2%)		58 (27.9%)	26 (19.0%)	
<i>0-25% adherence</i>	1 (0.3%)	1 (0.8%)	0 (0.0%)		1 (0.5%)	0 (0.0%)	
<i>25-50% adherence</i>	28 (8.1%)	8 (6.2%)	20 (9.3%)	0.3	16 (7.7%)	12 (8.8%)	0.8
<i>50-75% adherence</i>	24 (7.0%)	4 (3.1%)	20 (9.3%)		18 (8.7%)	6 (4.4%)	
<i>75-100% adherence</i>	1 (0.3%)	0 (0.0%)	1 (0.5%)		0 (0.0%)	1 (0.7%)	
<i>100% adherence</i>	207 (60.0%)	93 (72.1%)	114 (52.8%)		115 (55.3%)	92 (67.2%)	
Legumes							
<i>>100% no adherence</i>	27 (7.8%)	8 (6.2%)	19 (8.8%)		17 (8.2%)	10 (7.3%)	
<i>0-25% adherence</i>	73 (21.2%)	26 (20.2%)	47 (21.8%)	0.045	44 (21.2%)	29 (21.2%)	>0.9
<i>25-50% adherence</i>	98 (28.4%)	29 (22.5%)	69 (31.9%)		66 (31.7%)	32 (23.4%)	
<i>50-75% adherence</i>	71 (20.6%)	31 (24.0%)	40 (18.5%)		40 (19.2%)	31 (22.6%)	
<i>75-100% adherence</i>	6 (1.7%)	2 (1.6%)	4 (1.9%)		2 (1.0%)	4 (2.9%)	
<i>100% adherence</i>	70 (20.3%)	33 (25.6%)	37 (17.1%)		39 (18.8%)	31 (22.6%)	
Potatoes							
<i>>100% no adherence</i>	3 (0.9%)	0 (0.0%)	3 (1.4%)		2 (1.0%)	1 (0.7%)	
<i>0-25% adherence</i>	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
<i>25-50% adherence</i>	5 (1.4%)	2 (1.6%)	3 (1.4%)		2 (1.0%)	3 (2.2%)	
<i>50-75% adherence</i>	12 (3.5%)	0 (0.0%)	12 (5.6%)		7 (3.4%)	5 (3.6%)	
<i>75-100% adherence</i>	5 (1.4%)	0 (0.0%)	5 (2.3%)		3 (1.4%)	2 (1.5%)	

Categories of adherence	Overall	Stratified by center		q-value ¹	Stratified by sex		q-value ¹
	N = 345	Milan N = 129 (37.4%)	Udine N = 216 (62.6%)		Females N = 208 (60.3%)	Males N = 137 (39.7%)	
<i>100% adherence</i>	320 (92.8%)	127 (98.4%)	193 (89.4%)	0.11	194 (93.3%)	126 (92.0%)	0.8
Fish							
<i>>100% no adherence</i>	13 (3.8%)	9 (7.0%)	4 (1.9%)		6 (2.9%)	7 (5.1%)	
<i>0-25% adherence</i>	15 (4.3%)	4 (3.1%)	11 (5.1%)		10 (4.8%)	5 (3.6%)	
<i>25-50% adherence</i>	36 (10.4%)	13 (10.1%)	23 (10.6%)		26 (12.5%)	10 (7.3%)	
<i>50-75% adherence</i>	141 (40.9%)	47 (36.4%)	94 (43.5%)		85 (40.9%)	56 (40.9%)	
<i>75-100% adherence</i>	52 (15.1%)	16 (12.4%)	36 (16.7%)	0.7	30 (14.4%)	22 (16.1%)	0.9
<i>100% adherence</i>	88 (25.5%)	40 (31.0%)	48 (22.2%)		51 (24.5%)	37 (27.0%)	
Eggs							
<i>>100% no adherence</i>	2 (0.6%)	0 (0.0%)	2 (0.9%)		1 (0.5%)	1 (0.7%)	
<i>0-25% adherence</i>	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
<i>25-50% adherence</i>	5 (1.4%)	1 (0.8%)	4 (1.9%)		3 (1.4%)	2 (1.5%)	
<i>50-75% adherence</i>	12 (3.5%)	4 (3.1%)	8 (3.7%)	0.7	5 (2.4%)	7 (5.1%)	0.8
<i>75-100% adherence</i>	12 (3.5%)	3 (2.3%)	9 (4.2%)		7 (3.4%)	5 (3.6%)	
<i>100% adherence</i>	314 (91.0%)	121 (93.8%)	193 (89.4%)		192 (92.3%)	122 (89.1%)	
White meat							
<i>>100% no adherence</i>	11 (3.2%)	4 (3.1%)	7 (3.2%)		6 (2.9%)	5 (3.6%)	
<i>0-25% adherence</i>	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
<i>25-50% adherence</i>	5 (1.4%)	1 (0.8%)	4 (1.9%)	0.3	4 (1.9%)	1 (0.7%)	0.2
<i>50-75% adherence</i>	23 (6.7%)	12 (9.3%)	11 (5.1%)		17 (8.2%)	6 (4.4%)	
<i>75-100% adherence</i>	28 (8.1%)	11 (8.5%)	17 (7.9%)		18 (8.7%)	10 (7.3%)	
<i>100% adherence</i>	278 (80.6%)	101 (78.3%)	177 (81.9%)		163 (78.4%)	115 (83.9%)	
Red meat							
<i>>100% no adherence</i>	164 (47.5%)	53 (41.1%)	111 (51.4%)		86 (41.3%)	78 (56.9%)	
<i>0-25% adherence</i>	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
<i>25-50% adherence</i>	1 (0.3%)	1 (0.8%)	0 (0.0%)		1 (0.5%)	0 (0.0%)	
<i>50-75% adherence</i>	63 (18.3%)	25 (19.4%)	38 (17.6%)		41 (19.7%)	22 (16.1%)	
<i>75-100% adherence</i>	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
<i>100% adherence</i>	117 (33.9%)	50 (38.8%)	67 (31.0%)		80 (38.5%)	37 (27.0%)	

Categories of adherence	Overall	Stratified by center		q-value ¹	Stratified by sex		q-value ¹
	N = 345	Milan N = 129 (37.4%)	Udine N = 216 (62.6%)		Females N = 208 (60.3%)	Males N = 137 (39.7%)	
Processed meat				0.029			0.3
>100% no adherence	214 (62.0%)	66 (51.2%)	148 (68.5%)		128 (61.5%)	86 (62.8%)	
0-25% adherence	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
25-50% adherence	0 (0.0%)	0 (0.0%)	0 (0.0%)		0 (0.0%)	0 (0.0%)	
50-75% adherence	43 (12.5%)	17 (13.2%)	26 (12.0%)		20 (9.6%)	23 (16.8%)	
75-100% adherence	36 (10.4%)	17 (13.2%)	19 (8.8%)		23 (11.1%)	13 (9.5%)	
100% adherence	52 (15.1%)	29 (22.5%)	23 (10.6%)		37 (17.8%)	15 (10.9%)	
Sweets				0.049			0.2
>100% no adherence	184 (53.3%)	62 (48.1%)	122 (56.5%)		100 (48.1%)	84 (61.3%)	
0-25% adherence	18 (5.2%)	7 (5.4%)	11 (5.1%)		9 (4.3%)	9 (6.6%)	
25-50% adherence	15 (4.3%)	7 (5.4%)	8 (3.7%)		11 (5.3%)	4 (2.9%)	
50-75% adherence	24 (7.0%)	6 (4.7%)	18 (8.3%)		19 (9.1%)	5 (3.6%)	
75-100% adherence	41 (11.9%)	12 (9.3%)	29 (13.4%)		23 (11.1%)	18 (13.1%)	
100% adherence	63 (18.3%)	35 (27.1%)	28 (13.0%)		46 (22.1%)	17 (12.4%)	

¹Pearson's chi-squared test of independence with Benjamini & Hochberg correction for multiple testing, Bold p-values refer to the 95% confidence level significance; ²Values are expressed as portions per week of consumption for each food group (1 portion = 1 time of consumption); ³Adherence categories quantify the absolute percent deviation from each food group's recommended consumption cut-off: 100% adherence = intake at the target; 75–100% adherence = within $\pm 25\%$ of the target; 50–75% = 25–50% from the target; 25–50% = 50–75% from the target; 0–25% = 75–100% from the target. >100% no adherence indicates a deviation greater than 100% from the target (e.g., $>2\times$ above an upper-limit recommendation or $<0.5\times$ of a minimum recommendation)

9.4 DISCUSSION

This preliminary, cross-sectional description of the INDACO validation cohort describes middle-aged university employees recruited in Udine and Milan showing a balanced sex distribution across sites, high educational attainment (particularly in Milan), and a mainly administrative and academic occupational profile. Anthropometric indicators were broadly consistent across sites, with median BMI values around 24 kg/m² and comparable prevalence of overweight/obesity (38%). As expected, men were heavier and more often overweight or obese than women, while women (especially in Milan) showed a slightly higher frequency of underweight. Central adiposity, indexed by WHR, met or exceeded WHO risk thresholds (211) in men (Udine 0.90; Milan 0.92; threshold ≥ 0.90) and remained below in women (Udine 0.80; Milan 0.84; threshold ≥ 0.85), although the upper quartile in Milan exceeded the cut-off. These findings point to a measurable burden of central adiposity even in a sample of normal-weight, working-age adults, underscoring its relevance for cardiometabolic risk assessment.

Similarly, lifestyle indicators suggested a mixed but generally favorable profile. Never-smoking was common (more in Udine than Milan), and current smoking was uncommon overall; nevertheless, a sizeable tail of ever-smoking persisted with long histories (medians 15–19 years) and upper-quartile daily intensities of ~15–18 cigarettes/day among men. These observations indicate a profile with many never-smokers and relatively low current smoking, but this does not remove exposure-related harms, given that no safe level of tobacco smoke exists—particularly for second-hand exposure—and risk rises progressively with dose and duration (212,213). Median daily alcohol intake was low (Udine 0.4; Milan 0.3 units/day), albeit with high individual maxima interestingly recorded among women in both sites (Udine 5.9; Milan 6.0 units/day). From a prevention standpoint, these patterns should be interpreted cautiously in light of the fact that no level of alcohol consumption is safe with respect to health risk, including cancer (18,214). When examined within domain (i.e., occupational vs leisure), activity profiles diverge by site. Compared with Milan, Udine shows more occupational sedentariness (81% vs 62%) and lower leisure-time volume. Given the lack of consistent intensity data, mapping hours to guideline attainment remains cautious. Nevertheless, considering WHO guidelines (215) (150–300 min/week of moderate or 75–150 min/week of vigorous aerobic activity, or an equivalent mix), reporting ≥ 5 h/week (~300 min) of leisure activity would be sufficient if performed at least at moderate intensity. On this basis, the higher prevalence of ≥ 5 h/week in Milan (40% vs 29%), together with fewer reporting < 2 h/week (22% vs 37%), suggests a larger subset there likely met recommended activity levels, despite broadly sedentary jobs.

Food-group frequencies and adherence patterns revealed center- and sex-specific signatures. Udine participants reported higher intakes of vegetables, potatoes, bakery products, milk/yogurt, processed meat and sweets, while men overall consumed cereals, red meat and sweets more frequently. When benchmarked against Mediterranean-diet guidelines (208), adherence was heterogeneous: a favorable 75–100% adherence band encompassed >40% of participants for many groups, yet legumes were under-consumed (~20% in the 75–100% band) and red/processed meats and sweets showed pronounced excesses, with about one half (sweets, red meat) to nearly 60% (processed meat) surpassing the cut-off by more than two-fold. In addition, recent Italian updates of Mediterranean-diet guidelines (209), reinforce the need for a predominantly plant-based dietary model; however, several recommendations were not met in this cohort, particularly for legumes and for red/processed meats and sweets.

In multivariable logistic models, adjusted estimates broadly mirrored the univariate patterns while refining interpretation by accounting for confounding. Compared to Milan, Udine showed higher odds of adhering to the vegetable cut-off, whereas Milan exhibited higher adherence for milk/yogurt, bakery products, potatoes, and processed meat. Education related positively to adherence for several groups (e.g., cereals, sweets), men were more adherent than women for cereals, and older age favored adherence to bakery products. The presence of cardiovascular risk factors was associated with greater adherence to fish and eggs, which may reflect clinical counselling or selection effects, although causality cannot be inferred. Legumes displayed a borderline lower adherence in Udine ($p \sim 0.08$), reinforcing their role as a priority for improvement. Overall, the adjusted findings align with the descriptive profiles and delineate actionable targets by center and subgroup. Within the cohort, tailored counselling could prioritize: (1) increasing legumes consumption across both sites; (2) reducing red/processed meat and sweets consumption, especially among men; (3) in Udine, rebalancing potatoes and bakery products while sustaining the relative advantage in vegetables; and (4) sustaining or enhancing leisure-time activity toward WHO recommendations (215), particularly where occupational sedentariness is pervasive. Notably, even where average alcohol intake appears modest, individualized feedback should address high-end consumers in light of the “no safe level” stance (214).

Several limitations warrant emphasis. First, the analyses were baseline and cross-sectional, precluding causal inference. Second, diet was self-reported via FFQ (with potential recall and portion-size error, although partly mitigated by standardized digital administration); height was self-reported (with possible BMI bias); and physical-activity hours lacked uniform intensity metrics. In addition, although multiple comparisons were addressed with FDR, residual false-positive risk remains; three waist/hip measures were imputed before WHR calculation; and the cohort’s occupational/educational

composition limits generalizability to broader populations. Strengths include the use of a standardized, privacy-compliant digital platform (WALNUT-BDA); concurrent collection of anthropometry, bioimpedance, diet and activity data; and harmonized protocols across sites, which enhanced data comparability. The balanced sex distribution and diverse occupational composition also improved representativeness within the university context. Finally, the combined use of descriptive and adjusted analyses strengthened interpretation by accounting for confounding and by identifying center- and subgroup-specific targets.

9.5 CONCLUSION

In summary, this cohort of middle-aged university employees provides a detailed cross-sectional profile of lifestyle, anthropometric, and dietary profiles, showing partial adherence to Mediterranean guidelines and marked differences by center and subgroup. Despite some favorable aspects, several gaps remain (particularly for legumes, red/processed meat, and discretionary foods) together with widespread sedentariness. Beyond their descriptive value, these data establish a robust, well-characterized baseline for the validation of cancer risk models that will be developed within INDACO WP1 and WP2, supporting the assessment of nonlinear and nonadditive diet–disease relationships through both machine learning and advanced statistical approaches.

10. CONCLUSIONS

This thesis examines how deep learning, harmonized food composition databases, and a web-based workflow can support dietary assessment. The work moves from a review of reproducibility issues, to cross-country data harmonization, to prediction models, and finally to an epidemiological application.

The first part of the research (Chapter 4) addressed the reproducibility of PCA- and EFA-derived dietary patterns in Italian studies through two systematic reviews. Together, these analyses provided a detailed overview of the methodological diversity underlying dietary pattern identification and interpretation across cohorts. Results showed that food grouping schemes, factor extraction criteria, and labeling strategies were highly inconsistent, leading to poor comparability across studies and limiting the interpretability of associations with health outcomes. Overall, these findings highlight the need for standardized, transparent, and data-driven approaches to dietary assessment.

Chapter 5 addressed the challenge of cross-country data harmonization by adapting the U.S.-based Nutrition5k dataset to the Italian context through systematic integration with the Banca Dati di Composizione degli Alimenti per Studi Epidemiologici in Italia (BDA). The work revealed the methodological and semantic gaps between food composition databases, from differences in ingredient definitions to missing values and portion-size annotations. Through a standardized workflow, ~250 ingredients were reviewed and cross-linked across databases. This process not only improved the internal consistency of the dataset but also enabled the generation of an Italian-harmonized version of Nutrition5k suitable for direct use in model training and validation.

Chapters 6 and 7 investigated the ability of deep learning models to predict the nutritional composition of Nutrition5k dishes directly from images, or by recognizing ingredients. Several architectures (ResNet, Inception, Vision Transformer) were compared under different preprocessing strategies, including data curation, frame filtering, and ingredient–mass correction. The results showed that these preprocessing steps significantly improved prediction accuracy, confirming that data quality is a primary determinant of model performance. Among the tested algorithms, the ResNet (R101) and Vision Transformer (ViT-B-16) achieved best performances in nutrient content prediction, and were therefore selected for the subsequent analysis. The integration of ingredient recognition alongside nutrient prediction (Chapter 7) modestly enhanced the semantic coherence of predictions by linking visible food components to their nutritional values. Across models, ViT-B-16 showed the most consistent accuracy across datasets and frame-filtering scenarios. Issues remained in dish images affected by cropping and occlusion, indicating that 2D cues alone are insufficient for

reliable portion and macronutrient estimation. These findings justify selecting ViT-B-16 as the reference model and highlight the need to integrate ingredient recognition with volume estimation and standardized portions to stabilize predictions, while relying on more precisely annotated datasets such as the Italian pilot (Chapter 8), which will serve as an external validation set in future applications to the Italian context.

Chapter 8 described the design and development of this dataset. Fifty-four traditional Italian recipes were prepared in three portion sizes and documented through a controlled RGB-Depth imaging protocol. Dishes were nutritionally annotated using the *Banca Dati di Composizione degli Alimenti* (BDA), providing a consistent reference with quantified mass, energy, macro- and micro-nutrient content. This represents the first multimodal dataset developed for dietary assessment research in Italy and provides a reproducible foundation for extending validation to larger or population-specific datasets.

Chapter 9 described how the WALNUT-BDA platform was designed and developed to administer a web-based FFQ linked directly to the Italian BDA, enabling automatic computation of nutrient intake and integration with anthropometric and lifestyle data. The platform was used within the INDACO study to recruit and assess about 300 university employees from two Italian centers. Preliminary results showed high compliance, reliable self-reported data, and good differentiation of dietary and lifestyle profiles across sex and site, although adherence to Mediterranean guidelines was moderate. The dataset offers a solid baseline for future analyses of diet–disease relationships within INDACO.

Across Chapters 4 to 9, the thesis outlines a coherent methodological path. The systematic reviews identified the problem of limited reproducibility in dietary data (Chapter 4). The database harmonization provided a standardized foundation for model training (Chapter 5), while predictive modeling (Chapters 6 and 7) explored how algorithm design, data curation, and ingredient recognition jointly influence performance. The Italian pilot dataset (Chapter 8) established a controlled framework for external validation and cultural adaptation, and the web-based FFQ (Chapter 9) allowed automatic computation of nutrient intake within an epidemiological application.

Several insights emerge from this work. First, data quality and consistency, from the structure of FCDBs to image annotation, remain the strongest determinants of model performance. Second, algorithm design matters: architectures that learn contextual relationships (e.g., Vision Transformers) outperformed purely convolutional models across datasets and filtering scenarios. Third, semantic integration improves interpretability and robustness: explicit ingredient recognition links visual cues to nutritional meaning and constrains outputs to plausible compositions. Finally, cultural and

contextual adaptation matters: models trained on non-local data may perform sub-optimally unless they are harmonized and validated against national references.

Despite significant progress, several limitations must be acknowledged. First, the available image datasets (both Nutrition5k and the Italian pilot dataset) remain limited in size and diversity relative to the heterogeneity of real-world dietary habits. Second, current models rely exclusively on 2D imagery and cannot yet infer portion volume or density, leading to systematic biases in mass and nutrient content prediction. Third, while ingredient recognition enhances interpretability, it remains constrained by label completeness and visual ambiguity, particularly in composite dishes with sauces, grains, or blended components. Addressing these challenges will require expanding the multimodal approach to include depth, texture, and contextual metadata (e.g., recipe text, preparation method, or plate geometry). Future research should also move toward cross-country learning frameworks, allowing harmonized yet locally adapted models trained on diverse FCDBs. This would enable culturally aware, privacy-preserving collaboration between research institutions while increasing model generalizability. In addition, incorporating 3D reconstruction and multi-view imaging could further improve portion estimation accuracy. Finally, integrating AI-based predictions into digital epidemiological platforms, such as the WALNUT-BDA system, will make it possible to capture dietary exposures more efficiently in large cohorts, linking image-based data with biomarkers and health outcomes.

Overall, this thesis contributes to bridging the gap between nutritional epidemiology and artificial intelligence by demonstrating how harmonized data, curated imagery, and interpretable models can converge into a coherent framework for dietary assessment. The work delivers workflows and datasets that can be used, reproduced, and extended. These assets provide a practical basis for the next generation of image-based dietary assessment in epidemiological studies.

11. ADDITIONAL EXPERIENCES

11.1 RESEARCH VISIT AT UNIVERSITY OF BRITISH COLUMBIA, VANCOUVER

During my third year, I spent four months (02/02/2025 – 01/06/2025) in Vancouver on a research visit to the Faculty of Land and Food Systems at the University of British Columbia. This research stay was connected to the work presented in Chapter 5 (Project 2) and was carried out in collaboration with the research group of my Canadian co-supervisor. The placement focused on advancing data management and analysis skills in nutrition research.

I mainly contributed to the integration of the Nutrition5k dataset with the Canadian FCDB (CNF) (216), addressing key challenges related to data harmonization across food composition systems. Specifically, I adapted and expanded the Nutrition5k ingredient metadata to enable traceable matching with CNF entries. Each ingredient was reviewed through a structured workflow based on FAO/INFOODS guidelines (53), including verification of ingredient form (i.e., raw, cooked, processed), systematic keyword-based searches within the CNF database, and evaluation of alternative matches by comparing nutrient profiles. When multiple candidates were plausible, selections were justified using standardized quality ratings (A–C) and detailed notes to ensure reproducibility. The workflow also incorporated cross-linking between CNF and USDA SR Legacy (49) items via country and food codes, improving interoperability across databases.

This integration provided the basis for a collaborative grant concept aimed at developing a context-aware dietary assessment tool, leveraging Canadian dietary survey data. The conceptual framework of this tool builds on existing predictive platforms such as CVDPoRT and MPoRT, which I had the opportunity to review and discuss during the placement. I also presented our work (Project 3, Chapter 6) in a research seminar, outlining the modeling framework, preliminary findings, and next steps for my PhD and for potential integration within broader international collaborations. The discussion highlighted how the Italian pipeline could complement Canadian developments, opening avenues for joint work in personalized, image-based dietary assessment. Overall, this international research experience offered a valuable opportunity to expand my methodological skillset and engage in cross-national dialogue on emerging technologies in nutrition research.

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APPENDIX

Appendix A: Supplementary Materials Chapter 4

Table A1. Main characteristics of studies identifying dietary patterns using principal component and factor analyses in Italy

Reference, location, study name, study quality	Study design	Participants	Dietary questionnaire	Outcome/Dietary pattern driver/Correlate
Edefonti, 2008 (120) Breast cancer: northern Italy (Milan, Genoa, Gorizia, Forli), central and southern Italy (Latina, Naples) Ovarian cancer: northern Italy (Milan, Pordenone, Padua), central and southern Italy (Latina, Naples) Good quality	Case-control study; 2 companion studies on breast and ovarian cancers; hospital based; recruitment from 1991 to 1994 for the breast cancer study and from 1992 to 1999 for the ovarian cancer study; Italian multicentric	7013 total subjects (100% Fs); 2569 breast cancer cases 25-74 ys (median: 55 ys, NA); 1031 ovarian cancers cases 18-79 ys (median: 56 ys, NA); 3413 controls 17-79 ys (median: 57 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (30 NUTs)	Breast and ovarian cancer incidence
Bertuccio, 2009 (121) Milan (Lombardy) Good quality	Case-control study; gastric cancer; hospital based; recruitment from 1997 to 2007; single center/area	777 total subjects; 230 cases (143 Ms, 87 Fs) 22-80 ys (median: 63 ys, NA); 547 controls (286 Ms, 261 Fs) 22-80 ys (median: 63 ys, NA)	FFQ 2 ys before IA reproducible and valid 78 FIs (28 NUTs)	Gastric cancer incidence
Edefonti, 2010 (122) Milan (Lombardy), Pordenone (Friuli Venezia Giulia), Rome, Latina (Lazio) Good quality	Case-control study; oral cavity cancer; hospital based; recruitment from 1992 to 2005; Italian multicentric	2886 total subjects; 805 cases (659 Ms, 146 Fs) 22-78 ys (median: 58 ys, NA); 2081 controls (1302 Ms, 779 Fs); 19-79 ys (median: 58 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (29 NUTs)	Oral cavity and pharyngeal cancer incidence
Bravi, 2010 (123) Milan (Lombardy), Genoa (Liguria), Pordenone, Gorizia (Friuli Venezia Giulia), Forli (Emilia-Romagna), Latina (Lazio), Naples (Campania) Good quality	Case-control study; colorectal cancer; hospital based; recruitment from 1992 to 1996; Italian multicentric	6107 total subjects; 1225 colon cancer cases (688 Ms, 537 Fs) 19-74 ys (median: 62 ys, NA); 728 rectum cancer cases (437 Ms, 291 Fs) 23-74 ys (median: 62 ys, NA); 4154 controls (2073 Ms, 2081 Fs) 19-74 ys (median: 58 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Colorectal cancer incidence

Edefonti, 2010 (124) Milan (Lombardy), Pordenone (Friuli Venezia Giulia) Good quality	Case-control study; laryngeal cancer; hospital based; recruitment from 1992 to 2000; Italian multicentric	1548 total subjects; 460 cases (415 Ms, 45 Fs) 30-80 ys (median: 61 ys, NA); 1088 controls (863 Ms, 225 Fs) 31-79 ys (median: 61 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Squamous cell laryngeal cancer incidence
Bravi, 2012 (125) Milan (Lombardy), Pordenone (Friuli Venezia Giulia), Padua (Veneto) Good quality	Case-control study; esophageal cancer; hospital based; recruitment from 1992 to 1997; Italian multicentric	1047 total subjects; 304 cases (275 Ms, 29 Fs) 39-77 ys (median: 60 ys, NA); 743 controls (593 Ms, 150 Fs) 33-77 ys (median: 60 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Esophageal cancer incidence
Bosetti, 2013 (126) Milan (Lombardy), Pordenone (Friuli Venezia Giulia) Good quality	Case-control study; pancreatic cancer; hospital based; recruitment from 1991 to 2008; Italian multicentric	978 total subjects; 326 cases (174 Ms, 152 Fs) (median: 63 ys, NA); 652 controls (348 Ms, 304 Fs) (median: 62 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Pancreatic cancer incidence
Rosato, 2014 (127) Milan (Lombardy), Pordenone, Gorizia (Friuli Venezia Giulia) Latina (Lazio), Naples (Campania) Good quality	Case-control study; prostate cancer; hospital based; recruitment from 1991 to 2002; Italian multicentric	2745 total subjects (100% Ms); 1294 cases 46-74 ys (median: 66 ys, NA); 1451 controls 46-74 ys (median: 63 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Prostatic cancer incidence
Bravi, 2015 (128) Milan (Lombardy), Pordenone, Udine (Friuli Venezia Giulia), Naples (Campania) Good quality	Case-control study; endometrial cancer; hospital based; recruitment from 1992 to 2006; Italian multicentric	1362 total subjects (100% Fs); 454 cases 18-79 ys (median: 60 ys, NA); 908 controls 19-80 ys (median: 61 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Endometrial cancer incidence
Edefonti, 2015 (129) Milan (Lombardy), Pordenone (Friuli Venezia Giulia), Naples (Campania), Catania (Sicily) Good quality	Case-control study; nasopharyngeal cancer; hospital based; recruitment from 1992 to 2008; Italian multicentric	792 total subjects; 198 cases (157 Ms, 41 Fs) 18-76 ys (median: 52 ys, NA); 594 controls (471 Ms, 123 Fs) 19-76 ys (median: 52 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Nasopharyngeal cancer incidence

Dalmartello, 2020 (130) Milan (Lombardy), Pordenone, Udine (Friuli Venezia Giulia), Latina (Lazio), Naples (Campania) Good quality	Case-control study; renal cell cancer; hospital based; recruitment from 1992 to 2004; Italian multicentric	2301 total subjects; 767 cases (494 Ms, 273 Fs) 24- 79 ys (median: 62 ys, NA); 1534 controls (988 Ms, 546 Fs) 22-79 ys (median: 62 ys, NA)	FFQ 2 ys before IA Reproducible and valid 78 FIs (28 NUTs)	Renal cell cancer incidence
Edefonti, 2020 (131) Milan (Lombardy), Pordenone (Friuli Venezia Giulia), Naples (Campania), Catania (Sicily) Good quality	Case-control study; bladder cancer; hospital based; recruitment from 2003 to 2014; Italian multicentric	1355 total subjects; 690 cases (595 Ms, 95 Fs) 25- 84 ys (median: 67 ys, NA); 665 controls (561 Ms, 104 Fs) 27-84 ys (median: 66 ys, NA)	FFQ 2 ys before IA Reproducible and valid 80 FIs (28 NUTs)	Urothelial bladder cancer incidence
Edefonti, 2020 (132) Milan (Lombardy) Good quality	Cross-sectional study; rheumatoid arthritis disease activity; recruitment from January 2018 to December 2019; single center/area with recruitment at Pini Hospital (Milan)	205 total subjects (40 Ms, 165 Fs) 18-65 ys (median: 58.46 ys, IQR: 47.81-69.03 ys)	FFQ 6 mos before IA Reproducible and valid 110 FIs (33 NUTs)	Rheumatoid arthritis disease activity, measured with DAS28-CRP and SDAI
Marinoni, 2022 (133) Croatia, Greece, Italy (Friuli Venezia Giulia region) Good quality	Cross-sectional analysis nested within the NAC-II birth cohort which followed- up 632 eligible (i.e, 18-month children with neurodevelopment assessed) born from 767 mothers originally recruited between 2007 and 2009; international	379 total subjects (195 Ms, 184 Fs); mean: 7 ys, SD: 0.05 ys	3d-DR (2 weekdays and 1 weekend day, not necessarily consecutive) in the wk before IA Reproducible and valid 828 FIs (37 NUTs)	Cognitive abilities assessed with the validated Italian version of the WISC- IV and expressed by FSIQ, and other 4 indexes: VCI, PRI, WMI, and PSI
Centritto, 2009 (134) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 16704 subjects recruited from 2005 to 2008; single center/area	7646 total subjects (49% Ms, 51% Fs); age ≥ 35 ys (mean: 50 ys, SE: 10 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (45 FGs)	CVD risk profile according to a series of clinical parameters: total, HDL, and LDL cholesterol, SBP, DBP, TGs, blood glucose, CRP, and a global individual CVD risk score calculated applying the risk equation from the CUORE project

Bonaccio, 2012 (135) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 24325 subjects recruited from March 2005 to April 2010; single center/area	13262 total subjects (6590 Ms, 6672 Fs); age ≥ 35 ys (mean: 53.3 ys, SD: 10.6 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (43 FGs)	Household net income in categories (low, low-medium, medium-high, and high)
Bonaccio, 2012 (136) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 1132 subjects recruited from May 2009 to April 2010; single center/area	959 total subjects (479 Ms, 480 Fs) aged ≥ 35 ys (mean: 52.8 ys, SD: 9.6 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (45 FGs based on reference to a previous article)	Mass media exposure score obtained using principal component analysis (PCA) on items from an additional validated questionnaire on nutrition knowledge and mass media exposure
Bonaccio, 2013 (137) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 1132 subjects recruited from May 2009 to April 2010; single center/area	744 total subjects (50.3% Ms, 49.7% Fs); age ≥ 35 ys (mean: 52.1 ys, SD: 9.4 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (43 FGs)	Nutrition knowledge (categorical) obtained from an additional validated questionnaire on nutrition knowledge and mass media exposure

Bonanni, 2013 (138) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 1571 subjects recruited from May 2009 to April 2010; single center/area	883 total subjects (442 Ms, 441 Fs); age ≥ 35 ys (mean: 52.5 ys, SD: 9.6 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (45 FGs based on reference to a previous article)	Food labels reading (categorical) obtained from an additional validated questionnaire on nutrition knowledge and mass media exposure
Bonaccio, 2013 (139) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 24325 subjects recruited from March 2005 to April 2010; single center/area	16937 total subjects (48.4% Ms, 51.6% Fs); age ≥ 35 ys (mean: 53.0 ys, SD: 10.8 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (43 FGs)	Health-related quality of life (mental and physical health components) from the validated Italian version of SF-36 questionnaire (from 0 - worst possible condition - to 100 - best possible condition)
Bonaccio, 2016 (140) Molise Moli-sani Good quality	Prospective cohort study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 24325 subjects recruited from March 2005 to April 2010 for a final sample of 1995 patients with type 2 diabetes followed-up for mortality until December 2011; single center/area	1995 total subjects (1319 Ms, 676 Fs); age ≥ 35 ys (mean: 62.6 ys, SD: 10.2 ys)	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different form 188 FIs (46 FGs)	Overall mortality in diabetic subjects
Bonaccio, 2018 (141) Molise Moli-sani Good quality	Cross-sectional study; men and women living in Molise randomly recruited from city-hall registries of Molise by using electronically generated numbers; 24325 subjects recruited from March 2005 to April 2010; single center/area	11272 total subjects (46.2% Ms, 53.8% Fs) age ≥ 35 ys (mean: 52.7 ys, SD: 10.8 ys) reduced to 10812 due to unreliable medical or dietary questionnaires, implausible EIs or missing	Modified version of the reproducible and valid EPIC FFQ to include some typical southern Italy foods NA reference period SA Validated in a different	Psychological resilience from 25-item Connor-Davidson Psychological Resilience Scale (from 0 to 100 with a higher score reflecting greater psychological resilience)

		values for dietary information	form 188 FIs (46 FGs)	
Pala, 2006 (142) Denmark, France, Germany, Greece, Netherlands, Spain, Sweden, UK, Italy (Varese, Turin, Florence, Naples, Ragusa) EPIC (EPIC-Elderly) Good quality	Cross-sectional analysis nested within a prospective cohort study; elderly (≥ 60 ys) participants from EPIC study recruited voluntarily from 1993 to 1998 in 5 different areas covered by cancer registries in northern, central and southern Italy; international	100 059 total subjects; 5611 Italian participants: 1536 Ms (60.0-72.2 ys, median age at enrollment: 62.3 ys, IQR: NA), 4075 Fs (60.0-77.8 ys, median age at enrollment: 62.3 ys, IQR: NA)	3 different FFQs 1 y before NA Reproducible and valid 188 FIs (Varese, Turin, Florence), 217 FIs (Ragusa), 140 FIs (Naples), (57 FGs for all centers)	Lifestyle, anthropometry, education, and other health indicators
Masala, 2007 (143) Denmark, France, Germany, Greece, Netherlands, Spain, Sweden, UK, Italy (Varese, Turin, Florence, Naples, Ragusa) EPIC (EPIC-Elderly) Very good quality	Prospective cohort study; elderly (≥ 60 ys) participants from EPIC study recruited voluntarily in 5 different areas covered by cancer registries in northern, central and southern Italy between 1993 and 1998 and followed-up for overall mortality up to 2001 or 2002 (median follow-up of 6.2 ys after applying exclusion criteria); international	100 059 total subjects; 5611 Italian participants: 1536 Ms (60.0-72.2 ys, median age at enrollment: 62.3 ys, IQR: NA), 4075 Fs (60.0-77.8 ys, median age at enrollment: 62.3 ys, IQR: NA), 152 total deaths	3 different FFQs 1 y before NA Reproducible and valid 188 FIs (Varese, Turin, Florence), 217 FIs (Ragusa), 140 FIs (Naples), (57 FGs for all centers)	Overall mortality
Jannasch, 2019 (144) Italy, France, Spain, UK, Netherlands, Germany, Sweden, Denmark EPIC-InterAct Good quality	Case-cohort study nested within EPIC prospective cohort study and based on incident cases of type 2 diabetes in the full EPIC cohort (cases which occurred between 1991 and the 31 December 2007 in 8 countries) and a randomly drawn subcohort stratified by center (9 centers); international	25877 total subjects of which 14694 randomly drawn subcohort subjects and 11183 verified incident type 2 diabetes cases; 719 verified incident type 2 diabetes cases overlapping with the subcohort; 1927 Italian participants in the subcohort (32.3% Ms, 67.7% Fs), mean: 50.2 ys, SD: 7.9 ys at baseline	Reproducible and valid country specific FFQs 1 y before NA FIs (36 FGs)	Type 2 diabetes incidence
Balder, 2003 (118) Netherlands, Sweden, Finland, and Italy DIETSCAN Project (NLSC, SMC, ATBC, ORDET) Poor quality	Parallel analysis of 4 prospective cohort studies on diet and cancer according to the same strategy (no pooled analysis); NLSC (random subcohort of): population-based cohort of Ms and Fs from Dutch municipalities that began in 1986; SMC: population-based cohort of Fs based on a mammography screening	100911 total subjects; ORDET: 9208 Fs with complete dietary data (mean age at baseline: 48.6 ys, SE: 8.6 ys, 35–69 ys); median follow-up and number of deaths not reported	4 different but validated FFQs; ORDET-FFQ: 1 y before; SA; Reproducible and valid; 107 FIs (51 FGs, but final number equal to 32,	No outcomes, DP drivers, or correlates of interest; Evaluation of cross-study reproducibility of identified DPs

	in 2 countries in central Sweden from 1987 to 1990; ATBC: randomized placebo-controlled intervention study conducted among M smokers who lived in south-western Finland (1985–1988); ORDET: cohort study of Italian healthy volunteer Fs from the province of Varese, northern Italy (1987–1992); international		due to ORDET availability)	
Männistö, 2005 (119) Netherlands, Sweden, and Italy DIETSCAN Project (NLSC, SMC, ATBC, ORDET) Good quality	Parallel analysis of 3 prospective cohort studies on diet and cancer according to the same strategy (no pooled analysis); NLSC (random subcohort of): population-based cohort of Ms and Fs from Dutch municipalities that began in 1986; SMC: population-based cohort of Fs based on a mammography screening in 2 countries in central Sweden from 1987 to 1990; all invasive breast cancer cases were identified through national or local cancer registers; ORDET: cohort study of Italian healthy volunteer Fs from the province of Varese, northern Italy (enrollment from 1987 to 1992; 9 ys follow-up); international; re-analysis of DPs originally derived in Balder et al. 2003	73849 total subjects (3271 breast cancer cases with complete information on their diet); ORDET: 10788 Fs (mean age at baseline: 48 ys; SE: 8.5 ys, 35-69 ys), 212 breast cancer cases	3 different but validated FFQs: ORDET-FFQ: 1 y before; SA; Reproducible and valid; 107 FIs (51 FGs, but final number equal to 32)	Breast cancer incidence
Sieri, 2004 (145) Varese (Lombardy) ORDET Very good quality	Prospective cohort study; Italian healthy volunteer women from the province of Varese, northern Italy; cancer cases identified through local cancer registry; recruitment from 1987 to 1992; 9.5 ys of average follow-up; single center/area	8984 subjects 100% Fs (34-70 ys) based on a total of 10786 subjects; 207 incident breast cancer cases	FFQ 1 y before SA Reproducible and valid 107 FIs (34 FGs)	Breast cancer incidence

Sant, 2007 (146) Varese (Lombardy) ORDET Very good quality	Prospective cohort study; Italian healthy volunteer women from the province of Varese, northern Italy; cancer cases identified through local cancer registry; recruitment from 1987 to 1992; 11.5 ys of average follow-up; single center/area; re-analysis of DPs originally provided in Sieri et al. 2004	8861 subjects 100% Fs (34-70 ys) based on a total of 8984 subjects recruited in a previous ORDET study; 267 incident breast cancer cases by December 31, 2001, with availability of HER2 status in 238 of them	FFQ 1 y before SA Reproducible and valid 107 FIs (34 FGs)	Breast cancer incidence (HER2+ vs HER2-)
Menotti, 2012 (147) Italian Rural Areas of Seven Countries Study of Cardiovascular Disease Seven Countries Study Very good quality	Prospective cohort study; enrollment in 1960 from the Italian Rural Areas cohorts, follow-up of 20 ys for CHD events and 40 ys for mortality; international	1221 total subjects (100% Ms) 45-64 ys at the 5-y follow-up in 1965 (mean: 54.9 ys, SD: 5.0 ys); at 20-y follow-up CHD events were 185 (fatal and non-fatal); at 40-y follow-up deaths were 187 for CHD, 513 for CVD, 324 for cancer, and 1148 for all-cause mortality	Dietary history; Italian Rural Areas administered at the 5-y follow-up in 1965; IA Validated NA FIs (17 FGs)	CHD incidence in 20 ys; CHD, CVD, cancer, and overall mortality in 40 ys
Menotti, 2018 (148) Italian Rural Areas of Seven Countries Study of Cardiovascular Disease Seven Countries Study Very good quality	Prospective cohort study; enrollment in 1960 from the Italian Rural Areas cohorts, follow-up of 40 ys for mortality; comparison of the role of 4 dietary scores in a sample of middle-aged men followed up during 40 ys for CHD mortality; international	1284 total subjects with final sample size equal to 1214 after excluding 70 subjects with major prevalent CHD (100% Ms); 45-64 ys at the 5-y follow-up in 1965; at 40-y follow-up deaths were 200 from CHD	Dietary history IA Validated NA FIs (17 FGs)	CHD mortality
Maugeri, 2019 (149) Mamma & Bambino Catania (Sicily) Fair quality	Cross-sectional study nested within the "Mamma & Bambino" birth cohort of pregnant women referring to "Policlinico Vittorio Emanuele" (Catania, Italy) for the prenatal genetic counselling without pre-existing medical conditions and/or pregnancy complications; recruitment from November 2014 to 2019 (ongoing at publication); single center/area	332 total subjects (100% Fs); 15-50 ys (median: 37 ys, NA); gestational age at recruitment 4-20 gwks (median: 16 gwks, NA)	FFQ 1 mo before IA Adapted from a previously validated FFQ 95 FIs (39 FGs)	Socio-demographic (i.e., age, education level, and employment status), lifestyle (i.e., smoking status, pre-gestational BMI, use of folic acid, multivitamin and/or multi-mineral supplements) factors

Maugeri, 2019 (150) Mamma & Bambino Catania (Sicily) Fair quality	Cross-sectional study nested within the "Mamma & Bambino" birth cohort enrolling pregnant women referring to "Policlinico-Vittorio Emanuele" (Catania) at 4–20 gwks (median: 16 gwks) with additional exclusion criteria related to the current article; single center/area	232 total subjects (100% Fs); 15–50 ys (median: 37 ys, NA)	FFQ 1 mo before IA Adapted from a previously validated FFQ 95 FIs (39 FGs)	Pre-gestational BMI and total GWG
Magnano San Lio, 2022 (151) Catania (Sicily) Good quality	Cross-sectional analysis of data from two prospective cohorts; pregnant women enrolled before COVID-19 pandemic ("Mamma & Bambino" cohort, from November 2014 to December 2019, during the prenatal genetic counseling) and during COVID-19 pandemic ("MAMI-MED", from December 2020 to January 2022, during the first trimester visit) in two hospitals in Catania with the aim to evaluate how their dietary habits affect the health of mother-child pairs; Italian multicentric	1097 total subjects (100% Fs); 397 "Mamma & Bambino" (median: 37.0 ys, IQR: 4.0 ys); 801 "MAMI-MED" (median: 31.0 ys, IQR: 7.0 ys)	FFQ for both studies 1 mo before IA Adapted from a previously validated FFQ 95 FIs (39 FGs)	Impact of COVID-19 pandemic on the adherence to DPs in pregnant women
Ojeda-Granados, 2022 (152) Catania (Sicily), Guadalajara (Mexico) Fair quality	Cross-sectional study; age-matched Italian non-pregnant women with no history of severe diseases recruited among those referring to three clinical laboratories in Catania (Italy) from 2010 to 2017 and from the general adult population referring to University of Guadalajara (Mexico) from 2011 to 2015; international	1026 total subjects (100% Fs), age 18–72 ys; 811 Italian subjects (median: 40 ys, IQR: 19 ys); 215 Mexican subjects (median: 40 ys, IQR: 21 ys)	Italian FFQ: 1 mo before, IA, Adapted from a previously validated FFQ, 95 FIs (39 FGs); Mexican FFQ: NA reference period, IA, 64 FIs (20 FGs)	No outcomes, DP drivers, or correlates of interest; Combined tertile-based categories of adherence to two identified DPs
Barchitta, 2018 (153) Catania (Sicily) Good quality	Cross-sectional study; women diagnosed with an abnormal PAP test without previous treatments and referred to a cervical cancer screening unit in Catania, later classified according to hrHPV status and histological grade of CIN (from normal cervical epithelium to CIN3); recruitment from 2013 to 2015; single center/area	539 total subjects (100% Fs) of which 252 with normal cervical epithelium and 160 CIN1 (i.e., low-grade CIN); 84 hrHPV infections (+) (mean: 38.63 ys, SD: 10.53 ys) among the 251 (as reported in the text) with a normal cervical epithelium; 167 hrHPV	FFQ 1 mo before IA Validated 95 FIs (39 FGs)	hrHPV status (positive: infection by any of the 13 identified hrHPV types; negative: otherwise) and high-grade CIN incidence (CIN2+ which included CIN2, CIN3, or carcinoma in situ; ≤ CIN1 which included CIN1 or normal cervical epithelium)

		infections (-) (mean: 43.65 ys, SD: 9.62 ys) among the 251 (as reported in the text) with a normal cervical epithelium; 127 CIN2+ (mean: 36.01 ys, SD: 8.10 ys); 411 with normal cervical epithelium or CIN1 (as reported in the text) (mean: 41.50 ys, SD: 10.21 ys)		
Barchitta, 2019 (154) Catania (Sicily) Good quality	Cross-sectional study; non-pregnant women with no history of severe diseases referring for routine physical examination to three clinical laboratories in Catania; recruitment from 2010 to 2017; single center/area	349 total subjects (100% Fs); age 12-87 ys (median: 36 ys, NA)	FFQ 1 mo before IA Adapted from a previously validated FFQ 95 FIs (39 FGs)	Leukocyte LINE-1 methylation (surrogate marker of global DNA methylation)
Barchitta, 2019 (155) Eastern Sicily Fair quality	Cross-sectional study; adolescents attending three high schools in the urban area of Eastern Sicily; single center/area	213 total subjects; age 15-18 ys (median: 16 ys; IQR: 0 ys); 102 Ms (median: 16 ys, IQR: 0 ys), 111 Fs (median: 16 ys, IQR: 1 y)	FFQ NA SA Adapted from a previously validated FFQ 95 FIs (36 FGs)	School performance assessed through school marks by using the previous y as reference (Italian, English, History, Science, PE, Mathematics, Comportment, and GPA were used as indicators)
Fernández-Alvira, 2014 (156) Italy, Estonia, Cyprus, Belgium, Sweden, Hungary, Germany, and Spain IDEFICS Good quality	Cross-sectional analysis nested within a prospective cohort study of children aged 2–9 ys from 8 European countries (recruited between September 2007 and May 2008) with the aim to investigate the etiology of obesity and the possible interventions for its prevention; international	14233 total subjects (8028 Ms, 6205 Fs; 2-9 ys, of which 12462 with complete dietary and socioeconomic information; mean: 6.0 ys, SD: 1.8 ys at baseline); Italy 2110 subjects (NA Ms, NA Fs)	Same FFQ across all centers (Children's Eating Habits Questionnaire-FFQ) 1 mo before IA Reproducible and valid 43 FIs (14 FGs) to investigate the consumption frequency of obesity-related foods	SES (as an additive indicator constructed by Bamman et al. including equalized household income, parental education, and occupational position, and ranging from 3 for low SES to 15 for high SES)

Naska, 2006 (157) Belgium, France, Finland, Germany, Greece, Italy, Norway, Portugal, Spain, UK DAFNE Fair quality	Analysis of standardized and post-harmonized data collected through the national household budget surveys undertaken in 10 European countries during the 1990s (Italy 1996) on food, goods, and services available to household members during the reference period conducted by the National Statistical Offices of each country; international	94564 original subjects (NA Ms, NA Fs), age from 0 to over 75 ys, of which 15251 were excluded because they did not fit the pre-defined categories; Italy: 22740 original subjects (NA Ms, NA Fs) of which 16% (3638 subjects) was excluded	No dietary assessment tool used; collected data were availability of foods and beverages at the household level taking into consideration the households' purchases, contributions from all production and food items offered to members as gifts; 56 detailed original FGs further aggregated into 25 final FGs	Socio-demographic characteristics: locality (rural, semi-urban, and urban), education level of the household head (elementary, secondary, and higher education), occupation of the household head (manual, non-manual, retired, and other), and household composition (single adult households, two adult households, lone parent households, adults and children households, single elderly households, and 2 members elderly households)
Bravi, 2021 (158) Turin (Piemonte), Florence (Tuscany), Rome (Lazio), San Giovanni Rotondo (Apulia), Palermo (Sicily) MEDIDIET Fair quality	Cross-sectional study; exclusively breastfeeding and healthy women recruited in 5 hospital settings in northern, central and southern Italy had information on dietary habits and a sample of freshly expressed foremilk collected at 6±1 wks post-partum; recruitment between 2012 and 2014; Italian multicentric	300 total subjects (100% Fs), age 25-41 ys (mean: 33 ys, SD: 4.06 ys)	FFQ at 6±1 wks post-partum, same d of milk collection From partum to d of milk collection IA Reproducible and valid 78 FIs (31 NUTs)	Foremilk macronutrients and FAs composition
Lasalvia, 2021 (159) Varese (Lombardy) ROCAV Good quality	Cross-sectional study; men and women randomly selected among residents of the Varese city (Lombardy) without main chronic diseases with the aim to investigate the relation between dietary patterns and arterial stiffness; recruitment between 2013 and 2016; single center/area	2640 total subjects (mean: 65.5 ys, SD: 6.7 ys); 1608 Ms (50-75 ys), 1032 Fs (60-75 ys)	FFQ 1 y before SA Reproducible and valid 188 FIs (41 FGs)	CVD and metabolic risk factors, and carotid-femoral PWV levels as arterial stiffness indicator
Zupo, 2020 (160) Castellana Grotte (Apulia) Salus in Apulia Study (from MICOL study) Very good quality	Prospective cohort study originally enrolling participants from Apulia based center of MICOL study in 1985, with a follow-up for mortality until December 31, 2017; single center/area	2472 total subjects (1429 Ms, 1043 Fs); age > 30 ys (mean: 48.00 ys, SD: 10.71 ys) in a representative sample of the population of Apulia in 1985; 990 total deaths, no additional information on causes	FFQ administered in 1985 1 y before SA Validated 31 FIs (29 FGs)	Overall and cause-specific (cancer, CVD, and cerebrovascular disease) mortality

Tatoli, 2022 (161) Castellana Grotte (Apulia) Salus in Apulia Study (including also a major part of MICOL study participants) Poor quality	Cross-sectional study a part of which nested within the MICOL cohort; investigated dietary differences between subjects with and without diabetes among non-institutionalized older adults from Southern Italy, recruited between 2014 and 2018, based on health registry office list at December 31, 2014, as well as previous MICOL study participants; single center/area	1399 total subjects (mean: 73.43 ys, SD: 6.30 ys); 187 diabetic subjects (115 Ms, 72 Fs; mean: 74.66 ys, SD: 6.39 ys); 1212 non-diabetic subjects (634 Ms, 578 Fs; mean: 73.24 ys, SD: 6.26 ys)	FFQ administered between 2014 and 2018 1 y before SA with interviewer checks Validated 85 FIs (28 FGs)	No outcomes, DP drivers, or correlates of interest; Evaluation of internal reproducibility of identified DPs (i.e., between subjects with and without diabetes)
Giontella, 2019 (162) Verona (Veneto) Good quality	Cross-sectional study; children were recruited from the third and fourth classes of four primary schools in the Verona South district with the aim to assess the relationship between food, PA, and main CVD risk factors; single center/area	300 total subjects (7-10 ys); 150 Ms (mean: 8.7 ys, SD: 0.8 ys), 150 Fs (mean: 8.6 ys, SD: 0.7 ys)	FFQ NA NA Validated 61 FIs (10 FGs)	CVD risk factors including anthropometric, gluco-lipid, and hemodynamic parameters
Turrone, 2021 (163) Emilia-Romagna (Italy) Good quality	Pilot intervention study; based on Istituto Romagnolo per lo Studio dei Tumori "Dino Amadori" (Meldola, Emilia Romagna) recruitment from October 2018 to September 2019; 60 subjects with at least one among abdominal obesity, hypertension, dyslipidemia, impaired fasting glucose or insulin resistance, 33 of which consumed symbiotic agriculture food (SA-group) and 27 of which received probiotic supplementation (PROB-group) over 30 ds, with a follow-up of 15 ds and stool, urine, and blood samples collected over time; single center/area	60 total subjects (13 Ms, 47 Fs) 18.3-86.4 ys (median age at enrollment: 46.9 ys, IQR: NA); 33 subjects in SA-group (5 Ms, 28 Fs) 34.6-86.4 ys (median age at enrollment: 52.7 ys, IQR: NA); 27 subjects in PROB-group (8 Ms, 19 Fs) 18.3-64.2 ys (median age at enrollment: 45.3 ys, IQR: NA)	FFQ 1 y before IA Reproducible ad valid 188 FIs (27 NUTs)	No outcomes, DP drivers, or correlates of interest; Cluster analysis based on factor scores
Donati Zeppa, 2020 (164) Urbino (Marche) Fair quality	Trial; normal-weight M and F young adults were recruited by the University of Urbino to participate to a 9-wk HIIT program to investigate the role of PA in modulating food choices; single center/area	32 total subjects (21-24 ys at enrollment); 20 Ms (mean: 22.6 ys, SD: 1.7 ys), 12 Fs (mean: 21.5 ys, SD: 0.8 ys)	24HR in association with PHOTodietometer for portion size estimation from 2 wks before to the end of the training session IA	No outcomes, DP drivers, or correlates of interest Evaluation of identified DPs

			NA NA FIs (16 NUTs)	
Colica, 2017 (165) Catanzaro (Calabria) Fair quality	Cross-sectional study nested within the cohort reported in Mazza et al. 2017; Caucasian, community-dwelling individuals from Calabria, enrolled between 2013 and 2014, without any bone metabolism disfunctions, aged ≥ 65 ys and satisfying additional criteria underwent whole-body-dual X-ray absorptiometry scan, a fasting venous blood collection, and fractures and dietary intake assessments; single center/area	177 total subjects (37% Ms, 63% Fs); age ≥ 65 ys (mean: 70 ys, SD: 4.1 ys); 41 participants had fractures (52 total fractures)	24HR + 7d-DR NA IA NA NA FIs (10 FGs)	Prevalence of (previous) fractures measured as a dichotomous variable (yes vs. no) and as WB-BMD as indicator of fractures risk in the elderly
Mazza, 2017 (166) Catanzaro (Calabria) Good quality	Cross-sectional and longitudinal analysis of a prospective cohort enrolled between 2013 and 2014 including community-dwelling, Caucasian individuals from Calabria, aged ≥ 65 ys, who underwent a neuropsychological assessment (MMSE and ADAS-Cog) at baseline and 1-y follow-up, and satisfied additional criteria (e.g., MMSE >20); dietary guidance to promote a "healthy diet" was given by a dietitian to all participants during follow-up; 1-y follow-up; single center/area	214 total subjects ≥ 65 ys at baseline (mean: 70 ys, SD: 4 ys), 144 of which had complete data on ADAS-Cog at follow-up and were included in the follow-up analysis	24HR + 7d-DR at baseline IA Validated NA FIs (8 FGs + 10 NUTs)	Cognitive decline measured with MMSE and ADAS-Cog at baseline, at 12 mos, and as progression over time for ADAS-Cog

Palli, 2001 (167) Florence (Tuscany) Good quality	Case-control study; in high-risk area for gastric cancer in central Italy, 382 cases and 561 controls recruited from 1985 to 1987 and 142 additional controls at the end of the study period to have a more representative sample; population based; single center/area	943 total subjects; 382 cases (239 Ms, 143 Fs) 30 subjects <50 ys, 130 subjects 50-64 ys; 222 subjects >64 ys; 561 controls (328 Ms, 233 Fs) 122 subjects <50 ys, 188 subjects 50-64 ys, 251 subjects >64 ys	FFQ 1 y before NA NA 181 FIs (20 NUTs)	Gastric cancer incidence; Attributable risk estimation; Correspondence analysis based on factor scores
Anelli, 2022 (168) Milan (Lombardy), Naples (Campania) GIFt Study Very good quality	Prospective cohort study; Italian healthy normal-weight singleton pregnant women at 20±2 gwks recruited between January 2017 and June 2020 in 3 hospital settings in northern and southern Italy, followed-up until delivery for pregnancy outcomes; Italian multicentric	179 total subjects 20-40 ys at baseline (mean: 31.8 ys, SD: 4.3 ys); 85 enrolled in Milan (mean: 31.7 ys, SD: 4.5 ys); 94 enrolled in Naples (mean: 31.9 ys, SD: 4.1 ys);	7d-DR: at 25±1 gwks, IA by a trained dietitian; FFQ: at 29±2 gwks, 3 mos before (second trimester of pregnancy), SA but checked by a trained dietitian, adapted from a previously validated FFQ, 192 FIs (15 FGs)	Maternal biomarkers (red blood cells folate in ng/mL, serum vitamin D in ug/L, plasma hepcidin mature form in ng/mL, and plasma total antioxidant capacity in mM) at 29±2 gwks and delivery outcomes (maternal GWG in kg, gestational age at delivery in wks, placental weight in grams, neonatal to placental weight ratio, neonatal ponderal index in grams/cm ³ , neonatal length in cm, neonatal weight in grams, and neonatal head circumference in cm)
Ruggieri, 2022 (169) Crotone (Calabria), Milazzo and Augusta-Priolo (Sicily) NEHO Study Good quality	Cross-sectional study nested within a birth cohort; healthy pregnant women with no history of chronic diseases, not requiring special diets, and living in the areas surrounding the perimeter of National Priority Contaminated Sites in Southern Italy were voluntarily recruited starting from January 2018 when admitted to the maternity units of the public hospitals in Milazzo, Syracuse (for the Augusta-Priolo area) and Crotone; Italian multicentric	816 total subjects (100% Fs), age 18-40 ys (mean: 30.6 ys, SD: 5.1 ys); 534 Augusta-Priolo (mean: 30.4 ys, SD ± 5.1 ys); 165 Crotone (mean: 30.5 ys, SD: 5.4 ys); 117 Milazzo (mean: 31.5 ys, SD: 4.5 ys); 589 subjects with available data for risk perception analyses	FFQ Gestational period until FFQ administration (from 32 gwks onwards) IA Not validated 41 FIs (38 FGs)	No outcomes, DP drivers, or correlates of interest; Cluster analysis based on principal component scores

Abbreviations: 24HR, 24-hour recall; ADAS-Cog, Alzheimer's Disease Assessment Scale - Cognitive sub-scale; ATBC, Alpha-Tocopherol Beta-Carotene Cancer; BMI, body mass index; CHD, coronary heart disease; CIN, cervical intraepithelial neoplasia; COVID-19, Coronavirus disease 2019; CRP, C-reactive protein; CVD, cardiovascular disease; d, day(s); DAFNE, Data Food Networking; DAS28-CRP, Disease Activity Score on 28 joints and C-reactive protein; DBP, diastolic blood pressure; DIETSCAN, Dietary Patterns and Cancer; DP, dietary pattern; DR, dietary record; EI, energy intake(s); EPIC, European Prospective Investigation into Cancer and Nutrition; F, female(s); FFQ, Food Frequency Questionnaire; FG, food group(s); FI, food item(s); FL, factor loading(s); FSIQ, full scale intelligence quotient; GIFt, Gestational Intake of Food towards healthy outcomes; GPA, Grade Point Average; GWG, gestational weight gain; gwks, gestational week(s); HDL, high-density lipoprotein; HER2, human epidermal growth factor receptor 2; HIIT, high

intensity interval training; HR, hazard ratio; hrHPV, high-risk Human Papilloma Virus; IA, interviewer administered; IDEFICS, Identification and prevention of Dietary- and lifestyle-induced health Effects In Children and infantS; IQR, interquartile range; LDL, low-density lipoprotein; LINE-1, Long Interspersed nuclear elements-1; M, male(s); MAMI-MED, Multisetitoriale Alla salute Materno-Infantile Mediante valutazione dell'Esposoma nelle Donne; MMSE, Mini Mental State Examination; mo, month(s); NA, not available; NAC-II, Northern Adriatic Cohort II; NEHO, Neonatal Environment and Health Outcomes; NLSC, Netherlands Cohort Study; NUT, nutrient(s); ORDET, Ormoni e Dieta nell'Eziologia del Tumore della Mammella; PA, physical activity; PCA, Principal Component Analysis; PE, Physical Education; PRI, perceptual reasoning index; PSI, processing speed index; PWV, pulse wave velocity; ROCAV, Risk Of Cardiovascular diseases and abdominal aortic Aneurysm in Varese; SA, self-administered; SBP, systolic blood pressure; SD, standard deviation; SDAI, Simplified Disease Activity Index; SE, standard error; SES, socioeconomic status; SF-36, Short Form Healthy Survey 36; SMC, Swedish Mammography Cohort; TG, triglyceride(s); VCI, verbal comprehension index; vs., versus; WB-BMD, whole-body bone mineral density; WISC-IV, Wechsler Intelligence Scale of Children; wk, week(s); WMI, working memory index; y, year(s)

Table A2. Dietary patterns identified using principal component and factor analyses in Italy and their association with disease outcomes/dietary pattern drivers/correlates of interest

Reference, location, study name, study quality	Dietary pattern identification methods	Expl. Var. % (NF)	Dietary pattern composition	Models and tests	Adjustments	Association with disease outcomes/dietary pattern drivers/correlates of interest
Edefonti, 2008 (120) Breast cancer: northern Italy (Milan, Genoa, Gorizia, Forli), central and southern Italy (Latina, Naples) Ovarian cancer: northern Italy (Milan, Pordenone, Padua), central and southern Italy (Latina, Naples) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	75.70% (4)	ANIMAL PRODUCTS: animal protein and animal fat, calcium, cholesterol, SFAs, riboflavin, zinc, and phosphorus; VITAMINS AND FIBER: vitamin C and total fiber, total folate, potassium, beta-carotene equivalents, soluble carbohydrates, and vitamin B6; UNSATURATED FAT: vegetable fat and vitamin E, MUFAs and PUFAs; STARCH-RICH: starch, vegetable protein, and sodium	Multiple logistic regression models on quartiles of factor scores for all DPs as independent variables	Adjusted for age, education, parity, menopausal status, family history of digestive cancers, family history of female cancers, BMI, geographic area, and total EI	ANIMAL PRODUCTS: OR 0.74 (95%CI: 0.61–0.91) of breast cancer for 4th vs. 1st quartile, p-trend<0.01; VITAMINS AND FIBER: OR 0.77 (95%CI: 0.61–0.98) of ovarian cancer for 4th vs. 1st quartile, p-trend=0.026; UNSATURATED FAT: OR 0.83 (95%CI: 0.68–1.00) of breast cancer for 4th vs. 1st quartile, p-trend=0.03 STARCH-RICH: OR 1.34 (95%CI: 1.10–1.65) of breast cancer for 4th vs. 1st quartile, p-trend<0.01, and OR 1.85 (95%CI: 2.37–2.48) of ovarian cancer for 4th vs. 1st quartile, p-trend=0.03; Other DPs did not provide additional evidence
Bertuccio, 2009 (121) Milan (Lombardy) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency	75.09% (4)	ANIMAL PRODUCTS: animal protein, riboflavin, cholesterol, phosphorus, calcium, and zinc; VITAMINS AND FIBER: vitamin C, total fiber, potassium, total folate, beta-carotene equivalents, and soluble carbohydrates; VUFA: other PUFAs,	Multiple logistic regression models on quartiles of factor scores for all DPs as independent variables	Conditioned on age and sex; adjusted for quinquennia of period of interview, education, BMI, tobacco smoking, and family history of gastric cancer	ANIMAL PRODUCTS: OR 2.13 (95%CI: 1.34–3.40) of gastric cancer for 4th vs. 1st quartile, p-trend=0.0003; VITAMINS AND FIBER: OR 0.60 (95%CI: 0.37–0.99) of gastric cancer for 4th vs. 1st quartile, p-trend=0.0861; STARCH-RICH: OR 1.67 (95%CI: 1.01–2.77) of gastric cancer for 4th vs. 1st quartile, p-trend=0.0463; Other DPs did not provide additional evidence

	DP reproducibility (internal)		vitamin E, MUFAs, LA, and ALA; STARCH-RICH: starch, vegetable protein, and sodium			
Edefonti, 2010 (122) Milan (Lombardy), Pordenone (Friuli Venezia Giulia), Rome, Latina (Lazio) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	79.94% (5)	ANIMAL PRODUCTS: animal fat, calcium, SFAs, animal protein, phosphorus, cholesterol, and riboflavin; VITAMINS AND FIBER: vitamin C, total fiber, soluble carbohydrates, and beta-carotene equivalents; UNSATURATED FATS: vegetable fat and vitamin E, MUFAs and PUFAs; RETINOL AND NIACIN: retinol and niacin; STARCH-RICH: starch, vegetable protein, and sodium	Multiple logistic regression models on quintiles of factor scores computed among controls for all DPs as independent variables	Adjusted for age, sex, study center, education, BMI, tobacco smoking, and alcohol drinking	ANIMAL PRODUCTS: OR 1.56 (95%CI: 1.13–2.15) of oral and pharyngeal cancer for 5th vs. 1st quintile, p-trend<0.001; VITAMINS AND FIBER: OR 0.47 (95%CI: 0.34–0.65) of oral and pharyngeal cancer for 5th vs. 1st quintile, p-trend<0.001; UNSATURATED FATS: OR 0.63 (95%CI: 0.45–0.86) of oral and pharyngeal cancer for 5th vs. 1st quintile, p-trend=0.03; STARCH RICH: OR 0.71 (95%CI: 0.50–0.99) of oral and pharyngeal cancer for 5th vs. 1st quintile, p-trend=0.06; Other DPs did not provide additional evidence
Bravi, 2010 (123) Milan (Lombardy); Genoa (Liguria), Pordenone, Gorizia (Friuli Venezia Giulia), Forli (Emilia-Romagna), Latina (Lazio), Naples	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	81.36% (5)	ANIMAL PRODUCTS: calcium, animal protein, phosphorus, riboflavin, SFAs, and cholesterol; VITAMINS AND FIBER: vitamin C, total fiber, beta-carotene equivalents, soluble carbohydrates, and total folate; VUFA: LA, ALA, and vitamin E; AUFA: other PUFAs and vitamin D; STARCH-RICH: starch,	Multiple logistic regression models on quartiles of factor scores for all DPs as independent variables; stratified analysis by sex; separate analyses by colon and rectal cancer	Adjusted for age, sex, study center, education, occupational PA, and family history of colorectal cancer	VITAMINS AND FIBER: OR 0.61 (95%CI: 0.48–0.77) of rectal cancer for 4th vs. 1st quartile, p-trend<0.0001; VUFA: OR 0.79 (95%CI: 0.65–0.96) of colon cancer for 4th vs. 1st quartile, p-trend=0.0281, and OR 1.27 (95%CI: 1.00–1.62) of rectal cancer for 4th vs. 1st quartile, p-trend=0.0831; AUFA: OR 0.80 (95%CI: 0.66–0.98) of colon cancer for 4th vs. 1st quartile, p-trend=0.0232; STARCH-RICH: OR 1.68 (95%CI: 1.37–2.07) of colon cancer for 4th vs. 1st quartile, p-trend<0.0001, and OR 1.74 (95%CI: 1.34–2.26) of rectal cancer for 4th vs. 1st quartile, p-trend=0.0001; Other DPs did not provide additional evidence;

(Campania) Good quality			vegetable protein, and sodium			comparable results were observed in the stratified analyses by sex (data not provided in the article)
Edefonti, 2010 (124) Milan (Lombardy), Pordenone (Friuli Venezia Giulia) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	79.00% (5)	ANIMAL PRODUCTS: calcium, phosphorus, riboflavin, animal protein, SFAs, zinc, and cholesterol; VITAMINS AND FIBER: vitamin C and total fiber, beta-carotene equivalents, and total folate; VUFA: LA, ALA, and vitamin E; AUFA: other PUFAs and vitamin D; STARCH-RICH: starch, vegetable protein, and sodium	Multiple logistic regression models on quartiles of factor scores computed among controls for all DPs as independent variables; stratified analyses by age, education, alcohol drinking, tobacco smoking, BMI; separate analyses by anatomic subsite (i.e., supraglottis, glottis, other/unspecified) on tertiles of each DP	Adjusted for age, sex, study center, education, BMI, occupational PA, alcohol drinking, and tobacco smoking, when appropriate	ANIMAL PRODUCTS: OR 2.34 (95%CI: 1.59–3.45) of laryngeal cancer for 4th vs. 1st quartile, p-trend<0.001; OR 2.03 (95%CI: 1.07–3.84) of supraglottis cancer and OR 2.30 (95%CI: 1.51–3.49) of glottis cancer for 3rd vs. 1st tertile; VITAMINS AND FIBER: OR 0.35 (95%CI: 0.24–0.52) of laryngeal cancer for 4th vs. 1st quartile, p-trend<0.001; OR 0.47 (95%CI: 0.25–0.86) of supraglottis cancer, OR 0.57 (95%CI: 0.39–0.84) of glottis cancer, and OR 0.45 (95%CI: 0.26–0.77) of other/unspecified site of laryngeal cancer for 3rd vs. 1st tertile; subjects older than 60 ys did not show any protective effect of this DP; VUFA: OR 1.98 (95%CI: 1.00–3.92) of supraglottis cancer for 3rd vs. 1st tertile; AUFA: OR 2.07 (95%CI: 1.42–3.01) of laryngeal cancer for 4th vs. 1st quartile, p-trend<0.001; OR 2.05 (95%CI: 1.10–3.81) of supraglottis cancer, OR 2.02 (95%CI: 1.36–3.01) of glottis cancer, and OR 2.00 (95%CI: 1.16–3.46) of other/unspecified site of laryngeal cancer for 3rd vs. 1st tertile; Starch-rich DP did not provide additional evidence overall or in strata; other DPs did not provide additional evidence based on stratified analyses
Bravi, 2012 (125) Milan (Lombardy), Pordenone (Friuli Venezia Giulia); Padua (Veneto) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal	79.18% (5)	ANIMAL PRODUCTS AND RELATED COMPONENTS: calcium, phosphorus, riboflavin, animal protein, SFAs, cholesterol, and zinc; VITAMINS AND FIBER: vitamin C, total fiber, beta-carotene equivalents, soluble	Multiple logistic regression models on quartiles of factor scores computed among controls for all DPs as independent variables	Adjusted for age, sex, study center, education, alcohol drinking, tobacco smoking, and BMI	ANIMAL PRODUCTS AND RELATED COMPONENTS: OR 1.64 (95%CI: 1.06–2.55) of esophageal cancer for 4th vs. 1st quartile, p-trend=0.0062; VITAMINS AND FIBER: OR 0.50 (95%CI: 0.32–0.78) of esophageal cancer for 4th vs. 1st quartile, p-trend=0.0002; OTHER PUFA AND VITAMIN D: OR 0.48 (95%CI: 0.31–0.74) of esophageal cancer for 4th vs. 1st quartile, p-trend=0.0009; Other DPs did not provide additional evidence

	consistency DP reproducibility (internal)		carbohydrates, and total folate; STARCH-RICH: starch, vegetable protein, and sodium; OTHER PUFAs AND VITAMIN D: other PUFAs, vitamin D, and niacin; OTHER FATS: LA, ALA, and vitamin E			
Bosetti, 2013 (126) Milan (Lombardy), Pordenone (Friuli Venezia Giulia) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	75.84% (4)	ANIMAL PRODUCTS: calcium, animal protein, phosphorus, riboflavin, SFAs, cholesterol, and zinc; VITAMINS AND FIBER: vitamin C, total fiber, beta-carotene equivalents, soluble carbohydrates, total folate, and potassium; UNSATURATED FATS: LA, vitamin E, ALA, and other PUFAs; STARCH-RICH: starch, vegetable protein, and sodium	Conditional multiple logistic regression models on quartiles of factor scores computed among controls for all DPs as independent variables	Conditioned on age (categorical), sex, and study center; adjusted for y of interview (continuous), education (categorical), BMI (categorical), tobacco smoking (categorical, combination of status and intensity), alcohol drinking (categorical, intensity), and diabetes (categorical)	ANIMAL PRODUCTS: OR 2.03 (95%CI: 1.29–3.19) of pancreatic cancer for 4th vs. 1st quartile, p-trend=0.0008; VITAMINS AND FIBER: OR 0.55 (95%CI: 0.35–0.86) of pancreatic cancer for 4th vs. 1st quartile, p-trend=0.0035; STARCH-RICH: OR 1.69 (95%CI: 1.02–2.79) of pancreatic cancer for 4th vs. 1st quartile, p-trend=0.0592; Other DPs did not provide additional evidence
Rosato, 2014 (127) Milan (Lombardy), Pordenone, Gorizia (Friuli Venezia Giulia), Latina (Lazio), Naples (Campania) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency	78.27% (5)	ANIMAL PRODUCTS: calcium, phosphorus, riboflavin, animal protein, SFAs, zinc, and cholesterol; VITAMINS AND FIBER: vitamin C, total fiber, beta-carotene equivalents, total folate, and soluble carbohydrates; VUFA: LA, vitamin E,	Multiple logistic regression models on quintiles of factor scores for all DPs as independent variables	Adjusted for age (categorical), study center, education (categorical), BMI (categorical), tobacco smoking (categorical, combination of status and intensity), alcohol drinking (categorical, combination of status and intensity), and	ANIMAL PRODUCTS: OR 1.51 (95%CI: 1.16–1.96) of prostatic cancer for 4th vs. 1st quartile, p-trend=0.02; AUFA: OR 1.32 (95%CI: 1.02–1.70) of prostatic cancer for 4th vs. 1st quartile, p-trend=0.02; STARCH-RICH: OR 1.50 (95%CI: 1.16–1.93) of prostatic cancer for 4th vs. 1st quartile, p-trend<0.001; Other DPs did not provide additional evidence

	DP reproducibility (internal)		and ALA; AUFA: other PUFAs and vitamin D; STARCH-RICH: starch, vegetable protein, and sodium		family history of prostate cancer in first-degree relatives (categorical)	
Bravi, 2015 (128) Milan (Lombardy), Pordenone, Udine (Friuli Venezia Giulia), Naples (Campania) Good quality	PCFA Standardization EIG>1, Scree plot, and interepretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	80.04% (5)	WESTERN TYPE DIET: calcium, riboflavin, phosphorus, animal protein, SFAs, cholesterol, and zinc; VITAMINS AND FIBER: vitamin C, total fiber, potassium, total folate, beta-carotene equivalents, and soluble carbohydrates; STARCH-RICH: starch, vegetable protein, and sodium; ANIMAL DERIVED NUTRIENTS AND PUFA: vitamin D, other PUFAs, and niacin; OTHER FATS: LA, ALA, and vitamin E	Conditional multiple logistic regression models on quartiles of factor scores computed among controls for all DPs as independent variables; Stratified analyses by age (<60 ys, ≥ 60 ys) and BMI (<30 kg/m ² , ≥30 kg/m ²)	Conditioned on age and study center; adjusted for period of interview, education, BMI, history of diabetes, age at menarche, menopausal status, parity, OC and HRT use	WESTERN TYPE DIET: OR 1.63 (95%CI: 1.12–2.38) of endometrial cancer for 4th vs. 1st quartile, p-trend=0.0058; OR 1.45 (95%CI: 0.93–2.26) of endometrial cancer for 4th vs. 1st quartile among subjects with BMI<30 and OR 2.08 (95%CI: 0.92–4.69) of endometrial cancer for 4th vs. 1st quartile among subjects with BMI≥30 (p-heterogeneity<0.0001); non-significant heterogeneity across strata by age; ANIMAL DERIVED NUTRIENTS AND PUFA: OR 1.76 (95%CI: 1.23–2.52) of endometrial cancer for 4th vs. 1st quartile; p-trend=0.0004; OR 1.75 (95%CI: 1.16–2.64) of endometrial cancer for 4th vs. 1st quartile among subjects with BMI<30 and OR 2.30 (95%CI: 1.03–5.16) of endometrial cancer for 4th vs. 1st quartile among subjects with BMI≥30 (p-heterogeneity<0.0001); non-significant heterogeneity across strata by age; Other DPs did not provide additional evidence
Edefonti, 2015 (129) Milan (Lombardy), Pordenone (Friuli Venezia Giulia),	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63	79.60% (5)	ANIMAL PRODUCTS: calcium, riboflavin, phosphorus, SFAs, animal protein, and cholesterol; VITAMINS AND FIBER: vitamin C and total fibre, beta-carotene	Multiple logistic regression models on tertiles of factor scores computed among controls for all DPs as independent	Adjusted for age, sex, area of residence, education, y of interview, alcohol drinking, and tobacco smoking	ANIMAL PRODUCTS: OR 2.62 (95%CI: 1.67–4.13) of nasopharyngeal cancer for 3rd vs. 1st tertile, p-trend<0.001; STARCH-RICH: OR 2.05 (95%CI: 1.27–3.33) of nasopharyngeal cancer for 3rd vs. 1st tertile, p-trend=0.022; AUFA: OR 1.55 (95%CI: 1.00–2.39) of nasopharyngeal cancer for 3rd vs. 1st tertile, p-

Naples (Campania), Catania (Sicily) Good quality	Factorability checks DP internal consistency DP reproducibility (internal)		equivalents, and total folate; VUFA: LA, ALA, and vitamin E; AUFA: other PUFAs and vitamin D; STARCH-RICH: starch, vegetable protein, and sodium	variables; Stratified analyses by age, tobacco smoking status, and alcohol drinking intensity		trend=0.038; VUFA: OR 1.90 (95%CI: 1.22–2.96) of nasopharyngeal cancer for 3rd vs. 1st tertile, p-trend=0.011; VITAMINS AND FIBER: did not provide additional evidence; non-significant heterogeneity across strata for the 5 DPs
Dalmartello, 2020 (130) Milan (Lombardy), Pordenone, Udine (Friuli Venezia Giulia), Latina (Lazio), Naples (Campania) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	74.52% (4)	ANIMAL PRODUCTS: calcium, animal protein, riboflavin, phosphorus, cholesterol, SFAs, and zinc; VITAMINS AND FIBER: vitamin C, total fiber, soluble carbohydrates, beta-carotene equivalents, potassium, and total folate; COOKING OIL AND DRESSING: vitamin E, LA, and ALA; STARCH-RICH: starch, vegetable protein, and sodium	Conditional multiple logistic regression models on quartiles of factor scores for all DPs as independent variables computed among controls; Stratified analyses by education, history of hypertension, BMI, tobacco smoking, and alcohol drinking	Conditioned on study center, sex and quinquennia of age; adjusted for yrs of education (categorical), period of interview (categorical), family history of kidney cancer in first-degree relatives (categorical), hypertension (categorical), tobacco smoking (categorical, combination of status and intensity), alcohol drinking (categorical, combination of status and intensity), and BMI (categorical)	STARCH-RICH: OR 1.38 (95%CI: 1.04–1.82) of renal cell cancer for 4th vs. 1st quartile, p-trend=0.018; COOKING OILS AND DRESSING: OR 0.61 (95%CI: 0.47–0.80) of renal cell cancer for 4th vs. 1st quartile, p-trend<0.001; Other DPs did not provide additional evidence; significant heterogeneity was observed across strata of BMI and tobacco smoking for the VITAMINS AND FIBER DP, and of tobacco smoking for the ANIMAL PRODUCTS DP, but no significant results were found in strata
Edefonti, 2020 (131) Milan (Lombardy), Pordenone (Friuli Venezia Giulia), Naples	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability	78.09% (4)	ANIMAL PRODUCTS: calcium, SFAs, riboflavin, animal protein, cholesterol, phosphorus, and zinc; VITAMINS AND FIBER: vitamin C, total fiber, beta-carotene equivalents, vitamin E,	Multiple logistic regression models on quartiles of factor scores for all DPs as independent variables	Adjusted for age (categorical), sex, center of recruitment, education (categorical), cigarette smoking (categorical, combination of status and intensity),	ANIMAL PRODUCTS: OR 0.70 (95%CI: 0.48–1.01) of bladder cancer for 4th vs. 1st quartile, p-trend=0.026; VITAMINS AND FIBER: OR 0.70 (95%CI: 0.49–0.98) of bladder cancer for 4th vs. 1st quartile, p-trend=0.109; Other DPs did not provide additional evidence

(Campania), Catania (Sicily) Good quality	checks DP internal consistency DP reproducibility (internal)		potassium, and total folate; AUFA: other PUFAs and vitamin D; STARCH-RICH: starch, vegetable protein, and sodium		alcohol drinking intensity (categorical), history of occupational exposure in selected sectors relevant for bladder cancer risk (categorical), history of diabetes, history of cystitis, family history of bladder cancer, y of interview, and BMI	
Edefonti, 2020 (132) Milan (Lombardy) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	79.85% (5)	ANIMAL PRODUCTS: cholesterol and SFAs; ANTI-OXIDANT VITAMINS AND FIBER: soluble carbohydrates, potassium, vitamin C, vitamin A (Retinol Activity Equivalent), soluble and insoluble fiber, lignans, and flavonoids; VUFA: LA, ALA, and vitamin E; AUFA: EPA and DHA, and vitamin D; STARCH-RICH: total protein, starch, sodium, phosphorus, iron, zinc, magnesium, selenium, and vitamin B1 and B3	Multiple logistic regression models on tertiles of factor scores for all DPs as independent variables with DAS28-CRP and SDAI as dependent variables dichotomized in "presence of disease activity" or "remission"; Robust linear regression models on tertiles of factor scores for all DPs as independent variables with DAS28-CRP and SDAI as continuous dependent variables;	Adjusted for age (categorical), sex, education (categorical), BMI (categorical), cigarette smoking status (categorical), alcohol drinking intensity (categorical), disease duration (categorical), RF (categorical), ACPA (categorical), presence of any therapy (categorical), conventional synthetic DMARDs (categorical), biologic DMARDs (categorical), targeted synthetic DMARDs (categorical), and steroids (categorical) for both logistic and linear regression models	ANIMAL PRODUCTS: not associated with overall disease activity; heterogeneity among strata by RF and/or ACPA positivity and among strata by disease duration was detected in the robust linear regression model with SDAI for the highest vs. the lowest tertile-based category of adherence (p-heterogeneity=0), but associations pointed in the same direction (inverse) were not significant in all strata; ANTI-OXIDANT VITAMINS AND FIBER: not associated with overall disease activity; heterogeneity among strata by RF and/or ACPA positivity was detected in the robust linear regression model with SDAI for the highest vs. the lowest tertile-based category of adherence (p- heterogeneity=0), but association pointed in the same direction (positive) was not significant in both strata; VUFA: OR 0.39 (95%CI: 0.21–0.74) of rheumatoid arthritis activity according to DAS28- CRP for the highest vs. the lowest tertile-based category of adherence; being in the highest vs. the lowest category of adherence was associated with decreased DAS28-CRP (beta: -0.36, SE: 0.14, p=0); heterogeneity among strata by disease duration was detected in the robust linear regression model with SDAI for the highest vs.

				Stratified analyses by disease severity (i.e., RF and/or ACPA positivity status) and by disease duration (≤ 15 ys, >15 ys)		the lowest category of adherence (p-heterogeneity=0), with significant inverse association only with disease duration >15 ys (beta: -4.60, SE: 1.66, p=0); AUFA: OR 0.53 (95%CI: 0.28–1.00) of rheumatoid arthritis activity according to DAS28-CRP for the highest vs. the lowest tertile-based category of adherence; being in the highest vs. the lowest category of adherence was associated with decreased DAS28-CRP (beta: -0.25, SE: 0.14, p=0.05); heterogeneity among strata by RF and/or ACPA positivity and disease duration was detected in the robust linear regression model with SDAI (p-heterogeneity=0), with significant inverse association only with RF and/or ACPA positivity (beta: -3.85, SE: 1.27, p=0) and with disease duration >15 ys (beta: -4.75, SE: 1.61, p=0); STARCH-RICH: not associated with overall disease activity; heterogeneity among strata by disease duration was detected in the robust linear regression model with SDAI highest vs. the lowest tertile-based category (p-heterogeneity=0), but associations pointed in the same direction (inverse) were not significant in both strata
Marinoni, 2022 (133) Croatia, Greece, Italy (Friuli Venezia Giulia region) Good quality	PCFA Standardization EIG >1 , Scree plot, and interpretability Varimax rotation $ FL \geq 0.60$ Factorability checks DP internal consistency DP reproducibility (internal)	63.39% (5)	DAIRY PRODUCTS: calcium, biotin, magnesium, pantothenic acid, iodine, phosphorus, and vitamin B2; PLANT-BASED FOODS: total fiber, vitamin C, folate, potassium, beta-carotene, vitamin E, and iron; FATS: MUFAs, oleic acid, SFAs, and LA; MEAT AND POTATOES: niacin, vitamin B6, proteins,	Robust multiple linear regression models for assessing the association between all DPs as independent variables (continuous variables) and each of FSIQ, VCI, PRI, WMI, and PSI (from WISC-IV) as	Adjusted for father's education (categorical), maternal Raven's test score during pregnancy (continuous), folic acid supplementation before pregnancy (categorical), alcohol consumption during pregnancy (units per wk, continuous), breastfeeding (categorical), house	DAIRY PRODUCTS: inversely associated with PSI score (beta: -2.05, SE: 0.84, p-value <0.01); MEAT AND POTATOES: inversely associated with VCI score (beta: -1.28, SE: 0.66, p-value <0.05); SEAFOOD: positively associated with VCI score (beta: 1.24, SE: 0.64, p-value <0.05) and with PRI score (beta: 1.35, SE: 0.70, p-value <0.05); Other DPs did not provide additional evidence

			vitamin B1, and zinc; SEAFOOD: EPA, DHA, and selenium	dependent variable	property (categorical), child's sex (categorical), child's birth weight ≥4 kg (categorical), child's BMI at 7 ys (categorical), and child's extracurricular PA at 7 ys (categorical)	
Centritto, 2009 (134) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	15.7% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; PASTA AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee,	Multiple linear regression models on quintiles of each factor score as independent variable and total, HDL and LDL cholesterol, SBP, DBP, and log- transformed values for CRP, CUORE project CVD risk score across strata by sex, TGs, and blood glucose in the presence of asymmetry	Adjusted for sex, smoking, SES, age, BMI, total EI and total PA (continuous); Analyses on CRP further adjusted for TGs and performed only where CRP ≤10 mg/L; Analyses on CUORE project CVD risk were only adjusted for smoking, age, and total EI	OLIVE OIL AND VEGETABLES: higher factor scores were associated with reduced total cholesterol (p-trend=0.0006), LDL cholesterol (p- trend=0.039), SBP (p-trend=0.0012), DBP (p- trend=0.0002), CRP (p-trend=0.018), CUORE project CVD risk score in Ms (p-trend<0.0001), TGs (p-trend<0.0001), and blood glucose (p- trend=0.001); PASTA AND MEAT: higher factor scores were associated with increased total cholesterol (p- trend=0.0043), LDL cholesterol (p-trend=0.032), DBP (p-trend=0.098), CRP (p-trend<0.0001), CUORE project CVD risk score in Ms (p- trend=0.0007) and in Fs (p-trend<0.0001), TGs (p-trend=0.0002), and blood glucose (p- trend<0.0001); EGGS AND SWEETS: higher factor scores were associated with increased CRP (p-trend<0.0001) and CUORE project CVD risk score in Ms (p- trend=0.041), and with reduced TGs (p- trend=0.044)

			soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer			
Bonaccio, 2012 (135) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	NA% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; PASTA AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	Multiple linear regression models with each DP as dependent variable, and categories of household income as independent variable; ANOVA based on the regression models to test the presence of differences between means of factor scores of each DP across categories of household net income; Stratified analyses by age and sex	Adjusted for age, sex, daily EI, BMI, PA, smoking, alcohol consumption, and marital status	OLIVE OIL AND VEGETABLES: mean factor scores were not equal across the 4 categories of income ($p<0.0001$) with mean factor scores reported to be higher in higher categories of income; similar results were observed after stratification by age and sex; EGGS AND SWEETS: mean factor scores were not equal across the 4 categories of income ($p<0.0001$) with mean factor scores reported to be lower in both extreme categories of low and high income; similar results were observed after stratification by age and sex; Other DPs did not provide additional evidence

Bonaccio, 2012 (136) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	NA% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; PASTA AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	Multiple linear regression models with each DP as dependent variable, and tertiles of factor scores of mass media exposure (light/moderate/he avy exposure) as independent variables; ANOVA based on the regression models to test the presence of differences between means of factor scores of each DP across tertiles of factor scores of mass media exposure; Stratified analysis by SES (low/medium/hig h) and education (higher/lower)	Adjusted for sex, age and additionally for total EI, PA, log- transformed CRP (based on $p<0.10$ in a series of age and sex adjusted regression models) as well as the other two DPs and SES or education depending on the regression model; stratified models adjusted for sex, age, total EI, PA, log- transformed CRP, and the other two DPs	OLIVE OIL AND VEGETABLES: mean factor scores were not equal across tertiles of mass media exposure in the SES-adjusted ($p=0.0018$) and in the education-adjusted ($p=0.0027$) models, with mean factor scores reported to be higher in the heavy mass media exposure group; mean factor scores were not equal across tertiles of mass media exposure when analyses were restricted to the medium SES subgroup ($p=0.03$), with mean factor scores reported to be higher in the heavy mass media exposure group; mean factor scores were not equal across tertiles of mass media exposure when analyses were restricted to the higher ($p=0.015$) and lower ($p=0.09$) education subgroups, with mean factor scores reported to be higher in the heavy mass media exposure group; PASTA AND MEAT: mean factor scores were borderline not equal across tertiles of mass media exposure in the SES-adjusted ($p=0.068$) and in the education-adjusted ($p=0.034$) models, with mean factor scores reported to be lower in the heavy mass media exposure group; mean factor scores were not equal across tertiles of mass media exposure when analyses were restricted to the medium SES subgroup ($p=0.03$), with mean factor scores reported to be higher in the moderate mass media exposure group; mean factor scores were not equal across tertiles of mass media exposure when analyses were restricted to the lower education subgroup ($p=0.06$), with mean factor scores reported to be lower in the heavy mass media exposure group; Other DPs did not provide additional evidence
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Bonaccio, 2013 (137) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	NA% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; PASTA AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	ANOVA to provide adjusted estimates of mean factor scores across levels of nutrition knowledge; Multiple linear regression models with each DP as dependent variable and nutrition knowledge (low, medium, and high) as independent variable; Stratified analysis by education levels (≤8 ys, >8 ys)	ANOVA adjusted for age, sex, total EI; Multiple linear regression adjusted for age, sex, total EI, BMI, PA, education level, income, SES, marital status, and smoking	OLIVE OIL AND VEGETABLES: in the overall analysis, adjusted mean (SD) factor scores reported in the text were -0.11 (0.95), -0.04 (0.82), 0.16 (0.96) for low, medium and high levels of nutrition knowledge, respectively; in stratified analysis by education, mean (SD) factor scores reported in the text were -0.09 (0.95), - 0.07 (0.84), 0.16 (0.98) for low, medium and high levels of nutrition knowledge in high-educated subjects only, and -0.11 (0.96), 0.001 (0.80), 0.14 (0.92) for low, medium and high levels of nutrition knowledge in low-educated subjects only; higher mean factor scores were associated with higher nutrition knowledge levels overall (p- trend=0.001), in high-educated subjects only (p- trend=0.01), and borderline in low-educated subjects only (p-trend=0.05); Other DPs did not provide additional evidence
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Bonanni, 2013 (138) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation $ FL \geq 0.15$ Factorability checks NA DP internal consistency NA DP reproducibility (internal)	NA% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; PASTA AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	Multiple ANOVA with DPs as dependent variables and food labels reading status (yes/no) as independent variable	Adjusted for age, sex, total EI, SES, income, BMI, smoking, PA, and education level	OLIVE OIL AND VEGETABLES: mean factor scores were not equal across food labels reading categories (p-value<0.0001) with mean (SD) being 0.1 (0.8) in readers and -0.2 (0.8) in non- readers, as reported in the article; PASTA AND MEAT: mean factor scores were not equal according to food labels reading categories (p-value=0.009) with mean (SD) being 0.01 (0.9) in readers and 0.2 (0.8) in non-readers, as reported in the article; EGGS AND SWEETS: mean factor scores were not equal across food labels reading categories (p-value=0.02) with mean (SD) being 0.1 (0.8) in readers and 0.2 (0.9) in non-readers, as reported in the article
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Bonaccio, 2013 (139) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	NA% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; MEAT AND PASTA: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	Multiple linear regression models to assess association of each DP as independent variable (1 SD increase), and mental and physical health scores as continuous and dependent variables; Multiple logistic regression models on quartiles of factor scores for each DP as independent variable and extreme mental and physical health conditions (4th vs. 1st quartile-based score categories) as dependent variable; Stratified analysis by sex	Adjusted for age, sex, BMI, total EI, total PA, education, income, total SES, smoking, diabetes, hypertension and hypercholesterolemia , and additional adjustment for MUFAs, PUFAs, SFAs, FAC or dietary fiber in 5 separate models	OLIVE OIL AND VEGETABLES: 1 SD increase in mental component score was directly related with factor scores (beta: 0.50, 95%CI: 0.34–0.65, p-value<0.0001); further adjustment for MUFAs, PUFAs or SFAs in 3 separate models did not materially change point estimates, CIs, and p- values, but results changed with further adjustment for FAC (beta: 0.19, 95%CI: -0.003– 0.38, p-value=0.05) or dietary fiber (beta: 0.32, 95%CI: 0.15–0.50, p-value=0.0004) in 2 separate models; 1 SD increase in physical component score was directly associated with factor scores (beta: 0.15, 95%CI: 0.06–0.24, p-value=0.001); further adjustment for MUFAs, PUFAs, SFAs, FAC or dietary fiber in 5 separate models did not materially change point estimates, CIs, and p- values; ORs of being in the uppermost (4th) vs. 1st quartile of mental and physical component scores were 1.59 (95%CI: 1.39–1.83, p- trend<0.0001) and 1.22 (95%CI: 1.05–1.41, p- trend=0.01) for participants in the 4th vs. 1st quartile of factor scores; further adjustment for FAC or dietary fiber in 2 separate models did not materially change point estimates, CIs and p- trend values; MEAT AND PASTA: 1 SD increase in physical component score was inversely associated with factor scores (beta: -0.11, 95%CI: -0.20 to -0.02, p-value=0.02); further adjustment for MUFAs, PUFAs, SFAs, FAC or dietary fiber in 5 separate models did not materially change point estimates, and CIs; OR of being in the uppermost (4th) vs. 1st quartile of physical component scores was 0.86 (95%CI: 0.73–1.01, p-trend=0.02) for participants in the 4th vs. 1st quartile of factor scores; further adjustment for FAC or dietary fiber in 2 separate models did not materially change point estimates, CIs, and p-trend values; EGGS AND SWEETS: 1 SD increase in mental component score was inversely associated with
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						factor scores (beta=-0.33, 95%CI: -0.52 to -0.14, p-value=0.001); further adjustments for MUFAs, PUFAs or SFAs in 3 separate models did not materially change point estimates, CIs, and p-values but results changed with further adjustment for FAC (beta: -0.18, 95%CI: -0.39–0.01, p-value=0.06) or dietary fiber (beta: -0.16, 95%CI: -0.36–0.04, p-value=0.11) in 2 separate models; 1 SD increase in physical component score was not associated with factor scores; OR of being in the uppermost (4th) vs. 1st quartile of mental component score was 0.86 (95%CI: 0.73–1.01, p-trend=0.15) for participants in the 4th vs. 1st quartile of factor scores; further adjustment for FAC or dietary fiber in 2 separate models gave non-significant results; OR of being in the uppermost (4th) vs. 1st quartile of physical component score was 1.24 (95%CI: 1.05–1.47, p-trend=0.05) for participants in the 4th vs. 1st quartile of factor scores; further adjustment for FAC or dietary fiber in 2 separate models did not materially change point estimates, CIs, and p-trend values; Stratified analyses did not provide additional evidence
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Bonaccio, 2016 (140) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	13.5% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; PASTA AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	Cox proportional hazard model for overall mortality including factor scores for each DP (continuous variables, 1 SD increase) as independent variable	Adjusted for age, sex, education, EI, leisure- time PA, smoking, ys from diagnosis of diabetes, blood glucose levels, and hypercholesterolemia	No significant associations between overall mortality and DPs in the fully-adjusted model
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Bonaccio, 2018 (141) Molise Moli-sani Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.15 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	6.6% (3)	OLIVE OIL AND VEGETABLES: olive oil, cooked and raw vegetables, legumes, soups, fruits, fish, potatoes, bouillon, white meat, crustaceans and molluscs, crisp bread and rusks, nuts and dried fruits, yogurt, snacks, and fresh cheese; ANIMAL FATS AND MEAT: high on pasta and other grains, cooked tomatoes, red meat, white meat, olive oil, animal fats, other sauces, wine, beer, bread, offals, processed meat, and seasoned cheese; low on breakfast cereals and yogurt; EGGS AND SWEETS: eggs, margarines, processed meat, sugar and sweets, vegetable oils, snacks, mayonnaises, butter, seasoned cheese, fresh cheese, pizza, canned fish, fruit juices, coffee, soft drinks, potatoes, white meat, red meat, animal fats, bread, and beer	Standardized multiple linear regression with psychological resilience as dependent variable and all DPs as independent variable; stratified analyses by age (≤65 ys, >65 ys), sex (Ms, Fs), education (up to lower secondary school, upper secondary school, post-secondary school), CVD status, cancer status, hypertension status, hypercholesterole mia status, and antidepressant use; further adjusted for the other two DPs	Adjusted for age, sex, EI, education, leisure- time PA, smoking habit, and cancer	OLIVE OIL AND VEGETABLES: psychological resilience scale increases of 1.184 (95%CI: 0.927–1.441, p-value<0.0001) for each 1 SD increase in factor score; point estimates and 95%CI did not materially change after restricting the sample to a complete-case analysis of 10351 individuals (beta: 1.176, 95%CI: 0.914- 1.439), nor to a subgroup of 3263 healthy subjects free from CVD, cancer, diabetes, hypercholesterolemia, hypertension, and depression (beta: 0.944, 95%CI: 0.500–1.388); Stratified analyses revealed no material differences among strata except for sex (beta: 0.998, 95%CI: 0.643–1.354 among Ms; beta: 1.430, 95%CI: 1.053–1.807 among Fs), education (beta: 0.957, 95%CI: 0.516–1.399 among the "up to lower secondary school" group; beta: 1.358, 95%CI: 0.989–1.727 among the "upper secondary school"; beta: 1.264, 95%CI: 0.681– 1.846 among the "post-secondary school" group) and cancer status (beta: 2.616, 95%CI: 1.100– 4.133 among cancer subjects; beta: 1.154, 95%CI: 0.893–1.416 among non-cancer subjects) in the absence of any heterogeneity test; Other DPs did not provide additional evidence in fully adjusted models
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Pala, 2006 (142) Denmark, France, Germany, Greece, Netherlands, Spain, Sweden, UK, Italy (Varese, Turin, Florence, Naples, Ragusa) EPIC (EPIC-Elderly) Good quality	EFA Standardization EIG $\geq$ NA, Scree plot Varimax rotation FL $\geq$ 0.30 Factorability checks NA DP internal consistency NA DP reproducibility NA	21% (4)	PRUDENT: other vegetables, legumes, cooked leafy vegetables, onions and garlic, cabbage, fish, crustaceans and molluscs, mushrooms, seed oils, cooked tomatoes, fresh fruit (non-citrus), and nuts and seeds; PASTA & MEAT: high on pasta and other grains, beef, other animal fats, cooked tomatoes, wine, bread, processed meat, and pork; low on yogurt; OLIVE OIL & SALAD: olive oil, raw tomatoes, raw leafy vegetables, root vegetables, soup, and chicken and turkey; SWEET & DAIRY: sugar and honey and jam, ice cream, chocolate-based confectionery, cakes and puddings, coffee, processed meat, eggs, milk, butter, cheese, and patisserie and biscuits	Crude means of factor scores and t-test testing the differences between factor scores of each DP by sex; separate analyses by sex: t-test testing the differences between sex-standardized crude means of factor scores (for each DP) by presence of high school education, hypertension status, hyperlipidemia status, whether on a diet, presence of recent modification of habitual diet; Separate analyses by sex: simple linear regression models inserting the category number into the model for p-trend evaluation, testing the presence of a trend in sex-standardized crude means of factor scores for each DP by BMI	Not applicable	PRUDENT: different crude mean factor scores among Ms (-0.16) and Fs (0.06), p-value<0.001; different crude mean factor scores among Ms with (0.13) and without (-0.05) high school education (p-value=0.002) and Fs with (0.26) and without (-0.08) high school education (p-value<0.001); different crude mean factor scores among Fs with (-0.09) and without (0.02) recent modification of habitual diet (p-value=0.003); different crude mean factor scores among Fs with (0.07) and without (-0.04) hypertension (p-value=0.001), also when restricting the analysis to not on a diet Fs (p<0.001) with (0.11) and without (-0.03) hypertension; different crude mean factor scores among Fs with (0.04) and without (-0.02) hyperlipidemia (p-value=0.07), also when restricting the analysis to not on a diet Fs (p=0.02) with (0.01) and without (-0.02) hyperlipidemia; increasing crude mean factor scores were associated with higher BMI in Ms (p-trend=0.09) and Fs (p-trend<0.001), also when restricting the analysis to not on a diet Fs (p-trend<0.001); increasing crude mean factor scores were associated with higher WHR in Fs (p-trend<0.001), also when restricting the analysis to not on a diet Fs (p-trend<0.001); increasing crude mean factor scores were associated with higher PAL in Ms (p-trend<0.001) and lower PAL Fs (p-trend<0.001), also when restricting the analysis to not on a diet Ms (p-trend<0.001) and Fs (p-trend<0.001); crude mean scores were not equal among all recruitment centers in Ms (0.02 in Florence, -0.30 in Varese, 0.76 in Ragusa, and -0.76 in Turin, p-value<0.001) and Fs (-0.19 in Florence, -0.45 in Varese, 0.32 in Ragusa, -0.25 in Turin, and 1.73 in Naples, p-value<0.001); PASTA & MEAT: different crude mean factor scores among Ms (0.76) and Fs (-0.29), p-value<0.001; different crude mean factor scores
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				(<25, 25-29, 30-34, ≥35), WHR (in tertile-based on the distribution in men or women according to stratification), and PAL (in tertile-based on the distribution of the entire population); Separate analyses by sex: one-way ANOVA and F-test testing equality of sex-standardized crude means of factor scores for each DP among categories of recruitment center	among Ms with (-0.21) and without (0.08) high school education (p-value<0.001) and Fs with (-0.06) and without (0.02) high school education (p-value=0.05); different crude mean factor scores among Ms with (-0.34) and without (0.06) recent modification of habitual diet (p-value<0.001) and Fs with (-0.33) and without (0.08) recent modification of habitual diet (p-value<0.001); different crude mean factor scores among not on a diet Fs with (0.12) and without (0.06) hypertension (p-value=0.08); different crude mean factor scores among Ms with (-0.11) and without (0.05) hyperlipidemia (p-value=0.005) and Fs with (-0.11) and without (0.06) hyperlipidemia (p-value<0.001), also when restricting the analysis to not on a diet Fs (p-value=0.001) with (-0.01) and without (0.08) hyperlipidemia; increasing crude mean factor scores were associated with higher BMI in Ms (p-trend=0.001) and Fs (p-trend<0.001), also when restricting the analysis to not on a diet Ms (p-trend=0.004) and Fs (p-trend<0.001); increasing crude mean factor scores were associated with higher WHR in Ms (p-trend<0.001) and Fs (p-trend<0.001), also when restricting the analysis to not on a diet Ms (p-trend=0.001) and Fs (p-trend<0.001); increasing crude mean factor scores were associated with higher PAL (p-trend=0.003), also when restricting the analysis to not on a diet Ms (p-trend=0.003); crude mean scores were not equal among all recruitment centers in Ms (0.16 in Florence, 0.14 in Varese, -0.22 in Ragusa, and -0.13 in Turin; p-value<0.001) and Fs (0.11 in Florence, -0.13 in Varese, -0.13 in Ragusa, -0.32 in Turin, and 0.37 in Naples, p-value<0.001); OLIVE OIL & SALAD: different crude mean factor scores among Ms (0.16) and Fs (-0.06), p-value<0.001; different crude mean factor scores among Ms with (0.26) and without (-0.05) recent
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						modification of habitual diet (p-value<0.001) and Fs with (0.36) and without (-0.09) recent modification of habitual diet (p-value<0.001); different crude mean factor scores among Ms with (0.07) and without (-0.03) hyperlipidemia (p-value=0.06) and Fs with (0.09) and without (-0.05) hyperlipidemia (p-value<0.001), also when restricting the analysis to not on a diet Fs (p-value=0.001) with (-0.02) and without (-0.06) hyperlipidemia; increasing crude mean factor scores were associated with higher BMI in Ms (p-trend=0.014); decreasing crude mean factor scores were associated with higher WHR in Ms (p-trend=0.015) and Fs (p-trend<0.001), also when restricting the analysis to not on a diet Fs (p-trend<0.001); increasing crude mean factor scores were associated with higher PAL in Fs (p-trend<0.001), also when restricting the analysis to not on a diet Fs (p-trend<0.001); crude mean scores were not equal among all recruitment centers in Ms (0.09 in Florence, -0.05 in Varese, -0.65 in Ragusa, and 0.23 in Turin, p-value<0.001) and Fs (0.15 in Florence, 0.05 in Varese, -0.24 in Ragusa, 0.42 in Turin, and -0.81 in Naples, p-value<0.001); SWEET & DAIRY: different crude mean factor scores among Ms (-0.04) and Fs (0.02), p-value=0.046; different crude mean factor scores among Fs with (0.06) and without (-0.02) high school education (p-value=0.04); different crude mean factor scores among Ms with (-0.23) and without (0.04) recent modification of habitual diet (p-value<0.001) and Fs with (-0.19) and without (0.04) recent modification of habitual diet (p-value<0.001); different crude mean factor scores among Fs with (-0.04) and without (0.02) hypertension (p-value=0.06); different crude mean factor scores among Ms with (-0.19) and without (0.09) hyperlipidemia (p-value<0.001) and Fs with (-0.11) and without (0.06)
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						hyperlipidemia (p-value<0.001), also when restricting the analysis to not on a diet Ms (p-trend<0.001) with (-0.16) and without (0.12) hyperlipidemia and Fs (p-trend<0.001) with (-0.16) and without (0.12) hyperlipidemia; decreasing crude mean factor scores were associated with higher BMI in Fs (p-trend=0.003), also when restricting the analysis to not on a diet Fs (p-trend<0.001); decreasing crude mean factor scores were associated with higher WHR in Fs (p-trend<0.001), also when restricting the analysis to not on a diet Fs (p-trend<0.001); increasing crude mean factor scores were associated with higher PAL in Fs (p-trend<0.001), also when restricting the analysis to not on a diet Fs (p-trend<0.001); crude mean scores were not equal among all recruitment centers in Ms (0.05 in Florence, 0.28 in Varese, -0.09 in Ragusa, and -0.22 in Turin, p-value<0.001) and Fs (0.05 in Florence, 0.23 in Varese, -0.25 in Ragusa, -0.11 in Turin, and -0.50 in Naples, p-value<0.001)
Masala, 2007 (143) Denmark, France, Germany, Greece, Netherlands, Spain, Sweden, UK, Italy (Varese, Turin, Florence, Naples, Ragusa) EPIC (EPIC-Elderly) Very good quality	EFA Standardization NA EIG≥NA, Scree plot Varimax rotation FL ≥0.30 Factorability checks NA DP internal consistency NA DP reproducibility NA	21% (4)	PRUDENT: other vegetables, legumes, cooked leafy vegetables, onions and garlic, cabbage, fish, crustaceans and molluscs, mushrooms, seed oil, fresh fruit (non-citrus), cooked tomatoes, and nuts and seeds; PASTA & MEAT: high on pasta and other grains, beef, other animal fats, cooked tomatoes, wine, white bread, processed meat, and pork; low on yogurt; OLIVE OIL & SALAD:	Multiple Cox proportional hazard regression models to estimate overall mortality (HR) according to sex-specific quartiles of factor scores of each DP as independent variable in separate models; stratified analysis by recruitment center due to center-specific DPs and	Adjusted for sex, age, log-transformed EI, BMI, waist, smoking status, yrs of education, civil status, hypertension status at enrolment, and PAL	OLIVE OIL & SALAD: being in the 4th vs. 1st quartile of factor scores protected against overall mortality (HR: 0.50, 95%CI: 0.29–0.86, p-trend=0.02); stratified analyses by sex and geographic area (northern vs. central-southern centers) did not provide significant results; Other DPs did not additional evidence

			olive oil, raw tomatoes, raw leafy vegetables, root vegetables, soup, and chicken and turkey; SWEET & DAIRY: sugar and honey and jam, ice cream, chocolate-based confectionery, cakes and puddings, coffee, processed meat, eggs, milk, butter, cheese, and patisserie and biscuits	additional stratified analyses by sex and geographic area in center-specific models		
Jannasch, 2019 (144) Italy, France, Spain, UK, Netherlands, Germany, Sweden, Denmark EPIC-InterAct Good quality	Separate PCFAs on each country Standardization EIG>1, Scree plot, and interpretability Varimax rotation Simplified sum score with different cut-offs for FL values, but final cut-off equal to 0.4 Factorability checks NA DP internal consistency NA DP reproducibility (internal and cross-study)	18.3% (2)	PC1: leafy vegetables, fruiting vegetables, cabbage, other vegetables, legumes, fish, and vegetable oils; PC2: pasta and rice, red meat, processed meat, other fats, and sugar	Prentice-weighted multiple Cox proportional hazard regression models, investigating the association between DPs and hazard of type 2 diabetes incidence; Stratified analysis by country and center, if present, due to country/center-specific DPs; additional stratified analysis by integers of age; Cross-study reproducibility of DPs: meta-analysis of diabetes-associated country-specific	Adjusted for sex, PA, education level, smoking status, total EI, BMI, and waist circumference	PC1: increase in factor score was borderline associated with an increased hazard of type 2 diabetes in Italy (HR: 1.10, 95%CI: 0.98–1.23, p-value=0.1); the other DP did not provide additional evidence for Italy; data not shown on stratified analyses by integers of age; Cross-study reproducibility of DPs: among the country-specific DPs associated with diabetes risk, the positive association of the UK-Norfolk DP could potentially be replicated across other countries in the EPIC-InterAct study, but not those from Spain and France

				DPs using simplified or replicated scores		
Balder, 2003 (118) Netherlands, Sweden, Finland, and Italy DIETSCAN Project (NLSC, SMC, ATBC, ORDET) Poor quality	Separate PCFAs on each of the 4 studies (but NLSC separate analyses for Ms and Fs) Standardization EIG>1, Scree plot, and interpretability Varimax rotation $ FL \geq 0.35$ Factorability checks NA DP internal consistency NA DP reproducibility (internal and cross-study)	ORDET: 28.5% (4)	(SALAD) VEGETABLES: raw leafy vegetables, dressings, tomatoes, oil, and carrots; PORK, PROCESSED MEAT, POTATOES: butter, non-fermented whole milk, pasta, beef, potatoes, processed meat, cakes, and eggs; COOKED VEGETABLES: legumes, cabbages, cooked leafy vegetables, fish, carrots, rice, potatoes, and poultry; ALCOHOL: high on wine and spirits; low on coffee (with milk), non-fermented lowfat milk, cakes, and other fruits	Not applicable	Not applicable	Not applicable Cross-study reproducibility: From visual inspection of PCFA loadings across solutions, (SALAD) VEGETABLES: factors were qualitatively similar across studies and between Ms and Fs; PORK, PROCESSED MEAT, POTATOES: factors were qualitatively similar across studies and between Ms and Fs, but somewhat less consistently than (SALAD) VEGETABLES; COOKED VEGETABLES: found for ORDET and NLCS Ms; ALCOHOL: found for ORDET, ATBC, and SMC
Männistö, 2005 (119) Netherlands, Sweden, and Italy DIETSCAN Project (NLSC, SMC, ATBC, ORDET) Good quality	Separate PCFAs on each of the 3 studies Standardization EIG>1, Scree plot, and interpretability Varimax rotation $ FL \geq 0.35$ Factorability checks NA DP internal consistency NA DP	ORDET: 28.5% (2)	VEGETABLES (VEG): raw leafy vegetables, tomatoes, dressings, oil, and carrots; PORK, PROCESSED MEAT, POTATOES (PPP): butter, pasta, potatoes, beef and veal, and processed meat; Plus 2 additional DPs for ORDET (presented in Balder et al.) but not common to other cohorts and therefore not considered here	ORDET: multiple Cox proportional hazard regression models investigating the association between breast cancer incidence and factor scores of each DP in continuum and in quartiles, in separate models; Stratified analysis by country due to	Adjusted for age, BMI, height, education, smoking status, family history of breast cancer, OC and HRT use, alcohol intake, and EI	ORDET: no significant associations between any of the two DPs and breast cancer incidence was identified; stratified analyses by menopausal status did not provide any additional evidence

	reproducibility NA			region-specific DPs and additional stratified analysis by menopausal status in country- specific models		
Sieri, 2004 (145) Varese (Lombardy) ORDET Very good quality	EFA Standardization NA EIG>NA, Scree plot Varimax rotation FL >0.25 Factorability checks NA DP internal consistency NA DP reproducibility NA	30% (4)	SALAD VEGETABLES: raw and cooked leafy vegetables, mixed vegetables in salad, raw tomatoes, raw carrots, olive oil and other fruiting vegetables; WESTERN: butter, potatoes, other pasta, processed meat, veal, eggs, cakes, beef, seed oils, offal, pork, and cheese; CANTEEN: pasta, cooked tomatoes, olive oil, pulses, other fruiting vegetables, veal, bread and wine; PRUDENT: high on cooked carrots, cooked leafy vegetables, rice, fish, other fruiting vegetables, pulses, poultry, raw carrots, potatoes, yogurt, and olive oil; low on wine and spirits	Multiple Cox proportional hazard regression model investigating the association between breast cancer incidence and tertiles of factors scores for all DPs, using 1st tertile as reference; Stratified analysis by BMI (<25 kg/m ² , ≥25 kg/m ²)	Adjusted for EI, age, ys of education, parity, height, age at menarche, smoking, and menopausal status	SALAD VEGETABLES: being in the 3rd vs. 1st tertile of factor scores was associated with a lower risk of breast cancer (RR: 0.66, 95%CI: 0.47–0.95, p-trend=0.016); stratified analyses by BMI: in BMI<25 women RR=0.39, 95%CI: 0.22–0.69, p-trend=0.001; in BMI≥25 women RR did not give significant results; Other DPs did not provide additional evidence

Sant, 2007 (146) Varese (Lombardy) ORDET Very good quality	EFA Standardization EIG>NA, Scree plot Varimax rotation FL >0.25 Factorability checks NA DP internal consistency NA DP reproducibility NA	30% (4)	SALAD VEGETABLES: raw and cooked leafy vegetables, mixed vegetables in salad, raw tomatoes, raw carrots, olive oil and other fruiting vegetables; WESTERN: butter, potatoes, other pasta, processed meat, veal, eggs, cakes, beef, seed oils, offal, pork, and cheese; CANTEEN: pasta, cooked tomatoes, olive oil, pulses, other fruiting vegetables, veal, bread and wine; PRUDENT: high on cooked carrots, cooked leafy vegetables, rice, fish, other fruiting vegetables, pulses, poultry, raw carrots, potatoes, yogurt, and olive oil; low on wine and spirits	Multinomial multiple logistic regression model to assess risk of HER2+ and HER2- breast cancer (vs. non-cases) according to tertiles of factor scores for all DPs in the same model (1st tertile as reference); RR heterogeneity between HER2+ and HER2- assessed by Wald test	Adjusted for total EI, age, yrs of education, parity, height, weight, age at menarche, smoking, and menopausal status	SALAD VEGETABLES: being in the 3rd vs. 1st tertile of factor scores was associated with a reduced risk of HER2+ breast cancer (RR: 0.25, 95%CI: 0.10–0.64, p-trend=0.001), much stronger than risk of HER2- breast cancer (RR: 0.71, 95%CI: 0.48–1.03, p-trend=0.072) (p-heterogeneity=0.039); Other DPs did not provide additional evidence
Menotti, 2012 (147) Italian Rural Areas of Seven Countries Study of Cardiovascular Disease Seven Countries Study	PCFA Standardization NA Adjustment by weight EIG>1, Scree plot Varimax rotation FL ≥0.25 Factorability checks NA DP internal	≥82%* (3)	FACTOR 1: sugar, milk, meat, fruit, pastries, and cheese; FACTOR 2: bread, cereals, vegetables, fish, potatoes, and oils; FACTOR 3: eggs and alcoholic beverages	Multiple Cox proportional hazard models assessing HRs of CHD-specific incidence at 20-y follow-up, overall mortality and mortality from CHD, CVD or cancer at 40-y follow-up in separate models,	Adjusted for age, BMI, smoking status, SBP, and serum cholesterol	FACTOR 1: 1 SD increase in factor scores was associated with borderline reduced CHD mortality (HR: 0.87, 95%CI: 0.76–1.01) and cancer mortality (HR 0.91, 95%CI: 0.81–1.01) and with borderline increased CVD mortality (HR: 1.07, 95%CI: 0.98–1.18), at 40-y follow-up; FACTOR 2: 1 SD increase in factor scores was associated with reduced CHD incidence (HR: 0.88, 95%CI: 0.73–0.96) at 20-y follow-up, CHD mortality (HR 0.79, 95%CI: 0.66–0.95), CVD mortality (HR: 0.87, 95%CI: 0.78–0.96), cancer mortality (HR: 0.84, 95%CI: 0.74–0.96), and overall mortality (HR:0.89, 95%CI: 0.83–0.96),

Very good quality	consistency NA DP reproducibility (internal) with PCA			according to standardized factor scores for all DPs as independent variables		at 40-y follow-up; FACTOR 3: 1 SD increase in factor scores was associated with borderline increased CHD mortality (HR: 1.17, 95%CI: 0.97–1.40), with decreased cancer mortality (HR: 0.86, 95%CI: 0.77–0.97) and overall mortality (HR: 0.93, 95%CI: 0.97–1.00, as reported in the article), at 40-y follow-up
Menotti, 2018 (148) Italian Rural Areas of Seven Countries Study of Cardiovascular Disease Seven Countries Study Very good quality	PCA and EFA Standardization NA Energy adjustment (density method) EIG>1, Scree plot Varimax rotation FL ≥0.30 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	≥82%* (3)	FA2 (EFA-based FACTOR2 from Menotti 2012): bread, cereals, vegetables, fish, potatoes, and oils; PCA2 (PCA-based COMPONENT2 from Menotti 2012): bread, cereals, vegetables, fish, potatoes, and oils; Plus 2 additional factors and 2 additional principal components not further investigated due to the lack of association with CHD mortality	Multiple Cox proportional hazard models assessing HRs of CHD mortality at 40-y follow-up, according to tertiles of factor scores of FA2 and PC2 as separate independent variables; Kaplan-Meier curves and log-rank test to (unproperly due to competing risks) assess difference in CHD survival according to tertiles of factor scores	Adjusted for age, cigarettes smoking, SBP, serum cholesterol, BMI, and PA	FA2: being in the 3rd vs. 1st tertile of factor scores was associated with reduced hazard of CHD mortality (HR: 0.65, 95%CI: 0.45–0.94); PC2: being in the 3rd vs. 1st tertile of factor scores was associated with reduced hazard of CHD mortality (HR: 0.53, 95%CI: 0.37–0.77)

Maugeri, 2019 (149) Mamma & Bambino Catania (Sicily) Fair quality	PCFA Standardization Energy adjustment (residual method) EIG>2, Scree plot, and interpretability Varimax rotation $ FL \geq 0.25$ Factorability checks NA DP internal consistency NA DP reproducibility NA	15.6% (2)	PRUDENT: potatoes, raw and cooked vegetables, legumes, rice, and soup; WESTERN: red meat, fries, dipping sauces, salty snacks, and alcoholic drinks	Multiple logistic regression models assessing ORs for being in the 3rd tertile of each factor score vs. being in 1st or 2nd tertile combined, according to age, pre-gestational BMI, education level, employment status, smoking status, use of folic acid supplements, use of multivitamin supplements	(Mutually) adjusted for age, education level, employment status, smoking, pre-gestational BMI, use of folic acid supplements and use of multivitamin and/or multi-mineral supplements	PRUDENT: being in the 3rd factor score tertile was inversely associated with increases in pre-gestational BMI (continuous) (OR 0.920, 95%CI: 0.865–0.978; p-value=0.007); WESTERN: being in the 3rd factor score tertile was inversely associated with increases in age (continuous) (OR 0.885, 95%CI: 0.829–0.945; p-value=0.001) and directly associated with medium-low education level (OR 1.617, 95%CI: 1.006–3.374; p-value=0.047) and current smoking status (OR 1.812, 95%CI: 1.004–3.269; p-value=0.048); Other sociodemographic characteristics did not provide additional evidence for the previous DPs
Maugeri, 2019 (150) Mamma & Bambino Catania (Sicily) Fair quality	PCFA Standardization Energy adjustment (residual method) EIG>2, Scree plot, and interpretability Varimax rotation $ FL \geq 0.20$ Factorability checks NA DP internal consistency NA DP reproducibility (internal)	15.55% (2)	PRUDENT: potatoes, cooked vegetables, legumes, pizza, and soup; WESTERN: red meat, fries, dipping sauces, salty snacks, and alcoholic drinks	Multiple linear regression models with BMI or GWG as dependent variables in separate models, according to tertiles of each DP as independent variable; the interaction between gestational age at recruitment and adherence to DP on pre-gestational BMI was tested and found non-significant;	Pre-gestational BMI model adjusted for age, education level, employment status, smoking, total EI, gestational age at recruitment; GWG model adjusted for age, length of gestation, birth weight, education level, employment status, smoking, parity, newborn sex, total EI	WESTERN: no association with pre-gestational BMI in the overall model; no association with GWG in the overall model, but p-trend=0.013; being in the 3rd vs. 1st tertile of factor scores was positively associated with GWG in pre-pregnancy obese women (beta=13.701, SE=0.887, p-value=0.041, p-trend=0.005); PRUDENT: higher factor scores were associated with decreased pre-gestational BMI (beta=-0.631, SE=0.318, p-value=0.038) for a 1 SD increase; being in the 3rd vs. 1st tertile of factor scores was associated with decreased pre-gestational BMI (beta=-1.347, SE=0.598, p-value=0.024); no association with GWG in the overall model; no association with GWG in underweight and normal-weight women; being in the 3rd vs. 1st tertile of factor score was inversely associated with GWG in pre-pregnancy over-weight women (beta=-9.736, SE=4.302, p-value=0.037, p-trend=0.016) and in obese women with

				Stratified analysis by pre-gestational BMI categories (underweight, normal weight, overweight, and obese) for the model with GWG		borderline significance (beta=-10.730, SE=4.156, p-value=0.061, p-trend=0.031) in the absence of any heterogeneity test
Magnano San Lio, 2022 (151) Catania (Sicily) Good quality	PCFA on the overall sample Standardization Energy adjustment, NA method EIG>2, Scree plot, and interpretability Varimax rotation FL ≥0.4 Factorability checks NA DP internal consistency NA DP reproducibility NA	15.6% (2)	PRUDENT: cooked and raw vegetables, legumes, fruits, fish, and soup; WESTERN: white bread, vegetable oil, fries, salty snacks, dipping sauces, and sweets	Multiple logistic regression models assessing for each DP the ORs of being in the 3rd vs. 1st tertile (only) of factor scores according to the cohort of enrollment	Adjusted for maternal age, gestational age at recruitment, education level, employment status, pre-gestational BMI, and smoking status	PRUDENT: mothers enrolled during COVID-19 pandemic were less likely to adhere to this DP than those enrolled before: OR of being in the uppermost (3rd) vs. 1st tertile of adherence was 0.26 (95%CI: 0.15–0.43, p<0.001) for participants of Mamma & Bambino cohort compared to MAMI-MED cohort; Adjusted analysis on WESTERN DP did not provide additional evidence

Ojeda-Granados, 2022 (152) Catania (Sicily), Guadalajara (Mexico) Fair quality	Separate PCFAs on each country Standardization Energy adjustment (residual method) EIG>2, Scree plot, and interpretability Varimax rotation FL ≥0.2 Factorability checks NA DP internal consistency NA DP reproducibility NA	15.3% (2)	LEGUMES, VEGETABLES AND FISH (DP1): legumes, cooked and raw vegetables, vegetable soup, potatoes, and fish; SNACK FOODS, PROCESSED MEATS AND OILS (DP2): chips, dipping sauces, snacks, processed meat, vegetable oils, red meat, sugar and sweets, and fruit juice	One-way ANOVA (followed by post hoc comparisons) or Kruskal-Wallis test (followed by Mann-Whitney test as reported in the text) for age, weight, BMI, body fat, total EI, and various macro- and micro-nutrients as dependent variables, or chi-square test for BMI (in categories) and combined tertile-based categories of adherence to the two DPs (exclusively adherent for either DP, preferably adherent for either DP, or no preference)	Not applicable	Distribution of age (p=0.001), weight (p=0.065), PUFAs (p=0.001), folates (p<0.001), vitamin A (p<0.001), vitamin C (p<0.001), vitamin D (p<0.001), thiamin (p=0.054), pyridoxine (p<0.001), calcium (p=0.007), iron (p<0.001) magnesium (p<0.001), and zinc (p=0.039) according to tertile-based categories of DP adherence was not similar across the 5 combined categories of tertiles of the 2 DPs; EXCLUSIVELY LEGUMES, VEGETABLES AND FISH (DP1): age was higher compared to exclusively DP2 (p=0.006) and to preferably DP2 (p<0.001); percentage of PUFAs was lower compared to preferably DP2, and exclusively DP2 (p<0.032); folates (p<0.001) and vitamin A (p<0.012) were higher compared to all the other categories; vitamin C was higher compared to preferably DP2, exclusively DP2, and no preference (p<0.025); vitamin D (p<0.004), pyridoxine (p<0.002), magnesium (p<0.001), and zinc (p<0.015) were higher compared to all the other categories; calcium was higher compared to exclusively DP2 (p<0.016); iron was higher compared to preferably DP2 and exclusively DP2 (p<0.003); PREFERABLY LEGUMES, VEGETABLES AND FISH (DP1): age was higher compared to exclusively DP2 (p=0.046) and to preferably DP2 (p=0.002); percentage of PUFAs was lower compared to preferably DP2, and exclusively DP2 (p<0.032); folates (p<0.001) and vitamin A (p<0.012) were higher compared to all the other categories; vitamin C was higher compared to preferably DP2, exclusively DP2, and no preference (p<0.025); vitamin D was higher compared to preferably DP2 (p=0.007); pyridoxine was higher compared to preferably DP2 (p=0.028); iron was higher compared to preferably DP2 and exclusively DP2 (p<0.003); calcium was higher compared to exclusively DP2
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						(p<0.016); magnesium was higher compared to preferably DP2 and exclusively DP2 (p=0.001); NO PREFERENCE: age was higher compared to preferably DP2 (p=0.015)
Barchitta, 2018 (153) Catania (Sicily) Good quality	PCFA Standardization Energy adjustment (residual method) EIG>2, Scree plot, and interpretability Varimax rotation FL ≥0.2 Factorability checks NA DP internal consistency NA DP reproducibility (internal)	14.31% (2)	PRUDENT: legumes, vegetable soups, potatoes, cooked and raw vegetables, and olive oil; WESTERN: high on chips, snacks, dipping sauces, plant oils, processed and red meats; low on olive oil	Multiple logistic regression models assessing ORs of hrHPV infection (among women with normal epithelium) and OR of CIN2+, according to quartiles of factor scores or one unit increase of factor scores (independent variable) for identified DPs	hrHPV infection model: adjusted for age, BMI, smoking status, and parity; CIN2+ model: adjusted for age and hrHPV status	WESTERN: increasing factor scores were borderline significantly associated with increased risk of hrHPV infection (OR: 1.39, 95%CI: 0.97–1.99, p-value=0.069, for one unit increase); PRUDENT: increasing quartile-based categories of factor scores were borderline significantly associated with a reduced risk of CIN2+ (p-trend=0.076)

Barchitta, 2019 (154) Catania (Sicily) Good quality	PCFA Standardization Energy adjustment (residual method) EIG>2, Scree plot, and interpretability Varimax rotation FL ≥0.3 Factorability checks NA DP internal consistency NA DP reproducibility NA	17.2% (2)	PRUDENT: potatoes, cooked and raw vegetables, legumes, soup, and fish; WESTERN: high on canned fish, vegetable oil, processed meat, salty snacks, alcoholic drinks, and dipping sauces; low on fruits	Multiple linear regression models assessing the association between tertiles of factor scores and log-transformed leucocyte LINE-1 methylation (4 dependent variables CpG site 1, 2, 3, and average) for each DP; Multiple linear regression models assessing the association between combined tertile-based categories of adherence to DPs (exclusively adherent, preferably adherent, with no preference) and average leucocyte LINE-1 methylation level for each DP	Adjusted for age, education level, employment status, smoking status, use of folic acid supplement, total EI, and BMI	PRUDENT: mean leucocyte LINE-1 methylation levels were higher in the 3rd vs.1st tertile of factor scores at CpG site 1 (beta=0.009, SE=0.003, p=0.001, p-trend<0.001), CpG site 2 (beta=0.030, SE=0.005, p<0.001, p-trend<0.001), and CpG site 3 (beta=0.034, SE=0.003, p<0.001, p-trend<0.001); average leucocyte LINE-1 methylation levels were higher in the 3rd vs. 1st tertile of factor scores (beta=0.022, SE=0.003, p<0.001, p-trend<0.001); women who exclusively adhered to this DP had a higher average leucocyte LINE-1 methylation level than those who adhered to the no preference category (beta=0.013, SE=0.004, p=0.002), to the preferably adherent to WESTERN DP category (beta=0.023, SE=0.004, p<0.001), and to the exclusively adherent to WESTERN DP category (beta=0.030, SE=0.004, p<0.001); Other DPs did not provide additional evidence
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Barchitta, 2019 (155) Eastern Sicily Fair quality	PCFA Standardization Energy adjustment (residual method) EIG>2, Scree plot, and interpretability Varimax rotation FL ≥0.2 Factorability checks NA DP internal consistency NA DP reproducibility NA	26.8% (3)	PRUDENT: potatoes, cooked vegetables, legumes, fruits, nuts, yogurt, offals, shellfish, and tea; WESTERN: white bread, red and processed meat, shellfish, vegetable oil, dipping sauces, and fries; ENERGY DENSE: yogurt, butter and margarine, sweets and refined sugar, dipping sauces, pizza, and fries	Spearman correlation coefficient and hypothesis test to assess correlation between factor scores of each DP and school marks (Italian, English, History, Science, PE, Mathematics, Comportment, and GPA)	Not applicable	PRUDENT: adherence was positively associated with marks in Mathematics ($r=0.150$, $p\text{-value}<0.05$); WESTERN: adherence was negatively associated with marks in English ($r=-0.217$, $p\text{-value}<0.05$), History ($r=-0.174$, $p\text{-value}<0.05$), Science ($r=-0.158$, $p\text{-value}<0.05$), PE ($r=-0.221$, $p\text{-value}<0.05$), Comportment ($r=-0.168$, $p\text{-value}<0.05$), and GPA ($r=-0.220$, $p\text{-value}<0.05$); ENERGY DENSE: adherence was negatively associated with marks in Italian ($r=-0.165$, $p\text{-value}<0.05$)
Fernández-Alvira, 2014 (156) Italy, Estonia, Cyprus, Belgium, Sweden, Hungary, Germany, and Spain IDEFICS Good quality	Separate PCFA by center Standardization NA EIG>1, Scree plot Varimax rotation FL ≥0.3 Factorability checks NA DP internal consistency NA DP reproducibility (cross-study)	20.5% (3)	PROCESSED: crisps, corn crisps and popcorn, ketchup, chocolate and candy bars, mayonnaise and mayonnaise-based products, and sweetened drinks; HEALTHY: raw vegetables, cooked vegetables and beans, fresh fruits without added sugar, fresh or frozen fish (not fried), and fresh meat (not fried); SPREADS: reduced-fat products on bread, butter and/or margarine on bread, jam and honey, and chocolate or nut-based spread	Multiple linear regression models performed to assess the impact of SES (independent variable) on children's DP scores for one DP at a time (dependent variable); Stratified analysis by country due to country-specific DPs	Adjusted for sex, age, and migrant background	PROCESSED: increases in children factor scores were associated with reductions of the family SES indicator in the Italian cohort ($\beta=-0.063$, 95%CI: -0.077 to -0.049, $p\text{-value}<0.001$); Other DPs did not provide additional evidence in the Italian cohort Cross-study reproducibility: PROCESSED: identified in all the 8 regions; HEALTHY: identified in 7 investigated regions, but not in Cyprus; SPREADS: identified in Italy only

Naska, 2006 (157) Belgium, France, Finland, Germany, Greece, Italy, Norway, Portugal, Spain, UK DAFNE Fair quality	Separate PCAs by country on daily individual food availability defined as recorded food quantities divided by the corresponding household values (defined as age and sex specific consumption units calculated on the basis of the respective average energy requirements using energy requirements of males aged 18-29 ys as the reference unit) Standardization Log-transformation of individual food availability relative to the overall average DAFNE food availability (calculated for each FG as unweighted arithmetic mean of the country-specific mean availability	PC1: 15-20%; PC2: 6-8% (2)	WIDE RANGE: high on fruits, vegetables, cereals, meat, fish, and dairy products; BEVERAGE AND CONVENIENCE: high on beverages (alcoholic and nonalcoholic) and ready-to-eat dishes; low on plant foods and elaborate-to-cook dishes	Separate multiple linear regression models by country including factor scores of each DP as dependent variables and socio-demographic characteristics as independent variables; the analysis was based on a subset of households whose composition fits specific pre-defined categories (Italy: 16% households lost)	(Mutually) adjusted for education level, locality, occupation, and household composition	WIDE RANGE: compared to elementary education, secondary (beta: -0.22, 95%CI: -0.30 to -0.14) or higher (beta: -0.40, 95%CI: -0.55 to -0.25) education was inversely related to factor scores; compared to rural locality, living in semi-urban (beta: 0.14, 95%CI: 0.05–0.24) or urban localities (beta: 0.34, 95%CI: 0.25–0.43) was directly related to factor scores; compared to manual occupation of the household head, retirement (beta: 0.49, 95%CI: 0.38–0.60) or other occupation (beta: 0.41, 95%CI: 0.29–0.53) were directly related to factor scores; compared to a single adult household, being in a lone parent household (beta: 0.29, 95%CI: 0.02–0.57), in a single elderly household (beta: 0.33, 95%CI: 0.18–0.47), or in a 2 elderly members household (beta: 0.33, 95%CI: 0.17–0.50) was directly related to factor scores; BEVERAGE AND CONVENIENCE: compared to elementary education, secondary (beta: 0.21, 95%CI: 0.16–0.25) or higher (beta: 0.24, 95%CI: 0.15–0.32) education was directly related to factor scores; compared to rural localities, living in urban localities was inversely related to factor scores (beta: -0.17, 95%CI: -0.22 to -0.12); compared to manual occupation of household head, non-manual occupation was directly related to factor scores (beta: 0.09, 95%CI: 0.04–0.14), while retirement (beta: -0.16, 95%CI: -0.23 to -0.16) or other occupation (beta: -0.25, 95%CI: -0.32 to -0.19) were inversely related to factor scores; compared to a single adult household, being in a 2 members adult household (beta: 0.22, 95%CI: 0.15–0.29), in a lone parent household (beta: 0.41, 95%CI: 0.26–0.56), or in an adults and children household (beta: 0.46, 95%CI: 0.40–0.52) was directly related to factor scores, while being in a single elderly household (beta: -0.26, 95%CI: -0.34 to -0.18) or in a 2 members elderly household (beta: -0.17, 95%CI: -0.27 to -0.08)
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	values) EIG>1, and interpretability Rotation NA FL ≥0.2 Factorability checks NA DP internal consistency NA DP reproducibility (cross-study)					was inversely related to factor scores Cross-study reproducibility: WIDE RANGE: remarkably similar in all countries; BEVERAGE AND CONVENIENCE: slightly more varied among the 10 countries
Bravi, 2021 (158) Turin (Piemonte), Florence (Tuscany), Rome (Lazio), San Giovanni Rotondo (Apulia), Palermo (Sicily) MEDIDIET Fair quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency DP reproducibility (internal)	80.57% (5)	VITAMINS, MINERALS AND FIBERS: fiber, potassium, iron, folate, vitamin C, vitamin E, and beta-carotene equivalents; PROTEINS AND FATTY ACIDS WITH LEGS: animal protein, SFAs, cholesterol, calcium, phosphorus, zinc, and riboflavin; FATTY ACIDS WITH FINS: EPA, DHA, DPA, and vitamin D; FATTY ACIDS WITH LEAVES: MUFAs, LA, ALA, vitamin E, and lycopene; STARCH AND VEGETABLE PROTEINS: starch, vegetable protein, and sodium	One-way ANOVA to assess the presence of differences in means of foremilk characteristics (protein, lactose, fat, fat composition and energy density) according to quartiles of factor scores of each maternal DP	Not applicable	VITAMINS, MINERALS AND FIBERS: mean foremilk content in omega-3 (p-value= 0.0029), ALA (p-value=0.0507), EPA (p-value=0.0195), DHA (p-value=0.0093), and DPA (p- value=0.0273) was not equal among quartiles of factor scores and seemed to increase from 1st to 4th quartile; mean foremilk omega-3/omega-6 ratio (p-value=0.009), LA/ALA ratio (p- value=0.0780), AA/EPA ratio (p-value=0.0012), AA/DHA ratio (p-value=0.0193), and LA/DHA ratio (p-value=0.0277) were not equal among quartiles of factor scores and seemed to decrease from 1st to 4th quartile; PROTEINS AND FATTY ACIDS WITH LEGS: mean foremilk content in AA was not equal among quartiles of factor scores (p- value=0.0473) and seemed to increase from 1st to 4th quartile; mean foremilk content in omega-3 (p-value=0.0339), ALA (p-value=0.0354), EPA (p-value=0.0559), DHA (p-value=0.0640), AA/EPA ratio (p-value=0.0229), and AA/DHA ratio (p-value=0.0378) was not equal among quartiles of factor scores with unclear trends across quartiles; FATTY ACIDS WITH FINS: mean foremilk content in omega-3 (p-value=0.0038), EPA (p-

						value=0.0004), DHA (p-value=0.0013), DPA (p-value=0.0276) was not equal among quartiles of factor scores and seemed to increase from 1st to 4th quartile; mean foremilk omega-3/omega-6 ratio (p-value=0.0426), AA/EPA ratio (p-value=0.0004), AA/DHA ratio (p-value=0.0006), and LA/DHA (p-value=0.0012) were not equal among quartiles of factor scores and seemed to decrease from 1st to 4th quartile; FATTY ACIDS WITH LEAVES: mean foremilk content in SFA (p-value=0.0035), MUFA (p-value=0.0322), AA (p-value=0.0637), omega-3 (p-value=0.0735), ALA (p-value=0.0032) was not equal among quartiles of factor scores and seemed to decrease from 1st to 4th quartile for SFA, have unclear trend across quartiles for AA, and increase from 1st to 4th quartile for MUFA, omega-3, and ALA; STARCH AND VEGETABLE PROTEINS: mean foremilk AA/EPA ratio was not equal among quartiles of factor scores (p-value=0.0910) and seemed to increase from 1st to 4th quartile
Lasalvia, 2021 (159) Varese (Lombardy) ROCAV Good quality	PCFA EIG>1, Scree plot and total variance explained Varimax rotation FL$\geq$0.28 or FL$\leq$-0.15 Factorability checks NA DP internal consistency NA DP reproducibility NA	24.35% (4)	WESTERN: high on red meats, animal fats, processed meats, salty biscuits, vegetable oils, mayonnaise and other sauces, spirits, cheeses, eggs, pizza, crustaceans and molluscs, beer and cider, offals, wine, soft drinks, sugar and sweets, and butter; low on toasted bread and rusks, and fruits; MEDITERRANEAN: high on olive oil, cooked vegetables, raw vegetables, legumes,	Multiple linear regression models to derive mean differences (and corresponding 95% CIs) in metabolic and inflammatory parameters and risk factors (dependent variables) namely total cholesterol, HDL cholesterol, LDL cholesterol, TGs, glucose, SBP, DBP, MBP,	Multiple linear and logistic regressions models on metabolic and inflammatory parameters and risk factors adjusted for age, sex, and total EI whenever possible; Multiple linear regression on carotid-femoral PWV adjusted for age, sex, EI, cigarette smoking, education level, BMI, hypertension and dyslipidemia in Model 3 and for age,	WESTERN (PC1): mean difference between 5th and 1st quintile category of factor scores was significantly different from 0 for total cholesterol (9.12, 95%CI: 3.26–14.98), LDL cholesterol (6.78, 95%CI: 1.40–12.16), glucose (4.54, 95%CI: 2.22–6.86), BMI (0.86, 95%CI: 0.18–1.53), and leucocytes (0.62, 95%CI: 0.29–0.95); being in the 5th vs. 1st quintile of factor scores was associated with higher ODDS of being an ever-smoker (OR: 1.97, 95%CI: 1.43–2.72); a 1 SD increase in factor scores was associated with an increase in carotid-femoral PWV in Model 3 (beta=0.31, 95%CI: 0.11–0.52, p-value=0.003) and in Model 4 (beta=0.24, 95%CI: 0.03–0.45, p-value=0.03); leucocytes mediated 9.2% of the effect of factor scores on carotid-femoral PWV (Sobel test: p-value=0.047); glucose mediated 9.8% of the

			pasta and other grains, bouillon, cooked tomatoes, soups, fruits, fish, and potatoes; low on soft drinks; CARBOHYDRATE: high on pasta and other grains, cooked tomatoes, bread, and animal fats; low on yogurt, fish, nuts and seeds, breakfast cereals, crustaceans and molluscs, tea, cooked vegetables, fruit juices, fruits, snacks, and eggs; RESIDUAL: high on milk, coffee, and white meats; low on tea, wine, spirits	BMI, and leucocytes, between 5th and 1st quintile category of factor scores for the DPs with delta factor scores as independent variables; Multiple logistic regression to derive ORs of metabolic and inflammatory parameters and risk factors (dependent variables) namely ever smoking (vs never smoking), dyslipidemia, and hypertension according to adherence to DPs comparing the 5th vs. the 1st quintile (reference) of factor scores; Multiple linear regression models assessing mean differences in carotid-femoral PWV (dependent variable) according to 1SD increase of DP scores (independent	sex, EI, cigarette smoking, education level, glucose and leucocytes in Model 4	effect of factor scores on carotid-femoral PWV (Sobel test: p-value=0.059); MEDITERRANEAN (PC2): mean difference between 5th and 1st quintile category of factor scores was significantly different from 0 for glucose (-3.03, 95%CI: -5.08 to -0.98), SBP (-2.49, 95%CI: -4.88 to -0.10), MBP (-1.73, 95%CI: -3.43 to -0.03), and leucocytes (-0.57, 95%CI: -0.86 to -0.28); being in the 5th vs. 1st quintile of factor scores was associated with lower ODDS of being an ever-smoker (OR: 0.66, 95%CI: 0.50–0.88), and of hypertension (OR: 0.65, 95%CI: 0.48–0.86); a 1 SD increase in factor scores was borderline associated with a decrease in carotid-femoral PWV in Model 4 (beta=-0.17, 95%CI: -0.35 to 0.01, p-value=0.07); CARBOHYDRATE (PC3): mean difference between 5th and 1st quintile category of factor scores was significantly different from 0 for SBP (2.49, 95%CI: 0.34–4.64), DBP (1.29, 95%CI: 0.11–2.48), MBP (1.89, 95%CI: 0.36–3.42), BMI (0.72, 95%CI: 0.19–1.25); being in the 5th compared to the 1st quintile of factor scores was associated with higher ODDS of hypertension (OR: 1.25, 95%CI: 0.97–1.62); a 1 SD increase in factor scores was associated with an increase in carotid-femoral PWV in Model 3 (beta=0.11, 95%CI: -0.02 to 0.25, p-value=0.09); RESIDUAL (PC4): mean difference between 5th and 1st quintile category of factor scores was significantly different from 0 for HDL cholesterol (-3.62, 95%CI: -5.34 to -1.90), BMI (1.13, 95%CI: 0.59–1.66), and leucocytes (0.41, 95%CI: 0.15–0.68)
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				variables); Mediation analysis was conducted on BMI, hypertension, dyslipidemia, leucocytes, and glucose (possible mediators) using the procedures described in Preacher and Hayes and MacKinnon et al. to assess changes in the regression coefficient of Western DP with and without including the mediator in the model; Sobel test to assess whether the indirect effect of the mediator on the relationship was significantly different from 0		
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Zupo, 2020 (160) Castellana Grotte (Apulia) Apulia (from MICOL Study) Very good quality	PCA Percentage of explained variance Varimax rotation NA Descriptive labelling Factorability checks NA DP internal consistency NA DP reproducibility NA	NA% (5)	ENERGY-RICH: cured meat, sausages, lean ham, bacon, desserts, chocolate, and packaged/fried foods; FARM-HOUSE DIET: dairy products, vegetables, legumes, fruits, and semolina-type bread; SWEETS: desserts, chocolate, and package products; WINTER PATTERN: whole grains, poultry, fish, seafood, and legumes; ELDERLY PATTERN: whole milk, semolina-type bread, legumes, and vegetables	Multiple Cox proportional hazards model for overall mortality, including factor scores of each DPs as continuous independent variables in separate models; Multiple Cox proportional hazards model for cause-specific mortality including factor scores of FARM-HOUSE DIET DP as continuous independent variable	Adjusted for sex, age, BMI, education level, smoking, multimorbidity, wine consumption, and olive oil consumption	ENERGY-RICH: overall mortality was borderline inversely related to factor scores (HR: 0.96, 95%CI: 0.92–1.01); FARM-HOUSE DIET: overall mortality was positively related to factor scores (HR: 1.05, 95%CI: 1.00–1.10); WINTER PATTERN: overall mortality was borderline inversely related to factor scores (HR: 0.97, 95%CI: 0.92–1.02); Other DPs did not provide additional evidence on overall and cause-specific mortality
Tatoli, 2022 (161) Castellana Grotte (Apulia) Apulia (including also a major part of MICOL Study participants) Poor quality	Separate PCAs by diabetic status Standardization NA Subjective criteria (higher loadings in each group) Varimax rotation NA $ FL \geq 0.1$ Factorability checks NA DP internal consistency NA DP reproducibility NA	NA% (1 for each separate PCA)	DIABETIC/VEGETARIAN: dairy products, eggs, vegetables, nuts, legumes, potatoes, olive oil, fruits, sweets, and sugary foods; NOT DIABETIC: white, red and processed meat, seafood, grains, sweets, sugary foods, caloric drinks, ready-to-eat dishes, wine, beer, and spirits	Not applicable	Not applicable	Not applicable Internal reproducibility: From visual inspection of PCA loadings across solutions, older subjects with diabetes had a healthier diet than their non-diabetic counterparts

Giontella, 2019 (162) Verona (Veneto) Good quality	PCA Standardization EIG>1, Scree plot NA Varimax rotation FL ≥0.2 Factorability checks DP internal consistency NA DP reproducibility NA	45.5% (2)	HEALTHY: vegetables, fresh and dried fruit, legumes, fish, dairy products, cereals and tubers, eggs, and meat; UNHEALTHY: meat, fast food, sweets, cereals and tubers, eggs, fish, and dairy products	Spearman correlation coefficient to assess the association between one of hemodynamic or metabolic variables (BMI, z-score BMI, WHR, z-score WHR, brachial SBP, z-score brachial SBP, brachial DBP, z-score brachial DBP, central SBP, z-score central SBP, PWV (m/s), z-score PWV, capillary cholesterol, capillary TGs, and capillary glucose) and factor scores of each DP; Multiple linear regression models with variables significantly related to DPs (based on Spearman correlation test) as dependent variables in separate models and factor scores of the interested DP as	Adjusted for age, sex, ethnicity, BMI, quartiles of total EI, and quartiles of Children-Physical Activity Questionnaire scores	HEALTHY: capillary glucose was inversely associated with factor scores in the Spearman analysis ($r=-0.190$, $p<0.01$) and in the multiple regression model ($\beta=-0.016$, 95%CI: -0.027 to -0.005, $p\text{-value}<0.01$); UNHEALTHY: brachial DBP ($r=0.130$, $p<0.05$) and z-score brachial DBP ($r=0.130$, $p<0.05$) were directly associated with factor scores in the Spearman analysis; multiple regression model confirmed borderline the results on brachial DBP ($\beta=0.911$, 95%CI: -0.150–1.971, $p\text{-value}=0.092$), while results on z-score brachial DBP were not reported
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				independent variable		
Turrone, 2021 (163) Emilia-Romagna (Italy) Good quality	PCFA Standardization EIG>1, Scree plot, and interpretability Varimax rotation FL ≥0.63 Factorability checks DP internal consistency NA DP reproducibility NA	80.36% (3)	ANIMAL PRODUCTS: animal protein, cholesterol, niacin, zinc, SFAs, phosphorus, vitamin D, sodium, vitamin B6, retinol, riboflavin, thiamin, calcium, and LA; VITAMINS AND FIBER: vitamin C, beta-carotene, total fiber, total folate, vitamin E, potassium, MUFAs, and soluble carbohydrates; REGIONAL: vegetable protein, other PUFAs, and starch	Pearson correlation coefficients between EFA-based DP scores and daily amount of 37 selected food groups and condiments derived from the original FIs on the same subjects; 0.45 cut-off for identifying most correlated food groups	Not applicable	ANIMAL PRODUCTS: factor score was positively correlated with red meat (especially, beef and pork), offal, processed meat, fish, eggs, coffee, cheese, and olive oil; VITAMINS AND FIBER: factor score was positively correlated with root vegetables, other (than citrus) fruit, olive oil, leafy vegetables (raw and cooked), cabbages, soups and bouillon; REGIONAL: factor score was positively correlated with grains (whole meal), tea (including herbal tea), and leafy vegetables (raw and cooked)
Donati Zeppa, 2020 (164) Urbino (Marche) Fair quality	Principal Axis Factor Analysis Standardization NA Variables are expressed in terms of difference between values at time 3 (mean of the third mesocycle of training) and values at time 0 (mean of the 2 wks-before period)	71.61% (3)	FACTOR 1: fat, protein, carbohydrate, energy, MUFAs, SFAs, and vitamin E; FACTOR 2: PUFAs, omega 6, and omega 3; FACTOR 3: soluble fiber, insoluble fiber, vitamin C, vitamin A, starch, and iron	Not applicable	Not applicable	Not applicable Description of DPs found on the difference between the end and the beginning of the trial protocol, from visual inspection of Principal Axis Factor Analysis loadings

	EIG ≥ 1 , variance explained Descriptive labelling Factorability checks DP internal consistency NA DP reproducibility NA					
Colica, 2017 (165) Catanzaro (Calabria) Fair quality	PCA (not clear which dietary assessment tool is used) Standardization EIG ≥ 1 , Scree plot Varimax rotation FL >0.4 Factorability checks NA DP internal consistency NA DP reproducibility NA	55% (6)	PATTERN 1: meat, grains, olive oil, and potatoes; PATTERN 2: fish, vegetables, and milk; PATTERN 3: cheese, cakes, and fruit; PATTERN 4: cheese and animal-based fats; PATTERN 5: eggs, legumes, and wine; PATTERN 6: cakes, biscuits, and sugary drinks	Pearson's correlation coefficient to identify factor scores (as continuous variables) correlated to WB- BMD, to single and to multiple fractures; Multiple linear models to derive mean WB-BMD according to tertiles of factor scores for each DP, and post hoc analysis to test the presence of differences in mean WB-BMD among pairs of tertiles; tests for trend were calculated by using DPs scores as a continuous	Multiple linear models were adjusted for BMI, glucose, creatinine, sex, medications, and current smoking; adjusted for age, current smoking, and medications when analyses restricted to Ms, and for current smoking, and medications only when analyses restricted to Fs; multiple logistic regression models on fractures were adjusted for BMI, sex, medications, and current smoking, but all previous variables were finally excluded from the model for multiple fractures	PATTERN 1: continuous factor scores were directly associated with WB-BMD ($r=0.19$, $p=0.009$); mean WB-BMD in the 3rd tertile of factor scores (mean: 1.070 ± 0.01) was higher compared to the 1st (mean: 1.021 ± 0.01), with p from post hoc analyses equal to 0.040, and to the 2nd tertile (mean: 1.013 ± 0.01), with p from post hoc analyses equal to 0.019; and p -trend=0.043; in Fs mean WB-BMD in the 3rd tertile of factor scores (mean: 1.087 ± 0.02) is higher compared to the 1st (mean: 1.016 ± 0.02 , $p=0.009$) and 2nd tertile (mean: 1.013 ± 0.02 , $p=0.006$), and p -trend of borderline significant equal to 0.08; continuous factor scores were inversely associated with multiple fractures ($r=-0.32$, $p=0.038$) as reported in the text; a one unit increase in factor scores was associated to a reduced risk of multiple fractures (OR: 0.28, 95%CI: 0.08–0.89); PATTERN 2: continuous factor scores were borderline but directly associated with WB-BMD ($r=0.14$, $p=0.064$); mean WB-BMD in the 3rd tertile of factor scores (mean: 1.081 ± 0.01) was higher compared to the 1st (mean: 1.023 ± 0.01), with p from post hoc analyses equal to 0.018, and to the 2nd tertile (mean: 1.000 ± 0.01), with p from post hoc analyses equal to 0.001), and p - trend=0.003; in Ms, mean WB-BMD in the 3rd

				variable after control for possible confounding factors; stratified analyses by sex; Multiple logistic regression models to estimate ORs of having at least one fracture (vs. no fractures) for the 1st or 2nd compared to the 3rd tertile of the factor scores for each DP; Multiple logistic regression models to estimate ORs of having multiple fractures (vs. single fracture) according to increases in factor scores for each DP	tertile of factor scores (mean: 1.162 ± 0.02) was higher compared to the 1st (mean: 1.088 ± 0.03), with p from post hoc analyses equal to 0.041, and non-significant p-trend; in Fs, mean WB-BMD in the 3rd tertile of factor scores (mean: 1.078 ± 0.02) was higher compared to the 2nd (mean: 1.002 ± 0.02), with p from post hoc analyses equal to 0.006, and p-trend=0.023; PATTERN 5: continuous factor scores were borderline but directly associated with WB-BMD ($r=0.13$, $p=0.096$); continuous factor scores were inversely associated with at least one fracture ($r=-0.16$, $p=0.01$); compared to the 3rd, being in the 1st or in the 2nd tertile of factor scores was associated with a reduced risk of at least one fracture (OR: 0.213, 95%CI: 0.065–0.703 and OR: 0.209, 95%CI: 0.064–0.675, respectively); Other DPs did not provide additional evidence for the investigated outcomes
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Mazza, 2017 (166) Catanzaro (Calabria) Good quality	Separate PCA on FGs and NUTs (not clear which dietary assessment tool is used) Standardization EIG $\geq$ 1, Scree plot Varimax rotation FL $>$ 0.40 Factorability checks (authors' information: not reported in the article) DP internal consistency NA DP reproducibility NA	NA% (4+4)	FOOD-BASED PATTERNS: CEREALS/MEAT/FISH/OLIVE OIL PATTERN: cereals, meat, fish, and olive oil; CAKES/FRUIT PATTERN: cakes and fruit; ANIMAL FATS/MARGARINES PATTERN: animal fats and margarines; LEGUMES PATTERN: legumes; NUTRIENT-BASED PATTERNS: ANIMAL PROTEIN PATTERN: animal protein; VEGETAL OILS PATTERN: vegetal oils; FATS PATTERN: fats; PLANT PROTEINS/POLYUNSATURATED FATS PATTERN: plant proteins, PUFAs	Pearson's correlations to identify food-based and nutrient-based DPs correlated with MMSE and ADAS-Cog (both at baseline and at follow-up); Multiple linear regression models to assess the association of MMSE and ADAS-Cog (both after 1 y) as separate dependent variables with each DP selected through correlation coefficients and related statistical tests on correlation coefficients; Multiple logistic regression models to estimate ORs of ADAS-Cog improvement at 1 y (vs. non-improvement) according to continuous factor scores of each DP as independent variable	Multiple linear regression adjusted via stepwise based on correlations (excluded age, education level, and SBP for MMSE at follow-up for the LEGUMES PATTERN; included age and education level, but excluded waist circumference and glucose for ADAS-Cog at follow-up for the LEGUMES PATTERN); Multiple logistic regression adjusted for education level, but excluded SBP, DBP, and waist circumference for PLANT PROTEINS AND PUFAS PATTERN	FOOD-BASED DPs: LEGUMES PATTERN: factor scores were directly associated with MMSE at baseline ($r=0.15$, $p=0.062$) and at follow-up ($r=0.21$, $p=0.01$), and inversely associated with ADAS-Cog at baseline ($r=-0.12$, $p=0.068$) and at follow-up ($r=-0.23$, $p=0.004$); a unit increase in factor scores was associated with improved MMSE at follow-up ($B=0.23$, 95%CI: 0.04–0.42, $p=0.01$) and with decreased ADAS-Cog at follow-up ($B=-0.10$, 95% CI: -1.79 to -0.30, $p=0.006$); Other DPs did not provide additional evidence NUTRIENT-BASED DPs: PLANT PROTEINS AND PUFAS PATTERN: factor scores were directly associated with improved ADAS-Cog ($r=0.18$, $p=0.030$); a unit increase in factor scores was associated with improved ADAS-Cog with a significant OR=1.79 and corresponding beta=0.589 (95%CI: 0.04–0.42, $p=0.045$); Other DPs did not provide additional evidence
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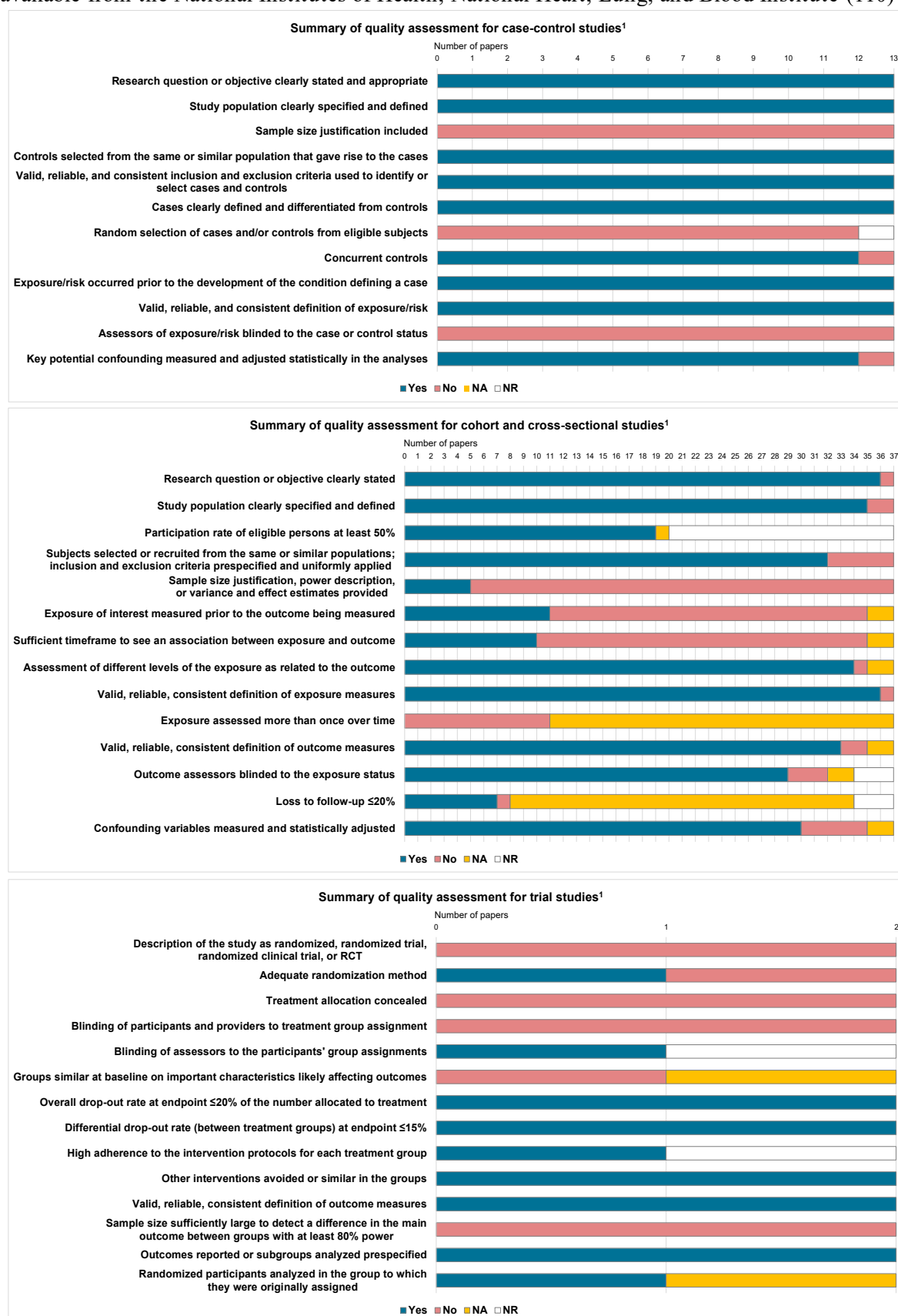
Palli, 2001 (167) Florence (Tuscany) Good quality	EFA Energy adjustment (residual method) EIG>NA, Scree plot NA, interpretability NA Varimax rotation FL ≥0.40 Factorability checks NA DP internal consistency NA DP reproducibility NA	75.3% (4)	VITAMIN-RICH: sugar, fiber, vitamin C, vitamin E, beta-carotene, and nitrates; TRADITIONAL: total protein, starch, alcohol, nitrite, and N- nitrosodimethylamine; REFINED: total protein, SFAs, other PUFAs, cholesterol, sugar, retinol, vitamin E, vitamin D, and N- nitrosodimethylamine; FAT-RICH: SFA, oleic acid, MUFAs, LA, ALA, cholesterol, and vitamin E	Multiple logistic regression models to derive ORs of gastric cancer according to tertiles computed among controls of factor scores for each DP in separate models; attributable risks computed by the method of Bruzzi et al. and the corresponding 95% CI estimated, as described by Benichou and Gail	Adjusted for age, sex, social class, family history of gastric cancer, area of residence, BMI tertiles, and EI	VITAMIN-RICH: OR 0.5 (95% CI: 0.4–0.7) of gastric cancer for 3rd vs. 1st tertile, p- trend=0.0003; TRADITIONAL: OR 3 (95% CI: 1.8–4.8) of gastric cancer for 3rd vs. 1st tertile, p- trend=0.0001; Other DPs did not provide additional evidence; Attributable fraction: 25.9% (95% CI: 8.8–43.0) of cases was attributable to the VITAMIN-RICH DP; 38.9% (95% CI: 21.7–56.1) of cases was attributable to the TRADITIONAL DP; when considered together, 44% (95% CI: 18.7–69.5) of cases was attributable to VITAMIN RICH and TRADITIONAL DPs
Anelli, 2022 (168) Milan (Lombardy), Naples (Campania) GIFt Study Very good quality	PCA on the overall sample Energy adjustment (NA method) on FGs from FFQ EIG≥1.1, Scree plot NA Rotation NA Descriptive labelling Factorability checks NA DP internal consistency NA DP reproducibility NA	33.4% (3)	HIGH MEAT, ANIMAL FATS, GRAIN: meat, animal fats, and grains; HIGH FISH, FRUIT, NUTS: fish, fruit, and nuts; HIGH EGGS AND SWEETS, LOW LEGUMES: high on eggs and sweets; low on legumes	Multiple linear models with log- transformed variables if non- normally distributed, to derive biomarker (red blood cells folate (ng/mL), serum vitamin D (in µg/L), plasma hepcidin mature form (ng/mL), and plasma total antioxidant capacity (mM) concentrations at 29±2 gwks and delivery outcomes (maternal GWG in kg, gestational	Adjusted for maternal age, pre-gestational BMI, education, working status, parity, geographical area, folic acid/multivitamin supplement use, and total EI; further adjustment for gestational age at blood sampling in case of biomarkers analyses, and for gestational age at delivery and GWG whenever possible in case of delivery outcomes analyses	HIGH MEAT, ANIMAL FATS, GRAIN: factor scores were associated directly with plasma hepcidin concentrations (beta=0.3, 95%CI: 0.0– 0.5, p-value<0.05) and inversely with serum vitamin D concentrations (beta=-3.9, 95%CI: -6.9 to -0.9, p-value<0.05) and with gestational age at delivery in pregnancies carrying F fetuses only (beta=-0.5, 95%CI: -0.9–0.0, p-value<0.05); stratified analyses for geographical subgroups provided comparable results; Other DPs did not provide additional evidence Cross-study reproducibility: HIGH EGGS AND SWEETS, LOW LEGUMES: participants from Naples showed a different adherence compared to Milan (Mann–Whitney U test: p=0.01), reported to be higher for Naples in the text

				age at delivery in wks, placental weight in grams, neonatal ponderal index in grams/cm ³ , neonatal lengths in cm, and neonatal head circumference in cm) according to continuous factor scores of each DP as independent variable in separate models; stratified analyses by geographical area and by fetus sex for gestational age at delivery; Cross-study reproducibility of DPs: hypothesis test on (continuous) component scores by geographical area with Mann–Whitney U test		
Ruggieri, 2022 (169) Crotone (Calabria), Milazzo and Augusta-Priolo (Sicily) NEHO Study Good quality	PCA Standardization NA EIG>NA, Scree plot NA, interpretability NA Rotation NA Descriptive labelling	24.9% (3)	PRUDENT: stem-leafy-cooked-raw vegetables, cauliflower, blue fish, fresh caught-farmed fish, fruit, legumes, beef, and yogurt; HIGH ENERGY: high on salty snacks, bakery products, cold meats, fries, mayonnaise, soft	Not applicable	Not applicable	Not applicable

	Factorability checks NA DP internal consistency NA DP reproducibility NA		drinks, bread, butter, pasta, fresh and aged cheese, potatoes, and pork; low on cereals; VEGETARIAN: high leafy-cooked-raw vegetables, lamb and mutton, tubers, fries, cereals, dried fruit, eggs, oil, butter, and potatoes; low on beef and fresh farmed fish			
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Abbreviations: AA, arachidonic acid; ACPA, anti-citrullinated protein antibodies; ADAS-Cog, Alzheimer's Disease Assessment Scale - Cognitive sub-scale; ALA, α -linolenic acid; ANOVA, analysis of variance; ATBC, Alpha-Tocopherol Beta-Carotene; AUFA, Animal Unsaturated Fatty Acids; BMI, body mass index; CHD, coronary heart disease; CI, confidence interval; CIN, cervical intraepithelial neoplasia; COVID-19, Coronavirus disease 2019; CRP, C-reactive protein; CVD, cardiovascular disease; DAFNE, Data Food Networking; DAS28-CRP, Disease Activity Score on 28 joints and C-reactive protein; DBP, diastolic blood pressure; DHA, docosahexaenoic acid; DIETSCAN, Dietary Patterns and Cancer; DMARDs, disease modifying anti-rheumatic drugs; DP, dietary pattern; DPA, docosapentaenoic acid; EFA, Exploratory Factor Analysis; EI, energy intake(s); EIG, eigenvalue; EPA, eicosapentaenoic acid; EPIC, European Prospective Investigation into Cancer and Nutrition; F, female(s); FA, fatty acid(s); FAC, food antioxidant content; FG, food group(s); FI, food item(s); FL, factor loading(s); FSIQ, full scale intelligence quotient; GiFt, Gestational Intake of Food towards healthy outcomes; GPA, Grade Point Average; GWG, gestational weight gain; gwk, gestational week(s); HDL, high-density lipoprotein; HER2, human epidermal growth factor receptor 2; HR, hazard ratio; hrHPV, high-risk Human Papilloma Virus; HRT, hormone replacement therapy; IDEFICS, Identification and prevention of Dietary - and lifestyle-induced health Effects In Children and infantS; LA, linoleic acid; LDL, low-density lipoprotein; LINE-1, Long Interspersed nuclear elements-1; M, male(s); MAMI-MED, Multisettoriale Alla salute Materno-Infantile Mediante valutazione dell'Esposomanele Donne; MBP, mean blood pressure; MICOL, Multicenter Italian Study on Epidemiology of Cholelithiasis; MMSE, Mini Mental State Examination; MUFA, monounsaturated fatty acid(s); NA, not available; NEHO, Neonatal Environment and Health Outcomes; NLSC, Netherlands Cohort Study; NUT, nutrient(s); OC, oral contraceptive; OR, odds ratio; ORDET, Ormoni e Dieta nell'Eziologia del Tumore della Mammella; PA, physical activity; PAL, physical activity level; PC, principal component; PCA, Principal Component Analysis; PCFA, Principal Component Factor Analysis; PE, Physical Education; PRI, perceptual reasoning index; PSI, processing speed index; PUFA, polyunsaturated fatty acid(s); PWV, pulse wave velocity; RF, rheumatoid factor; ROCAV, Risk Of Cardiovascular diseases and abdominal aortic Aneurysm in Varese; RR, relative risk; SBP, systolic blood pressure; SD, standard deviation; SDAI, Simplified Disease Activity Index; SE, standard error; SES, socioeconomic status; SFA, saturated fatty acid(s); SMC, Swedish Mammography Cohort; TG, triglyceride(s); VCI, verbal comprehension index; vs., versus; VUFA, Vegetable Unsaturated Fatty Acids; WB-BMD, whole-body bone mineral density; WHR, waist-to-hip ratio; WISC-IV, Wechsler Intelligence Scale of Children; wk, week(s); WMI, working memory index; y, year(s)

Figure A1. Summary of quality assessment for studies included in the systematic review by single rating tool available from the National Institutes of Health, National Heart, Lung, and Blood Institute (110)



¹For each quality assessment tool, each row reported the distribution of replies (“Yes”, “No”, “Not applicable”, and “Not reported”) to single questions. The “Cannot determine” reply was never used during this quality assessment. Abbreviations: NA, Not Applicable; NR, Not reported.

Appendix B: Supplementary Materials Chapter 5

Table B1. Indirect matching: ingredients from Nutrition5k matched with the most similar food items in Italian FCDB

Ingredients from the Nutrition5k dataset	Food items from the Italian FCDB
<i>Bagels</i>	BREAD, prepared with milk
<i>Black beans</i>	BEANS, canned
<i>Blue cheese</i>	GORGONZOLA CHEESE
<i>Bok choy</i>	SWISS CHARD
<i>Buttermilk</i>	MILK, COW, SKIMMED, PASTEURIZED
<i>Chayote squash</i>	PUMPKIN or SQUASH
<i>Country rice</i>	RICE, BROWN, WHOLEGRAIN, cooked
<i>Cranberries</i>	RAISINS
<i>Green onions</i>	SHALLOTS
<i>Hominy</i>	SWEETCORN, CANNED, drained
<i>Jalapenos</i>	PEPPERS, CHILI, RED
<i>Jicama</i>	POTATOES
<i>Kale</i>	CABBAGE, JANUARY KING
<i>Noodles</i>	PASTA, WHITE, dried, cooked
<i>Nopales</i>	PRICKLY PEAR
<i>Parsnips</i>	CARROTS
<i>Pepperoni</i>	SALAMI, pork and beef meat
<i>Pilaf</i>	RICE SALAD (prepared from recipe)
<i>Pinto beans</i>	BEANS, canned
<i>Rice noodles</i>	PASTA, WHITE, dried, cooked
<i>Snow peas</i>	PEAS, canned
<i>Tacos</i>	PIADINA (Italian flatbread)
<i>Tatsoi</i>	SWISS CHARD
<i>Tomatillo</i>	TOMATOES
<i>Turkey bacon</i>	BACON (pork meat, salted, smoked)
<i>Wild rice</i>	RICE, VENERE, cooked
<i>Yam</i>	BATATAS or SWEET POTATOES

Abbreviations: FCDB, Food Composition Database.

Table B2. Indirect matching: ingredients from Nutrition5k unavailable in the Italian FCDB and matched with US FCDB

Ingredients from the Nutrition5k dataset	Food items from the US FCDB
<i>Barbecue sauce</i>	Sauce, barbecue
<i>Chia seeds</i>	Seeds, chia seeds, dried
<i>Cilantro</i>	Coriander (cilantro) leaves, raw
<i>Edamame</i>	Edamame, frozen, unprepared
<i>Ginger</i>	Ginger root, raw
<i>Ketchup</i>	Catsup
<i>Mustard</i>	Mustard
<i>Pumpkin seeds</i>	Seeds, pumpkin and squash seed kernels, dried
<i>Sunflower seeds</i>	Seeds, sunflower seed kernels, dried
<i>Teriyaki sauce</i>	Sauce, teriyaki, ready-to-serve

Abbreviations: FCDB, Food Composition Database.

Table B3. Indirect matching: generic ingredients from Nutrition5k were imputed with a group of related food items from the Italian FCDB, whose nutrients were averaged

Ingredients from the Nutrition5k dataset	Italian FCDB food items used for mean value calculation
<i>Berries</i>	Mulberries; Blackberries; Strawberries; Raspberries; Blueberries or bilberries
<i>Mushroom</i>	Mushrooms, "Ovuli" TYPE; Mushrooms, "Porcino" TYPE; Mushrooms, common; Mushrooms, "Porcinelli" TYPE; Mushrooms, Honey; Mushrooms, Morel; Mushrooms, Chanterelle
<i>Cheese, and Goat cheese</i>	Asiago cheese; Bra cheese; Crescenza cheese; Edam cheese, aged; Cottage cheese; Gouda cheese, fresh; Gouda cheese, aged; Montasio cheese; Pecorino cheese, for grating; Pecorino romano cheese; Provoloncino cheese, sweet; Provolone cheese, hot; Ricotta cheese, german type, whole; Ricotta cheese, german type, light; Robiola cheese; Taleggio cheese; Provola cheese, smoked; Ricotta cheese (made from cow milk); Mozzarella cheese (buffalo); Soft cheese (Bel Paese type); Burrini cheese; Caciocavallo cheese; Caciotta romana cheese (made with sheep milk); Caciotta toscana cheese; Caciottina cheese, fresh; Cheddar cheese; Dolce Verde cheese; Emmental cheese; Fior di latte cheese; Fontina cheese; processed cheese; processed cheese, low fat; Gorgonzola cheese; Grana cheese; Groviera cheese; Latteria cheese; Mascarpone cheese; Mozzarella cheese (cow); Pastorella cheese; Pecorino cheese; Provolone cheese; Ricotta cheese (made from sheep milk); Scamorza cheese; Stracchino cheese; Parmigiano cheese; Processed cheese, plain, slices; Full fat soft cheese (Philadelphia type); Pecorino cheese, fresh; Rochefort cheese; Edam cheese, fresh; Caciocavallo cheese, smoked; Caciotta cheese, smoked; Scamorza cheese, smoked; Camembert cheese; Brie cheese; Feta cheese; soft cheese, light; Butirro calabro cheese; Cacioricotta cheese; Caciottina cheese, made with sheep and cow milk; Italico cheese; Pecorino siciliano cheese; Ricotta cheese (made from buffalo milk); Caciotta cheese, made with sheep and cow milk; Caciottina cheese, made with cow milk; Gorgonzola and Mascarpone (mixed cheese); Gorgonzola cheese with nuts; Burrata cheese; Ricotta cheese (made from cow and sheep milk)
<i>Nuts</i>	Peanuts, raw; Peanuts, roasted; Walnuts, fresh; Walnuts, dried; Hazelnuts, dried; Pine nuts; Pistachio nuts, fresh; Pistachio nuts, dried; Pistachio nuts, roasted and salted; Peanuts, roasted and salted; Pecan nuts; Cashew nuts; Pistachio nuts, " <i>Pistacchio di Bronte PDO</i> "
<i>Seeds</i>	Fennel, seeds; Cumin seeds; Linseed; Herbs (seeds); Seeds, pumpkin and squash seed kernels, dried ¹ ; Seeds, chia seeds, dried ¹ ; Seeds, sunflower seed kernels, dried ¹

¹For the entry "seeds", the Italian FCDB food items were integrated with previously selected US FCDB food items to improve comparability across indirect matching procedures. Abbreviations: FCDB, Food Composition Database.

Table B4. Indirect matching: composite recipes expressed as ingredients in Nutrition5k were created by using Italian FCDB food items

Ingredients from the Nutrition5k dataset	Italian FCDB food items used to create recipes
<i>Brownies</i> ^a	Chocolate, dark (cocoa 70%); Butter; Sugar, cane, brown; Flour, wheat, type 00 (fine ground); Eggs, chicken, whole; Cocoa, unsweetened, powder; Vanilla extract, with alcohol; Yeast, powder
<i>Caesar dressing</i> ^a	Vegetable oil, olive, extravirgin; Juice, lemon, fresh; Lemon, peel; Eggs, chicken, yolk; Mustard ¹ ; Sauce, worcestershire ¹
<i>Caesar salad</i> ^a	Lettuce; Parmigiano cheese; Croutons; Vegetable oil, olive, extravirgin; Juice, lemon, fresh; Lemon, peel; Eggs, chicken, yolk; Mustard ¹ ; Sauce, Worcestershire ¹ ; Chicken breast, without skin, cooked, pan fried
<i>Cheese pizza</i> ^b	Pizza with mozzarella and tomatoes; Mozzarella cheese, cow; Gorgonzola cheese; Scamorza cheese; Taleggio cheese
<i>Chicken salad</i> ^a	Lettuce; Parmigiano cheese; Vegetable oil, olive, extravirgin; Juice, lemon, fresh; Lemon, peel; Eggs, chicken, yolk; Mustard ¹ ; Sauce, Worcestershire ¹ ; Chicken breast, without skin, cooked, pan fried
<i>Chilaquies</i> ^a	Tortillas; Peppers, chili, red; Onions; Tomatoes; Garlic, fresh; Vegetable oil, olive, extravirgin; Eggs, chicken, whole; Avocado
<i>Chili</i> ^a	Beef, 15-18 months, fat and lean meat, with visible fat; Peppers, sweet type; Peppers, chili, red; Onions; Cumin, seeds; Sugar, cane, brown; Beans, canned; Tomato puree ¹ (dry matter 18%); Garlic, fresh; Vegetable oil, olive, extravirgin; Coriander (cilantro) leaves, raw; Pepper, black
<i>Coleslaw</i> ^a	Cabbage, january king; Onions; Carrots; Yoghurt, whole milk; Mustard ¹ ; Chives, fresh; Vinegar; Sugar, white; Mayonnaise
<i>Crepes</i> ^a	Butter; Flour, wheat, type 00 (fine ground); Eggs, chicken, whole; Milk, cow, semi-skimmed, pasteurized
<i>Curries</i> ^a	Chicken, leg-lower part, without skin; Spices, curry powder ¹ ; Coriander (cilantro) leaves, raw ¹ ; Onions; Vegetable oil, olive, extravirgin; Cream (20% fat); Cinnamon; Pepper, black
<i>Dumplings</i> ^a	Flour, wheat, type 00 (fine ground); Water; Sausages, pork meat, raw; Swiss chard (bok choy); Vegetable oil, sesame; Tamari, soya sauce
<i>Fried rice</i> ^b	Rice, white, polished, raw; Vegetable oil, olive, extravirgin
<i>Frozen yogurt</i> ^a	Yoghurt, whole milk; Cream (20% fat); Sugar, white; Chocolate, milk
<i>Greek salad</i> ^b	Tomatoes; Cucumber; Feta cheese; Olives, black type; Vegetable oil, olive, extravirgin
<i>Ground turkey</i> ^b	Turkey hen, whole, without skin; Eggs, chicken, whole; Grana cheese; Parsley, fresh; Vegetable oil, olive, extravirgin
<i>Hash browns</i> ^a	Potatoes; Starch, potato; Onions; Vegetable oil, mixed seeds
<i>Hummus</i> ^a	Chick peas, canned; Tahina (seeds, sesame butter, tahini, from roasted and toasted kernels (most common type)) ¹ ; Vegetable oil, olive, extravirgin; Juice, lemon, fresh
<i>Kimchi</i> ^a	Cabbage, january king; Onions; Carrots; Daikon; Ginger root, raw; Chives, fresh; Garlic, fresh; Sugar, white; Flour, rice; Water
<i>Lasagna</i> ^b	Pasta, made with eggs, dried, raw; Beef, 15-18 months, fat and lean meat, with visible fat; Onions; Carrots; Celery; Tomatoes, canned, whole content; Milk, cow, semi-skimmed, pasteurized; Grana cheese; Flour, wheat, type 00 (fine ground); Vegetable oil, olive, extravirgin; Butter
<i>Mashed potatoes</i> ^b	Potatoes; Milk, cow, whole, pasteurized; Butter
<i>Oatmeal</i> ^a	Flakes, oat; Milk, cow, semi-skimmed, pasteurized; Honey
<i>Omelette</i> ^b	Eggs, chicken, whole; Vegetable oil, olive, extravirgin
<i>Pasta salad</i> ^c	Salad, unspecified; Pasta, white, dried, raw
<i>Pepperoni pizza</i> ^b	Pizza with mozzarella and tomatoes; Salami, pork and beef meat

<i>Pesto</i> ^b	Pine nuts; Pecorino cheese, for grating; Vegetable oil, olive, extravirgin; Garlic, fresh; Basil, fresh
<i>Roasted potatoes</i> ^b	Potatoes; Vegetable oil, olive, extravirgin
<i>Sandwiches, and toast</i> ^b	Bread, white, sandwich type, packaged; Ham; Processed cheese, plain, slices
<i>Scrambled eggs</i> ^b	Eggs, chicken, whole; Vegetable oil, olive, extravirgin
<i>Sour cream</i> ^a	Cream (20% fat); Yoghurt, whole milk
<i>Succotash</i> ^a	Sweetcorn, canned, drained; Beans, canned; Tomatoes; Onions; Vegetable oil, olive, extravirgin
<i>Tortillas</i> ^a	Flour, corn; Vegetable oil, unspecified; Water
<i>Tuna salad</i> ^c	Tuna, canned in oil, drained; Onions; Carrots; Celery
<i>Vinaigrette</i> ^a	Vegetable oil, olive, extravirgin; Vinegar
<i>Waffles</i> ^a	Butter; Sugar, white; Flour, wheat, type 00 (fine ground); Eggs, chicken, whole; Vanilla extract, with alcohol; Yeast, powder

¹For the indicated ingredient in the recipe, the corresponding food item was sourced from the selected US FCDB. The recipe composition was obtained from the following sources in order of appearance of the corresponding ingredients: dedicated websites for recipes (a) (170,171), food atlas (b) (19), food image from Nutrition5k dataset (c) (95). Abbreviations: FCDB, Food Composition Database.

Table B5. Top 25 dishes showing the most extreme (i.e., >99.5%) differences in absolute value across FCDBs for energy content

DISH_ID	INGREDIENTS	Δ Energy (kcal)	Δ Proteins (g)	Δ Fats (g)	Δ Carbohydrates (g)
dish_1567714934	Parmesan cheese, Caesar dressing ¹ , avocado, mixed greens, chicken, olives	754.00 (ITA) ²	8.32	91.53	15.35
dish_1566850031	Olives, carrot, chicken, Caesar dressing , cherry tomatoes, onions	715.80 (ITA)	9.06	87.68	11.37
dish_1566246626	Feta cheese, <i>broccoli</i> ¹ , mixed greens, chicken, olives, Caesar dressing	710.47 (ITA)	5.77	85.51	13.51
dish_1566332268	Olives, chicken, spinach (raw), avocado, Caesar dressing , cucumbers	637.40 (ITA)	3.94	74.52	14.61
dish_1565987201	Cucumbers, spinach (raw), parmesan cheese, Caesar dressing , chicken, olives	589.94 (ITA)	7.23	71.08	10.04
dish_1565123881	Caesar salad , olive oil, onions, cheese pizza , <i>zucchini</i> , salt, spinach (cooked), <i>millet</i> , <i>beef</i> , <i>shallots</i> , <i>bok choy</i> , <i>chayote squash</i> , vinegar	562.49 (ITA)	24.91	44.72	12.27
dish_1566502211	Caesar salad	453.86 (ITA)	20.56	36.11	8.65
dish_1566502271	<i>Chard</i> , parsley, <i>chive</i> , olive oil, carrot, Caesar salad , garlic, salt, basil, chicken, lemon juice, brown rice, rosemary	449.37 (ITA)	17.56	37.82	8.54
dish_1561492228	Cherry tomatoes, <i>fish</i> , blueberries, <i>jalapenos</i> , vinegar, pepper, salt chicken, parsley, lemon juice, tomatoes, garlic mustard, olive oil, <i>chive</i> , <i>shallots</i> , spinach (raw), <i>chard</i> , radishes, <i>millet</i> , bell peppers, fried rice , onions, wheat berry	390.08 (ITA)	0.16	5.68	62.65
dish_1565725244	Parmesan cheese, cherry tomatoes, chicken, bell peppers, carrot, olives, onions, Caesar dressing	380.81 (ITA)	8.35	50.59	13.03
dish_1567801468	Caesar salad	375.34 (ITA)	17.01	29.86	7.15
dish_1565204931	Onions, vinegar, chicken thighs, pineapple, white rice, Caesar salad , salt,	361.03 (ITA)	20.01	30.60	4.63

	cilantro, pepper, lemon, <i>kale</i> juice, garlic, olive oil, <i>Brussels sprouts</i>				
dish_1561492204	Olive oil, blueberries, onions, tomatoes, salt, fried rice , chicken, pepper, mustard, garlic, bell peppers, <i>millet</i> , <i>jalapenos</i> , spinach (raw), vinegar, radishes	358.14 (ITA)	0.45	15.45	60.10
dish_1566502315	White rice, <i>pork</i> , soy sauce, <i>chard</i> , brown rice, lemon juice, garlic, parsley, olive oil, Caesar salad , carrot, <i>chive</i> , salt, pepper, <i>bok choy</i> , sugar, chicken, rosemary, basil	356.32 (ITA)	11.87	31.22	7.86
dish_1563984729	Scrambled eggs , chicken apple sausage	355.67 (ITA)	16.02	36.49	7.48
dish_1563984835	Vinaigrette , raspberries, blackberries, mixed greens, granola, scrambled eggs , <i>salsa</i> , chicken apple sausage	343.82 (ITA)	14.85	35.30	9.84
dish_1566849387	Parmesan cheese, Caesar salad , olives, chicken, mixed greens, avocado	336.26 (ITA)	8.51	33.04	6.44
dish_1573232499	<i>Bacon</i> , scrambled eggs , <i>broccoli</i> , olive oil, fried rice	334.52 (ITA)	2.44	21.64	43.37
dish_1568056258	Olives, carrot, chicken, Caesar dressing , cherry tomatoes, onions	331.70 (ITA)	7.92	43.78	6.67
dish_1563984771	Mixed greens, raspberries, chicken apple sausage, granola blackberries, scrambled eggs , <i>vinaigrette</i>	324.84 (ITA)	15.29	35.16	13.34
dish_1565972674	Salt, scrambled eggs , chicken apple sausage, cherry tomatoes, onions, pepper, lettuce, mixed greens, lime, olive oil, vinegar, cucumbers	317.83 (ITA)	12.97	33.69	8.47
dish_1565972628	Chicken apple sausage, scrambled eggs	317.13 (ITA)	13.05	33.64	7.34
dish_1561492182	Spinach (raw), vinegar, radishes, fried rice , garlic, salt, mustard, olive oil, blueberries	315.04 (ITA)	1.68	13.05	51.63
dish_1566844766	Caesar salad	314.06 (ITA)	14.23	24.99	5.98

dish_1563913709	Olive oil, cucumbers, fried rice, Caesar salad, salt, cheese pizza , figs, cherry tomatoes, <i>chard</i> , mustard, vinegar, spinach (raw)	312.83 (ITA)	12.24	22.25	15.95
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¹Single ingredients in Nutrition5k that are actually composite recipes are indicated in bold. Ingredients in Nutrition5k without a corresponding cooked food item in the Italian FCDB are indicated in italics. ²The tag “ITA” and “USA” at the bottom identified which nutrient is the highest one. For example, 754.00 ^(ITA) indicates that Italian nutritional values were higher than the corresponding US ones, and vice versa. Abbreviations: FCDB, Food Composition Database; SD, standard deviation; USDA, United States Department of Agriculture.

Table B6: Top 25 dishes showing the most extreme (i.e., >99.5%) differences in absolute value across FCDBs for protein content

DISH_ID	INGREDIENTS	Δ Energy (kcal)	Δ Proteins (g)	Δ Fats (g)	Δ Carbohydrates (g)
dish_1558115364	Potatoes, Apples with peel, almonds, <i>bacon</i> ¹	67.42	25.82 (USA) ²	3.63	9.26
dish_1565123881	Caesar salad ¹ , olive oil, onions, cheese pizza , <i>zucchini</i> , spinach (cooked), <i>millet</i> , salt, <i>shallots</i> , <i>bok choy</i> , <i>beef</i> , <i>chayote squash</i> , vinegar	562.49	24.91 (ITA)	44.72	12.27
dish_1565898659	Cherry tomatoes, <i>tuna</i> , olives, <i>salmon</i> , spinach (raw), onions, chili , salt, cilantro, lime, ginger, brown rice, <i>jalapenos</i> , lemon juice, olive oil, carrot, <i>shallots</i> , garlic	97.62	24.00 (USA)	24.88	4.02
dish_1565898758	<i>Tuna</i> , olives, <i>green beans</i> , spinach (raw), ginger, brown rice, <i>shallots</i> , garlic, cilantro, carrot, cherry tomatoes, <i>salmon</i> , <i>jalapenos</i> , lemon juice, olive oil, onions, salt, lime, chili	91.45	23.87 (USA)	24.88	7.10
dish_1565898723	<i>Shallots</i> , <i>green beans</i> , cherry tomatoes, ginger, <i>jalapenos</i> , onions, olive oil, <i>tuna</i> , garlic, lime, cilantro, <i>salmon</i> , olives, salt, brown rice, spinach (raw), lemon juice, carrot, chili	94.33	23.85 (USA)	24.88	6.31
dish_1558122740	Grapes, mixed greens, Apples with peel, <i>potatoes</i> , <i>bacon</i>	59.84	23.70 (USA)	3.43	12.02
dish_1566502211	Caesar salad	453.86	20.56 (ITA)	36.11	8.65
dish_1558115047	Mixed greens, almonds, Apples with peel	5.87	20.16 (USA)	0.90	8.39
dish_1558380181	Almonds, apples with peel, grapes	0.18	20.15 (USA)	1.74	4.14

dish_1565204931	Onions, vinegar, chicken thighs, pineapple, white rice, Caesar salad , pepper, salt, lemon juice, garlic, olive oil, <i>Brussels sprouts</i> , <i>cilantro, kale</i>	361.03	20.01 (ITA)	30.60	4.63
dish_1558114284	Apples with peel, <i>grapes, cantaloupe</i>	15.59	19.90 (USA)	0.30	11.34
dish_1558115282	Apples with peel	11.52	19.87 ^(USA)	0.22	13.97
dish_1558116547	Apples with peel	11.52	19.87 ^(USA)	0.22	13.97
dish_1558109945	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558114086	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558114875	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558372433	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558376768	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558379588	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558380152	Apples with peel	11.44	19.73 ^(USA)	0.21	13.87
dish_1558373074	Apples with peel	11.36	19.60 ^(USA)	0.21	13.77
dish_1558375506	Apples with peel	11.36	19.60 ^(USA)	0.21	13.77
dish_1560356523	<i>Bacon</i>	243.80	19.50 ^(USA)	16.93	1.29
dish_1564502063	<i>Bacon</i>	243.80	19.50 ^(USA)	16.93	1.29
dish_1564073860	<i>Bacon</i>	241.15	19.29 ^(USA)	16.74	1.27

¹Single ingredients in Nutrition5k that are actually composite recipes are indicated in bold. Ingredients in Nutrition5k without a corresponding cooked food item in the Italian FCDB are indicated in italics. ²The tag “ITA” and “USA” at the bottom identified which nutrient is the highest one. For example, 25.82^(USA) indicates that US nutritional values were higher than the corresponding Italian ones, and vice versa. Abbreviations: FCDB, Food Composition Database; SD, standard deviation; USDA, United States Department of Agriculture.

Table B7: Top 25 dishes showing the most extreme (i.e., >99.5%) differences in absolute value across FCDBs for fats content

DISH_ID	INGREDIENTS	Δ Energy (kcal)	Δ Proteins (g)	Δ Fats (g)	Δ Carbohydrates (g)
dish_1567714934	Parmesan cheese, Caesar dressing ¹ , avocado, mixed greens, chicken, olives	754.00	8.32	91.53 (ITA) ²	15.35
dish_1566850031	Olives, carrot, chicken, Caesar dressing , cherry tomatoes, onions	715.80	9.06	87.68 (ITA)	11.37
dish_1566246626	Feta cheese, <i>broccoli</i> ¹ , mixed greens, chicken, olives, Caesar dressing	710.47	5.77	85.51 (ITA)	13.51
dish_1566332268	Olives, chicken, spinach (raw), avocado, Caesar dressing , cucumbers	637.40	3.94	74.51 (ITA)	14.61
dish_1565987201	Cucumbers, spinach (raw), parmesan cheese, Caesar dressing , chicken, olives	589.94	7.23	71.08 (ITA)	10.04
dish_1565725244	Parmesan cheese, cherry tomatoes, chicken, bell peppers, carrot, olives, onions, Caesar dressing	380.81	8.35	50.59 (ITA)	13.03
dish_1565123881	Caesar salad , olive oil, onions, cheese pizza , <i>zucchini</i> , spinach (cooked), <i>millet</i> , salt, <i>shallots</i> , <i>bok choy</i> , <i>beef</i> , <i>chayote squash</i> , vinegar	562.49	24.91	44.72 (ITA)	12.27
dish_1568056258	Olives, carrot, chicken, Caesar dressing , cherry tomatoes, onions	331.70	7.92	43.78 (ITA)	6.67
dish_1566502271	<i>Chard</i> , parsley, <i>chive</i> , olive oil, carrot, Caesar salad , garlic, chicken, salt, lemon juice, basil, brown rice, rosemary	449.37	17.56	37.81 (ITA)	8.54
dish_1563984729	Scrambled eggs , chicken apple sausage	355.67	16.02	36.49 (ITA)	7.48
dish_1566502211	Caesar salad	453.86	20.56	36.11 (ITA)	8.65
dish_1563984835	Vinaigrette , raspberries,	343.82	14.85	35.30 (ITA)	9.84

	blackberries, mixed greens, granola, scrambled eggs , <i>salsa</i> , chicken apple sausage				
dish_1563984771	Mixed greens, raspberries, chicken apple sausage, granola blackberries, scrambled eggs , vinaigrette	324.84	15.29	35.16 (ITA)	13.34
dish_1562790855	Radishes, <i>fish</i> , cherry tomatoes, <i>shallots</i> , onions, mustard, <i>pork</i> , parsley, garlic, basil, salt, pepper, lemon juice, brown rice, bell peppers, country rice, cucumbers, olive oil, vinegar, <i>broccoli</i> , <i>green onions</i>	84.77	9.87	34.81 (USA)	2.49
dish_1567022383	Onions, Caesar dressing , bell peppers, carrot, cherry tomatoes, olives, chicken, parmesan cheese	242.67	7.78	34.48 (ITA)	9.93
dish_1565972674	Salt, scrambled eggs , chicken apple sausage, cherry tomatoes, pepper, lettuce, mixed greens, lime, olive oil, vinegar, onions, cucumbers	317.83	12.97	33.69 (ITA)	8.47
dish_1565972715	Cucumbers, vinegar, <i>green beans</i> , scrambled eggs , pepper, lettuce, chicken apple sausage, cherry tomatoes, lime, mixed greens, salt, olive oil, onions	312.41	13.21	33.69 (ITA)	12.24
dish_1565972628	Chicken apple sausage, scrambled eggs	317.13	13.05	33.64 (ITA)	7.34
dish_1568144954	Carrot, chicken, salt, onions, Caesar dressing , olive oil, pepper, cherry tomatoes, olives	250.08	5.48	33.15 (ITA)	8.47
dish_1566849387	Parmesan cheese, Caesar salad , olives, chicken, mixed greens, avocado	336.26	8.51	33.04 (ITA)	6.44
dish_1566502315	White rice, <i>pork</i> , soy sauce, <i>chard</i> , brown rice, lemon juice,	356.32	11.87	31.22 (ITA)	7.86

	garlic, parsley, olive oil, Caesar salad , carrot, <i>chive</i> , salt, pepper, <i>bok choy</i> , sugar, chicken, rosemary, basil				
dish_1565204931	Onions, vinegar, chicken thighs, pineapple, white rice, Caesar salad , <i>kale</i> , cilantro, pepper, salt, lemon juice, garlic, olive oil, <i>Brussels sprouts</i>	361.03	20.01	30.60 (ITA)	4.63
dish_1568144925	Olive oil, onions, salt, carrot, olives, pepper, cherry tomatoes, Caesar dressing	258.58	0.21	30.09 (ITA)	8.47
dish_1567801468	Caesar salad	375.34	17.00	29.86 (ITA)	7.15
dish_1563567372	Cherry tomatoes, <i>fish</i> , salt, wheat berry, lemon juice, <i>chard</i> , <i>kale</i> , parsley, olive oil, pizza, <i>shallots</i> , garlic, <i>chive</i>	56.13	0.83	28.83 (USA)	11.43

¹Single ingredients in Nutrition5k that are actually composite recipes are indicated in bold. Ingredients in Nutrition5k without a corresponding cooked food item in the Italian FCDB are indicated in italics. ²The tag “ITA” and “USA” at the bottom identified which nutrient is the highest one. For example, 91.53 ^(ITA) indicates that Italian nutritional values were higher than the corresponding US ones, and vice versa. Abbreviations: FCDB, Food Composition Database; SD, standard deviation; USDA, United States Department of Agriculture.

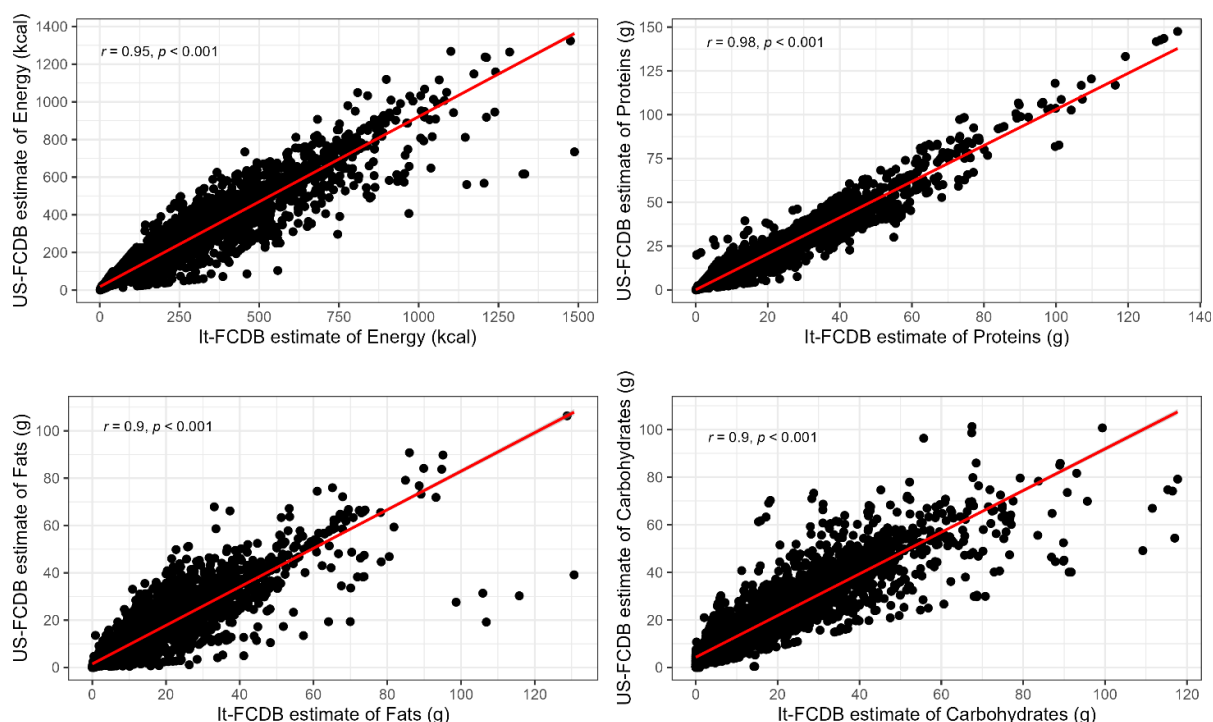
Table B8: Top 25 dishes showing the most extreme (i.e., >99.5%) differences in absolute value across FCDBs for carbohydrates content

DISH_ID	INGREDIENTS	Δ Energy (kcal)	Δ Proteins (g)	Δ Fats (g)	Δ Carbohydrates (g)
dish_1561492228	Cherry tomatoes, blueberries, <i>jalapenos</i> ^l , vinegar, pepper, chicken, parsley, salt, lemon juice, tomatoes, mustard, olive oil, <i>chive</i> , <i>shallots</i> , spinach (raw), <i>chard</i> , radishes, <i>millet</i> , bell peppers, garlic, <i>fish</i> , fried rice ^l , onions, wheat berry	390.08	0.16	5.68	62.65 (ITA) ²
dish_1561492204	Olive oil, blueberries, onions, tomatoes, salt, fried rice , chicken, pepper, mustard, garlic, bell peppers, <i>millet</i> , <i>jalapenos</i> , spinach (raw), vinegar, radishes	358.14	0.45	15.45	60.10 (ITA)
dish_1563389199	<i>Broccoli</i> , garlic, pepper, arugula, vinegar, <i>chard</i> , blueberries, bulgur, olive oil, pecans, mustard, <i>tofu</i> , salt, carrot	198.79	6.27	0.97	51.99 (USA)
dish_1561492182	Spinach (raw), vinegar, radishes, fried rice , garlic, salt, mustard, olive oil, blueberries	315.04	1.68	13.05	51.63 (ITA)
dish_1563389153	Olive oil, vinegar, arugula, <i>chard</i> , pepper, carrot, bulgur, mustard, salt, <i>broccoli</i> , pecans, garlic, blueberries	203.59	6.33	0.97	51.27 (ITA)
dish_1571932448	Oatmeal	291.25	7.70	6.10	51.12 (ITA)
dish_1560801041	<i>Pork</i> , <i>zucchini</i> , arugula, chicken breast, cherry tomatoes, rosemary, lemon juice, thyme, olive oil, onions, wheat berry, parmesan cheese, pepper, spinach (raw), <i>cauliflower</i> , garlic, chickpeas, white rice, salt, bulgur, parsley, <i>kale</i>	210.31	6.50	3.67	46.07 (USA)
dish_1560800988	Pepper, <i>cauliflower</i> , chickpeas, salt, bulgur,	173.12	4.37	0.94	45.93 (USA)

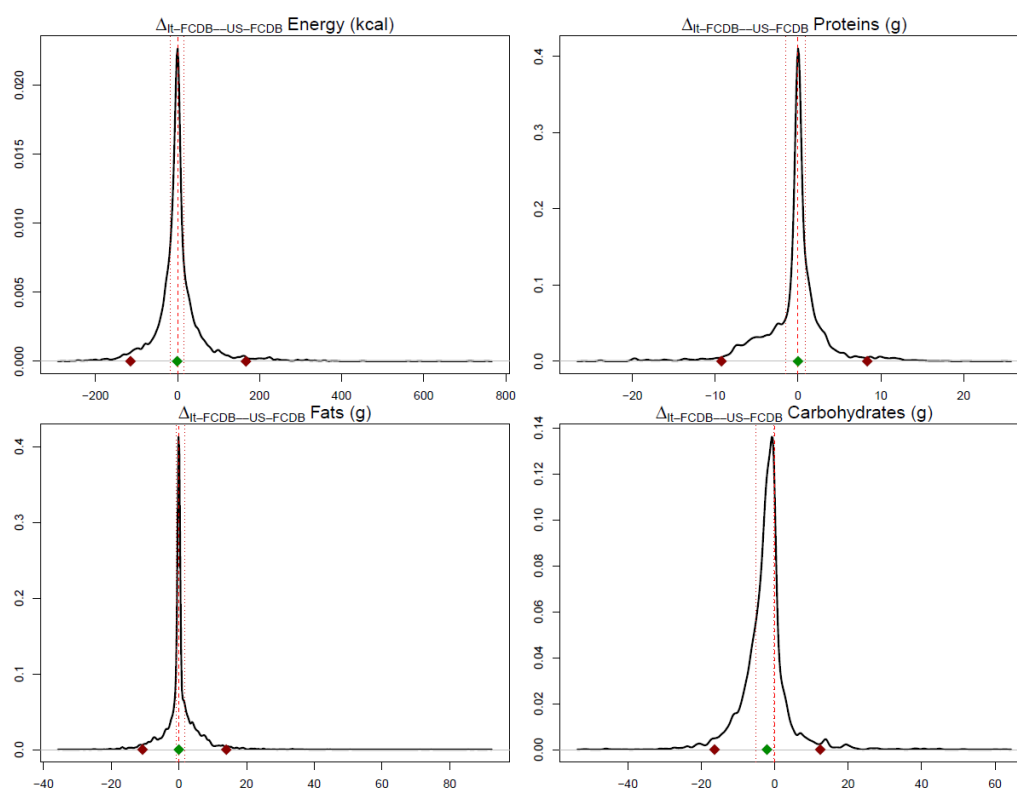
	olive oil, <i>kale</i> , lemon juice, parsley				
dish_1560801020	<i>Cauliflower</i> , garlic, spinach (raw), parmesan cheese, wheat berry, chickpeas, pepper, chicken breast, cherry tomatoes, thyme, lemon juice, olive oil, parsley, <i>kale</i> , bulgur, salt	178.20	4.51	1.36	45.83 (USA)
dish_1563909550	Cucumbers, mustard, mustard greens, olive oil, garlic, <i>green beans</i> , tomatoes, salt, fried rice , vinegar, spinach (raw)	295.72	1.74	12.47	45.15 (ITA)
dish_1568404889	Olive oil, vinegar, radishes, soy sauce, carrot, fried rice , mixed greens, garlic, <i>green onions</i> , <i>cabbage</i> , rice noodles	272.17	3.99	10.18	44.84 (ITA)
dish_1566328988	<i>Bok choy</i> , shallots, beef, vinegar, <i>jalapenos</i> , bell peppers, spinach (raw), pepper, onions, olive oil, tomatoes, garlic, fried rice , chicken, cheese pizza , salt, spinach (cooked), <i>millet</i>	218.38	1.57	8.71	44.65 (ITA)
dish_1573849915	Dumplings , spinach (cooked)	36.17	2.70	14.43	44.45 (USA)
dish_1573232499	<i>Bacon</i> , scrambled eggs , <i>broccoli</i> , olive oil, fried rice	334.52	2.44	21.64	43.37 (ITA)
dish_1573849852	Dumplings	37.31	2.81	14.14	42.62 (USA)
dish_1563909580	Mustard greens, cucumbers, tomatoes, salt, mustard, garlic, fried rice , cheese pizza , vinegar, spinach (raw), <i>green beans</i> , olive oil	291.52	3.59	12.99	42.34 (ITA)
dish_1568404850	Fried rice	244.10	1.20	10.14	40.85 (ITA)
dish_1573849990	<i>Bacon</i> , onions, olive oil, dumplings , goat cheese, grapes, spinach (cooked), <i>chive</i> , pizza dough	43.31	0.85	13.02	40.66 (USA)
dish_1566329021	Bell peppers, shallots, beef, garlic, vinegar,	223.09	0.87	8.88	40.61 (ITA)

	spinach (raw), pepper, olive oil, tomatoes, cheese pizza , salt, chicken, <i>bok choy</i> , <i>jalapenos</i> , <i>Brussels</i> <i>sprouts</i> , onions, fried rice , spinach (cooked), <i>millet</i>				
dish_1568060501	Tomatoes, cherry tomatoes, garlic, lemon juice, cucumbers, mustard greens, olive oil, parsley, rosemary, lime, fried rice , mangos, white rice, <i>pork</i> , <i>zucchini</i> , <i>jalapenos</i> , arugula, onions, cilantro, salt	142.17	6.47	2.32	40.52 (ITA)
dish_1564761426	<i>Egg whites</i> , fried rice	227.33	1.90	9.68	38.94 (ITA)
dish_1566329049	Bell peppers, <i>cauliflower</i> , <i>beef</i> , <i>jalapenos</i> , spinach (raw), <i>Brussels sprouts</i> , onions, olive oil, pepper, garlic, salt, <i>shallots</i> , spinach (cooked), chicken, <i>bok</i> <i>choy</i> , <i>millet</i> , vinegar, cheese pizza , tomatoes, fried rice	227.54	0.38	8.80	38.56 (ITA)
dish_1564761457	Fried rice , <i>turkey</i> <i>bacon</i> , egg whites	205.55	0.90	8.73	38.29 (ITA)
dish_1563897870	Oatmeal	217.13	5.74	4.54	38.11 (ITA)
dish_1562603895	Blackberries, mixed greens, vinaigrette , hash browns , scrambled eggs , raspberries, granola, sausage	167.30	3.25	4.76	37.53 (USA)

¹Single ingredients in Nutrition5k that are actually composite recipes are indicated in bold. Ingredients in Nutrition5k without a corresponding cooked food item in the Italian FCDB are indicated in italics. ²The tag “ITA” and “USA” at the bottom identified which nutrient is the highest one. For example, 62.65 ^(ITA) indicates that Italian nutritional values were higher than the corresponding US ones, and vice versa. Abbreviations: FCDB, Food Composition Database; SD, standard deviation; USDA, United States Department of Agriculture.

Figure B1. Scatterplots of nutrient content obtained across Italian and US FCDBs¹

¹The Pearson correlation coefficients are indicated with the “r” letter. The corresponding p-values from the statistical test on Pearson correlation coefficients are indicated aside. Abbreviations: FCDB, Food Composition Database.

Figure B2. Kernel density estimation plots of the difference between Italian and US FCDBs for energy and macronutrients¹

¹The dashed line indicates the reference value 0, and the dotted lines indicate the 1st and 3rd quartiles. The green diamond indicates the median value, and the red diamonds indicate the 2.5th and 97.5th percentiles. Abbreviations: FCDB, Food Composition Database.

Appendix C: Supplementary Materials Chapter 6

Table C1. Descriptive statistics on predicted values for mass, energy, and macronutrients content of dishes before and after ingredient-mass correction and matching with either US- or Italian-Food Composition Database-specific nutritional values for dishes in the test set from the Nutrition5k dataset. Information was separately provided by dataset and algorithm. Nutrition5k test set (n = 676)

Target variable, dataset ¹ , and algorithm	Minimum	Q1	Median	Q3	Maximum	Mean	SD
Mass (g)							
US FCDB-no correction							
<i>IncV3_2+1</i>	11.989	78.460	149.029	243.804	667.309	175.567	119.070
<i>IncV3_2+2</i>	8.345	82.692	154.692	257.083	920.139	185.216	131.994
<i>R101_2+1</i>	10.483	77.415	154.325	260.761	804.408	182.848	131.531
<i>R101_2+2</i>	12.549	80.182	155.870	264.914	811.699	186.869	132.116
<i>R50_2+1</i>	10.995	76.166	153.896	259.977	794.653	183.216	131.574
<i>R50_2+2</i>	12.439	79.555	155.980	258.996	812.958	184.906	132.786
<i>ViT-B-16_2+1</i>	8.600	77.167	148.562	246.794	811.833	176.981	122.878
<i>ViT-B-16_2+2</i>	8.345	82.692	154.692	257.083	920.139	185.216	131.994
US FCDB-correction							
<i>IncV3_2+1</i>	13.209	76.956	150.509	248.492	700.395	176.779	122.460
<i>IncV3_2+2</i>	13.676	76.691	146.318	245.957	773.388	176.409	123.264
<i>R101_2+1</i>	11.898	74.558	151.948	254.598	810.591	179.795	129.482
<i>R101_2+2</i>	11.175	76.655	152.266	251.004	811.542	179.710	128.035
<i>R50_2+1</i>	10.065	77.313	151.532	246.361	794.116	178.766	126.415
<i>R50_2+2</i>	10.110	78.152	151.895	249.858	767.742	179.521	127.690
<i>ViT-B-16_2+1</i>	10.736	77.782	146.475	245.508	827.270	174.745	121.122
<i>ViT-B-16_2+2</i>	8.499	76.318	148.641	254.667	805.071	177.517	124.557
IT FCDB-no correction							
<i>IncV3_2+1</i>	14.362	78.523	151.278	252.297	840.150	179.400	127.828
<i>IncV3_2+2</i>	16.683	81.294	151.601	248.388	774.850	179.322	124.699
<i>R101_2+1</i>	12.251	76.848	155.851	251.390	811.516	179.98	127.058
<i>R101_2+2</i>	11.778	78.182	156.242	256.914	858.812	183.928	131.479
<i>R50_2+1</i>	13.519	79.803	155.035	257.478	775.501	180.828	125.393
<i>R50_2+2</i>	14.628	77.307	151.389	255.324	831.289	180.053	130.101
<i>ViT-B-16_2+1</i>	9.468	77.178	148.882	247.837	858.081	176.779	124.204
<i>ViT-B-16_2+2</i>	9.601	76.350	145.187	244.340	803.312	174.455	122.162
IT FCDB-correction							
<i>IncV3_2+1</i>	12.741	76.896	149.564	246.829	846.107	177.086	126.658

Target variable, dataset ¹ , and algorithm	Minimum	Q1	Median	Q3	Maximum	Mean	SD
<i>IncV3_2+2</i>	14.563	76.606	144.564	239.602	705.234	172.109	118.026
<i>R101_2+1</i>	12.973	78.508	158.148	258.043	784.960	182.376	128.297
<i>R101_2+2</i>	12.464	76.302	153.909	249.132	832.611	177.936	126.631
<i>R50_2+1</i>	12.340	75.194	149.358	243.864	818.391	175.475	124.730
<i>R50_2+2</i>	12.476	73.248	147.020	244.284	794.214	173.613	123.567
<i>ViT-B-16_2+1</i>	9.903	76.584	146.949	243.318	828.733	173.389	120.967
<i>ViT-B-16_2+2</i>	10.333	74.397	143.945	247.973	802.560	173.938	123.074
<i>Energy content (kcal)</i>							
US FCDB-no correction							
<i>IncV3_2+1</i>	4.749	73.189	171.423	318.103	839.947	211.837	164.620
<i>IncV3_2+2</i>	2.450	71.426	179.457	324.222	782.837	217.700	169.879
<i>R101_2+1</i>	3.061	74.806	176.549	338.438	957.235	223.536	178.885
<i>R101_2+2</i>	2.727	73.597	176.066	328.564	847.582	219.088	173.332
<i>R50_2+1</i>	3.682	70.818	174.440	334.196	903.971	220.078	176.532
<i>R50_2+2</i>	3.809	69.867	170.604	329.921	919.872	217.213	175.830
<i>ViT-B-16_2+1</i>	1.582	73.160	177.642	317.225	797.581	211.354	162.167
<i>ViT-B-16_2+2</i>	2.450	71.426	179.457	324.222	782.837	217.700	169.879
US FCDB-correction							
<i>IncV3_2+1</i>	4.486	72.799	174.193	312.210	806.510	211.116	161.165
<i>IncV3_2+2</i>	5.012	70.902	172.772	325.804	866.676	216.743	169.466
<i>R101_2+1</i>	3.076	67.133	165.719	324.468	897.445	215.453	176.270
<i>R101_2+2</i>	4.326	71.626	172.578	324.581	901.615	216.787	173.480
<i>R50_2+1</i>	3.795	68.516	169.911	323.592	893.864	213.064	170.517
<i>R50_2+2</i>	3.174	72.027	172.450	328.393	903.872	217.691	174.358
<i>ViT-B-16_2+1</i>	2.962	71.442	175.015	313.451	778.592	206.272	158.485
<i>ViT-B-16_2+2</i>	2.510	72.592	178.562	321.872	788.018	210.252	161.242
IT FCDB-no correction							
<i>IncV3_2+1</i>	6.000	72.641	187.025	328.627	801.535	222.230	175.832
<i>IncV3_2+2</i>	6.456	73.068	186.211	325.874	866.069	220.955	175.866
<i>R101_2+1</i>	4.081	72.029	185.674	327.314	925.241	223.643	180.005
<i>R101_2+2</i>	3.254	76.821	190.447	336.735	928.852	230.404	183.906
<i>R50_2+1</i>	6.110	76.244	184.142	325.792	957.968	223.189	178.599
<i>R50_2+2</i>	4.434	71.126	183.998	339.073	982.392	227.805	188.426
<i>ViT-B-16_2+1</i>	2.277	75.039	184.466	315.538	930.568	213.937	167.283
<i>ViT-B-16_2+2</i>	3.123	72.620	188.120	315.731	942.894	215.169	169.504
IT FCDB-correction							
<i>IncV3_2+1</i>	5.259	69.017	167.787	308.190	850.381	208.964	168.689

Target variable, dataset ¹ , and algorithm	Minimum	Q1	Median	Q3	Maximum	Mean	SD
<i>IncV3_2+2</i>	5.918	71.143	172.486	321.870	834.231	214.939	171.573
<i>R101_2+1</i>	3.873	71.336	181.510	320.481	951.214	218.884	177.677
<i>R101_2+2</i>	4.869	67.796	165.120	310.273	972.667	208.651	172.866
<i>R50_2+1</i>	5.991	70.739	178.455	325.476	952.355	220.980	180.643
<i>R50_2+2</i>	3.684	71.431	192.502	328.854	942.238	225.362	181.261
<i>ViT-B-16_2+1</i>	2.787	73.943	182.214	308.889	940.190	212.008	168.041
<i>ViT-B-16_2+2</i>	3.564	71.106	179.319	303.868	941.397	208.321	165.006
Protein content (g)							
US FCDB-no correction							
<i>IncV3_2+1</i>	0.258	2.682	9.153	20.197	57.919	13.204	12.720
<i>IncV3_2+2</i>	-1.761	1.439	8.598	19.083	60.461	12.620	13.405
<i>R101_2+1</i>	0.225	2.462	10.519	24.047	76.708	15.351	15.861
<i>R101_2+2</i>	0.166	2.366	9.821	21.938	71.668	14.274	14.557
<i>R50_2+1</i>	0.111	2.314	10.113	23.206	75.478	15.000	15.620
<i>R50_2+2</i>	0.305	2.286	9.284	22.069	76.524	14.299	15.046
<i>ViT-B-16_2+1</i>	0.184	1.931	8.922	20.276	77.313	13.234	13.750
<i>ViT-B-16_2+2</i>	-1.761	1.439	8.598	19.083	60.461	12.620	13.405
US FCDB-correction							
<i>IncV3_2+1</i>	-0.542	2.172	8.594	19.062	54.704	12.083	11.961
<i>IncV3_2+2</i>	0.011	2.659	9.390	21.970	55.664	13.995	13.264
<i>R101_2+1</i>	0.135	1.887	9.047	21.284	73.106	13.829	14.772
<i>R101_2+2</i>	0.269	2.198	9.611	21.483	73.009	14.141	14.665
<i>R50_2+1</i>	0.251	2.343	9.967	22.711	67.562	14.624	14.965
<i>R50_2+2</i>	0.169	2.142	9.821	22.430	75.023	14.392	15.021
<i>ViT-B-16_2+1</i>	0.090	2.070	8.921	20.743	75.446	13.450	14.024
<i>ViT-B-16_2+2</i>	0.222	2.091	9.577	22.418	80.511	14.186	14.641
IT FCDB-no correction							
<i>IncV3_2+1</i>	0.251	2.826	9.737	20.065	60.003	13.462	12.914
<i>IncV3_2+2</i>	-0.264	3.184	10.562	20.955	50.125	13.425	11.94
<i>R101_2+1</i>	0.281	2.310	10.213	20.878	62.977	13.979	14.003
<i>R101_2+2</i>	0.239	2.839	10.369	22.484	62.131	14.719	14.125
<i>R50_2+1</i>	0.022	2.016	9.084	19.959	59.613	13.014	13.315
<i>R50_2+2</i>	0.289	2.422	10.036	21.301	62.323	14.017	14.035
<i>ViT-B-16_2+1</i>	0.212	2.685	10.108	21.260	75.095	14.237	14.2
<i>ViT-B-16_2+2</i>	0.254	2.223	9.481	19.968	76.143	13.356	13.566

Target variable, dataset ¹ , and algorithm	Minimum	Q1	Median	Q3	Maximum	Mean	SD
IT FCDB-correction							
<i>IncV3_2+1</i>	-0.824	1.871	7.720	17.582	57.707	11.474	11.703
<i>IncV3_2+2</i>	-0.211	2.892	9.748	19.928	47.937	12.886	11.590
<i>R101_2+1</i>	0.296	2.919	11.678	23.584	67.515	15.706	15.091
<i>R101_2+2</i>	0.204	2.320	8.961	19.170	52.351	12.502	12.020
<i>R50_2+1</i>	0.266	2.418	9.993	21.084	63.177	14.189	14.135
<i>R50_2+2</i>	0.199	2.435	10.409	21.577	62.285	14.155	13.960
<i>ViT-B-16_2+1</i>	0.188	2.448	9.984	19.953	70.286	13.563	13.537
<i>ViT-B-16_2+2</i>	0.250	2.519	9.970	21.141	72.847	14.020	14.201
Fat content (g)							
US FCDB-no correction							
<i>IncV3_2+1</i>	0.049	2.306	8.087	17.772	64.362	11.025	10.405
<i>IncV3_2+2</i>	-0.316	2.127	8.464	17.465	61.856	11.163	10.671
<i>R101_2+1</i>	-0.037	2.254	8.577	18.486	81.061	11.815	11.971
<i>R101_2+2</i>	-0.021	2.226	7.997	17.183	65.257	10.751	10.372
<i>R50_2+1</i>	-0.046	2.225	8.398	17.988	73.499	11.425	11.278
<i>R50_2+2</i>	0.127	1.887	7.581	17.136	71.026	10.710	10.764
<i>ViT-B-16_2+1</i>	-0.075	1.963	7.690	16.291	50.987	10.390	10.030
<i>ViT-B-16_2+2</i>	-0.316	2.127	8.464	17.465	61.856	11.163	10.671
US FCDB-correction							
<i>IncV3_2+1</i>	0.032	2.226	7.328	16.262	56.520	10.076	9.151
<i>IncV3_2+2</i>	0.082	1.591	7.144	16.571	60.302	10.206	9.970
<i>R101_2+1</i>	-0.188	1.414	6.810	15.987	69.566	10.013	10.535
<i>R101_2+2</i>	0.050	1.773	8.092	17.650	71.250	11.083	11.050
<i>R50_2+1</i>	-0.051	1.897	7.676	16.661	69.234	10.574	10.637
<i>R50_2+2</i>	0.032	1.673	7.768	17.266	70.341	10.820	10.966
<i>ViT-B-16_2+1</i>	-0.244	1.721	7.343	16.194	53.147	10.191	10.103
<i>ViT-B-16_2+2</i>	0.032	1.948	7.992	16.605	54.339	10.493	10.311
IT FCDB-no correction							
<i>IncV3_2+1</i>	0.047	2.782	9.540	19.400	67.807	12.307	11.427
<i>IncV3_2+2</i>	0.075	2.163	8.314	17.672	64.835	11.248	10.952
<i>R101_2+1</i>	0.002	2.231	9.313	19.399	81.143	12.613	12.651
<i>R101_2+2</i>	-0.071	1.830	8.588	18.269	74.048	11.566	11.589
<i>R50_2+1</i>	-0.243	1.709	8.178	17.724	78.881	11.422	11.749
<i>R50_2+2</i>	0.023	1.958	8.503	19.241	82.211	12.308	12.763
<i>ViT-B-16_2+1</i>	-0.638	2.028	8.455	16.814	75.945	11.207	11.414
<i>ViT-B-16_2+2</i>	0.040	1.822	8.689	17.461	74.336	11.537	11.508

Target variable, dataset ¹ , and algorithm	Minimum	Q1	Median	Q3	Maximum	Mean	SD
IT FCDB-correction							
<i>IncV3_2+1</i>	-0.905	1.257	6.077	15.345	70.096	9.478	10.460
<i>IncV3_2+2</i>	0.072	2.012	7.759	17.470	62.927	11.084	10.735
<i>R101_2+1</i>	-0.172	1.869	8.416	18.138	83.503	11.889	12.384
<i>R101_2+2</i>	0.025	1.660	7.673	17.014	74.644	10.921	11.180
<i>R50_2+1</i>	-0.273	1.736	8.247	17.877	78.931	11.599	12.093
<i>R50_2+2</i>	0.018	2.037	8.955	18.768	79.813	12.257	12.368
<i>ViT-B-16_2+1</i>	0.183	2.724	9.055	17.764	79.600	12.018	11.571
<i>ViT-B-16_2+2</i>	0.010	1.740	8.033	16.086	74.283	10.653	10.715
Carbohydrates content (g)							
US FCDB-no correction							
<i>IncV3_2+1</i>	0.183	7.859	15.551	23.424	51.955	16.474	10.050
<i>IncV3_2+2</i>	-0.543	7.963	17.041	25.075	57.654	17.998	11.801
<i>R101_2+1</i>	0.627	7.004	15.583	25.650	61.715	17.784	12.678
<i>R101_2+2</i>	0.216	6.801	15.178	24.537	61.924	17.313	12.375
<i>R50_2+1</i>	0.164	6.475	14.396	24.164	56.764	16.642	12.069
<i>R50_2+2</i>	0.472	7.039	15.238	25.068	60.413	17.330	12.259
<i>ViT-B-16_2+1</i>	-0.024	6.241	13.419	22.832	53.762	15.614	11.624
<i>ViT-B-16_2+2</i>	-0.543	7.963	17.041	25.075	57.654	17.998	11.801
US FCDB-correction							
<i>IncV3_2+1</i>	0.462	7.348	13.614	20.555	45.103	14.584	8.883
<i>IncV3_2+2</i>	0.969	8.176	15.331	21.614	48.728	15.633	8.859
<i>R101_2+1</i>	0.162	6.419	14.234	24.158	62.601	16.665	12.219
<i>R101_2+2</i>	0.166	6.158	13.933	22.480	56.584	15.897	11.546
<i>R50_2+1</i>	0.226	6.508	14.732	23.882	57.620	16.795	12.020
<i>R50_2+2</i>	0.349	6.607	14.294	23.429	58.718	16.403	11.776
<i>ViT-B-16_2+1</i>	-0.181	6.409	13.789	22.836	58.202	15.974	11.840
<i>ViT-B-16_2+2</i>	0.013	6.381	14.040	23.301	56.766	16.202	12.066
IT FCDB-no correction							
<i>IncV3_2+1</i>	-0.154	4.904	12.230	19.168	49.066	13.106	9.338
<i>IncV3_2+2</i>	0.855	4.806	10.629	16.534	46.382	11.683	8.187
<i>R101_2+1</i>	-1.306	3.367	10.326	18.651	55.249	12.500	10.788
<i>R101_2+2</i>	-0.023	3.995	10.654	19.133	55.214	12.872	10.463
<i>R50_2+1</i>	-0.138	3.876	10.970	19.902	53.981	13.240	10.790
<i>R50_2+2</i>	-0.034	3.620	10.551	19.574	54.379	12.986	11.029
<i>ViT-B-16_2+1</i>	-0.387	4.058	10.698	19.386	58.382	13.263	11.203
<i>ViT-B-16_2+2</i>	0.040	3.738	10.825	19.674	59.867	13.311	11.299

Target variable, dataset ¹ , and algorithm	Minimum	Q1	Median	Q3	Maximum	Mean	SD
IT FCDB-correction							
<i>IncV3_2+1</i>	-1.257	4.006	10.534	16.942	41.867	11.260	8.240
<i>IncV3_2+2</i>	0.595	4.365	9.778	15.774	42.196	11.086	7.861
<i>R101_2+1</i>	0.101	4.222	11.726	20.884	62.814	14.046	11.484
<i>R101_2+2</i>	1.132	4.353	10.209	17.604	45.489	12.060	8.928
<i>R50_2+1</i>	-2.055	2.800	9.419	18.342	52.611	11.625	10.148
<i>R50_2+2</i>	0.076	3.238	9.819	18.717	55.693	12.294	10.592
<i>ViT-B-16_2+1</i>	0.069	4.059	10.457	19.231	56.605	13.148	11.080
<i>ViT-B-16_2+2</i>	-0.150	3.367	9.541	18.818	61.622	12.570	10.973

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Abbreviations: FCDB, Food Composition Database.

Table C2. Percentages of perfect agreement obtained by cross-classifying dishes based on quartiles of observed and predicted values. Nutrition5k test set (n = 676)

Target variable and dataset ¹	IncV3_2+1	IncV3_2+2	R101_2+1	R101_2+2	R50_2+1	R50_2+2	ViT-B-16_2+1	ViT-B-16_2+2
<i>Mass (g)</i>								
US FCDB-no correction	0.786	0.803	0.808	0.808	0.806	0.811	0.808	0.803
US FCDB-correction	0.802	0.778	0.817	0.821	0.817	0.805	0.817	0.822
IT FCDB-no correction	0.788	0.766	0.814	0.817	0.814	0.821	0.815	0.809
IT FCDB-correction	0.800	0.796	0.809	0.822	0.817	0.811	0.827	0.812
<i>Energy content (kcal)</i>								
US FCDB-no correction	0.778	0.771	0.803	0.800	0.780	0.806	0.818	0.771
US FCDB-correction	0.784	0.778	0.794	0.806	0.809	0.805	0.814	0.811
IT FCDB-no correction	0.756	0.756	0.783	0.787	0.788	0.788	0.781	0.763
IT FCDB-correction	0.774	0.778	0.799	0.787	0.791	0.791	0.794	0.787
<i>Protein content (g)</i>								
US FCDB-no correction	0.672	0.716	0.765	0.746	0.759	0.763	0.778	0.716
US FCDB-correction	0.691	0.641	0.775	0.763	0.769	0.759	0.771	0.766
IT FCDB-no correction	0.680	0.624	0.784	0.768	0.763	0.772	0.769	0.772
IT FCDB-correction	0.703	0.648	0.769	0.756	0.759	0.768	0.783	0.771
<i>Fat content (g)</i>								
US FCDB-no correction	0.651	0.678	0.719	0.712	0.712	0.714	0.753	0.678
US FCDB-correction	0.675	0.654	0.725	0.735	0.738	0.732	0.763	0.754
IT FCDB-no correction	0.669	0.655	0.735	0.716	0.744	0.735	0.777	0.780
IT FCDB-correction	0.683	0.660	0.743	0.714	0.744	0.731	0.757	0.783
<i>Carbohydrates content (g)</i>								
US FCDB-no correction	0.525	0.572	0.691	0.666	0.666	0.670	0.720	0.572
US FCDB-correction	0.525	0.491	0.697	0.704	0.683	0.683	0.722	0.728
IT FCDB-no correction	0.562	0.491	0.740	0.683	0.701	0.700	0.759	0.760
IT FCDB-correction	0.541	0.506	0.706	0.612	0.706	0.720	0.762	0.780

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum and maximum percentages of perfect agreement for each target variable. Abbreviations: FCDB, Food Composition Database

Table C3. Unweighted Cohen's kappa coefficients obtained by cross-classifying dishes based on quartiles of observed and predicted values. Nutrition5k test set (n = 676)

Target variable and dataset ¹	IncV3_2+1	IncV3_2+2	R101_2+1	R101_2+2	R50_2+1	R50_2+2	ViT-B-16_2+1	ViT-B-16_2+2
Mass (g)								
US FCDB-no correction	0.714* ²	0.738*	0.744*	0.744*	0.742*	0.748*	0.744*	0.738*
US FCDB-correction	0.736*	0.704*	0.755*	0.761*	0.755*	0.740*	0.755*	0.763*
IT FCDB-no correction	0.718*	0.688*	0.751*	0.755*	0.751*	0.761*	0.753*	0.746*
IT FCDB-correction	0.734*	0.728*	0.746*	0.763*	0.755*	0.748*	0.769*	0.750*
Energy content (kcal)								
US FCDB-no correction	0.704*	0.694*	0.738*	0.734*	0.706*	0.742*	0.757*	0.694*
US FCDB-correction	0.712*	0.704*	0.726*	0.742*	0.746*	0.740*	0.751*	0.748*
IT FCDB-no correction	0.675*	0.675*	0.710*	0.716*	0.718*	0.718*	0.708*	0.684*
IT FCDB-correction	0.698*	0.704*	0.732*	0.716*	0.722*	0.722*	0.726*	0.716*
Protein content (g)								
US FCDB-no correction	0.562*	0.621*	0.686*	0.661*	0.679*	0.684*	0.704*	0.621*
US FCDB-correction	0.588*	0.521*	0.700*	0.684*	0.692*	0.679*	0.694*	0.688*
IT FCDB-no correction	0.574*	0.499*	0.712*	0.690*	0.684*	0.696*	0.692*	0.696*
IT FCDB-correction	0.604*	0.531*	0.692*	0.675*	0.679*	0.690*	0.710*	0.694*
Fat content (g)								
US FCDB-no correction	0.535*	0.570*	0.625*	0.615*	0.615*	0.619*	0.671*	0.570*
US FCDB-correction	0.566*	0.538*	0.633*	0.647*	0.651*	0.643*	0.684*	0.673*
IT FCDB-no correction	0.558*	0.540*	0.647*	0.621*	0.659*	0.647*	0.702*	0.706*
IT FCDB-correction	0.578*	0.546*	0.657*	0.619*	0.659*	0.641*	0.677*	0.710*
Carbohydrates content (g)								
US FCDB-no correction	0.367*	0.430*	0.588*	0.554*	0.554*	0.560*	0.627*	0.430*
US FCDB-correction	0.367*	0.321*	0.596*	0.606*	0.578*	0.578*	0.629*	0.637*
IT FCDB-no correction	0.416*	0.321*	0.653*	0.578*	0.602*	0.600*	0.679*	0.680*
IT FCDB-correction	0.389*	0.341*	0.607*	0.483*	0.607*	0.627*	0.682*	0.706*

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum and maximum Cohen's kappa coefficients for each target variable. ²The asterisk indicates that the corresponding Cohen's kappa coefficient was different from zero at the 0.05 level. Abbreviations: FCDB, Food Composition Database

Table C4. Performance metrics for single target variables, algorithms, and available datasets, as well as median metrics across datasets before frame filtering. Nutrition5k test set (n = 676)

Dataset ¹ and algorithm	Mass (g)			Energy content (kcal)			Protein content (g)			Fat content (g)			Carbohydrates content (g)		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
US FCDB-no correction															
<i>IncV3_2+1</i>	310.54	47.64	25.19	505.73	80.84	32.07	12.12	7.04	44.85	46.99	7.04	51.79	29.64	9.48	49.49
<i>IncV3_2+2</i>	309.16	44.31	23.43	503.79	78.23	31.03	11.28	6.20	39.50	46.69	6.68	49.10	29.30	8.57	44.75
<i>R101_2+1</i>	309.34	43.45	22.97	502.78	75.45	29.93	9.70	5.28	33.60	46.57	6.24	45.87	28.88	7.47	38.99
<i>R101_2+2</i>	309.51	45.13	23.86	503.06	75.88	30.10	10.20	5.58	35.53	46.66	6.35	46.65	28.92	7.45	38.89
<i>R50_2+1</i>	309.48	44.84	23.71	503.49	76.87	30.49	10.22	5.73	36.47	46.65	6.50	47.75	28.91	7.31	38.18
<i>R50_2+2</i>	309.63	45.26	23.93	503.53	77.08	30.57	10.49	5.60	35.63	46.68	6.27	46.13	28.83	7.25	37.88
<i>ViT-B_2+1</i>	309.13	44.17	23.35	504.08	78.20	31.02	10.23	5.39	34.34	46.68	6.27	46.06	28.84	6.83	35.67
<i>ViT-B_2+2</i>	309.16	44.31	23.43	503.79	78.23	31.03	11.28	6.20	39.50	46.69	6.68	49.10	29.30	8.57	44.75
US FCDB-correction															
<i>IncV3_2+1</i>	56.28	35.36	19.95	88.99	54.92	24.52	11.64	6.90	44.76	7.96	5.02	45.34	12.18	8.03	45.97
<i>IncV3_2+2</i>	55.41	35.91	20.25	84.35	53.51	23.89	11.49	7.15	46.38	7.43	4.54	41.02	12.53	8.63	49.39
<i>R101_2+1</i>	48.83	30.52	17.22	77.62	46.65	20.82	9.11	5.19	33.69	6.72	3.96	35.73	8.66	5.47	31.29
<i>R101_2+2</i>	48.47	30.36	17.12	76.99	46.44	20.73	9.16	5.09	33.06	6.30	3.69	33.35	8.96	5.53	31.66
<i>R50_2+1</i>	49.92	31.15	17.57	80.90	47.91	21.39	9.44	5.39	34.96	6.41	3.75	33.90	9.03	5.73	32.80
<i>R50_2+2</i>	50.43	31.46	17.75	77.53	47.48	21.20	9.23	5.14	33.33	6.29	3.67	33.10	8.98	5.60	32.04
<i>ViT-B_2+1</i>	51.10	32.89	18.55	87.33	51.07	22.80	9.18	5.16	33.52	6.74	3.88	34.99	8.52	5.21	29.82
<i>ViT-B_2+2</i>	50.22	32.13	18.12	86.76	51.42	22.95	8.74	4.80	31.12	6.51	3.63	32.80	8.30	4.97	28.42
IT FCDB-no correction															
<i>IncV3_2+1</i>	453.01	64.15	31.15	660.97	96.65	36.52	11.40	6.51	42.78	65.36	8.49	54.97	14.07	7.97	52.98
<i>IncV3_2+2</i>	452.77	64.14	31.15	660.75	96.07	36.30	12.40	7.36	48.33	65.57	8.41	54.44	15.54	9.29	61.74
<i>R101_2+1</i>	451.84	60.64	29.45	658.11	89.52	33.82	10.04	5.23	34.35	65.10	7.88	51.06	11.91	5.71	37.96
<i>R101_2+2</i>	451.29	60.27	29.27	657.65	90.90	34.34	10.13	5.44	35.71	65.14	7.65	49.54	12.47	6.35	42.20
<i>R50_2+1</i>	452.14	61.63	29.93	658.77	90.11	34.04	10.35	5.22	34.29	65.18	7.53	48.75	12.14	6.16	40.97
<i>R50_2+2</i>	452.17	61.83	30.02	657.77	89.64	33.87	10.19	5.21	34.20	65.04	7.55	48.88	11.94	5.98	39.74
<i>ViT-B_2+1</i>	451.36	60.00	29.14	658.79	90.86	34.33	9.79	5.03	33.02	65.13	7.41	47.99	11.07	5.16	34.34
<i>ViT-B_2+2</i>	451.79	60.52	29.39	658.66	90.72	34.27	9.83	4.80	31.51	65.10	7.28	47.15	10.91	5.05	33.56
IT FCDB-correction															
<i>IncV3_2+1</i>	54.09	34.54	19.46	99.69	57.54	25.30	10.56	6.28	42.29	8.92	4.98	41.82	13.52	7.98	54.48
<i>IncV3_2+2</i>	56.30	35.40	19.95	98.52	57.56	25.30	11.33	6.96	46.85	8.75	4.95	41.56	14.24	8.80	60.14
<i>R101_2+1</i>	51.11	31.94	18.00	89.95	51.87	22.80	8.28	5.03	33.82	7.29	3.90	32.76	10.08	5.56	37.96
<i>R101_2+2</i>	48.86	30.22	17.03	93.59	51.61	22.69	9.66	5.49	36.93	8.29	4.35	36.60	12.06	7.17	48.94
<i>R50_2+1</i>	50.02	30.97	17.45	91.01	52.53	23.09	8.70	5.13	34.52	7.54	4.08	34.28	11.19	5.87	40.09
<i>R50_2+2</i>	51.20	31.70	17.87	91.33	53.18	23.38	8.35	4.77	32.08	7.41	3.97	33.37	10.61	5.45	37.22

Dataset ¹ and algorithm	Mass (g)			Energy content (kcal)			Protein content (g)			Fat content (g)			Carbohydrates content (g)		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
<i>ViT-B_2+1</i>	51.12	32.12	18.10	91.38	52.80	23.21	8.18	4.80	32.32	6.95	4.05	34.08	9.51	4.79	32.74
<i>ViT-B_2+2</i>	51.84	32.84	18.51	95.03	54.75	24.07	7.72	4.40	29.64	7.36	3.85	32.38	9.49	4.64	31.68
Overall median															
<i>IncV3_2+1</i>	183.41	41.50	22.57	302.71	69.19	28.68	11.52	6.71	43.77	27.95	6.03	48.56	13.80	8.00	51.23
<i>IncV3_2+2</i>	182.73	40.11	21.84	301.16	67.90	28.17	11.41	7.05	46.61	27.72	5.81	45.33	14.89	8.72	54.76
<i>R10I_2+1</i>	180.22	37.69	20.49	296.36	63.66	26.36	9.40	5.21	33.76	26.93	5.10	40.80	11.00	5.63	37.96
<i>R10I_2+2</i>	179.19	37.74	20.49	298.33	63.75	26.39	9.90	5.46	35.62	27.47	5.35	41.63	12.27	6.76	40.55
<i>R50_2+1</i>	179.75	38.00	20.64	297.25	64.70	26.79	9.83	5.30	34.74	27.10	5.29	41.02	11.67	6.01	39.13
<i>R50_2+2</i>	180.42	38.48	20.90	297.43	65.13	26.97	9.71	5.17	33.77	27.04	5.12	39.75	11.28	5.79	37.55
<i>ViT-B-16_2+1</i>	180.12	38.53	20.95	297.73	65.50	27.12	9.49	5.10	33.27	26.82	5.16	40.52	10.29	5.19	33.54
<i>ViT-B-16_2+2</i>	180.50	38.58	20.97	299.41	66.49	27.55	9.29	4.80	31.32	27.02	5.27	39.97	10.20	5.01	32.62

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum performance metrics (i.e., the minimum error) for each target variable; similarly values with an orange cell background indicate the maximum performance MAPE (i.e., the maximum error) for each target variable as commented in the text. Abbreviations: FCDB, Food Composition Database

Table C5. List of 68 incorrectly predicted dishes across target variables and datasets, as grouped by similarity in ingredient content. Nutrition5k test set (n = 664)

Dish ID	Total original frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames	Number of algorithms wrongly predicting the dish	Number of ingredients per dish	List of ingredients per dish
Salad-based group (median number of ingredients per dish: 16, IQR: 11.25–20.5)								
dish_1560367952	28	1	27	3.6%	96.4%	8	9	Fish, spinach (raw), pizza, onions, country rice, olive oil, salt, garlic, green onions
dish_1560367980	28	2	26	7.1%	92.9%	8	10	Asparagus, salt, onions, country rice, olive oil, green onions, pizza, spinach (raw), fish, garlic
dish_1560368506	28	15	13	53.6%	46.4%	7	18	Brown rice, fish, shallots, honeydew melons, broccoli, lemon juice, parsley, pork, vinegar, cherry tomatoes, pepper, garlic, salt, country rice, basil, olive oil, onions, green onions
dish_1560368570	28	2	26	7.1%	92.9%	8	24	Honeydew melons, pepper, cherry tomatoes, lettuce, mixed greens, pork, mustard, olive oil, lemon juice, onions, carrot, broccoli, green onions, shallots, arugula, vinegar, brown rice, fish, pumpkin seeds, basil, parsley, country rice, salt, garlic
dish_1560800988	24	11	13	45.8%	54.2%	8	9	Pepper, cauliflower, chickpeas, salt, bulgur, olive oil, kale, lemon juice, parsley
dish_1560801020	24	12	12	50.0%	50.0%	8	16	Cauliflower, garlic, spinach (raw), parmesan cheese, wheat berry, chickpeas, pepper, chicken breast, cherry tomatoes, thyme, lemon juice, olive oil, parsley, kale, bulgur, salt
dish_1560801041	26	10	16	38.5%	61.5%	8	22	Pork, zucchini, arugula, chicken breast, cherry tomatoes, rosemary, lemon juice, thyme, olive oil, onions, wheat berry, parmesan cheese, pepper, spinach (raw), cauliflower, garlic, chickpeas, white rice, salt, bulgur, parsley, kale
dish_1561577848	28	19	9	67.9%	32.1%	8	17	Salt, white wine, cream, oregano, arugula, lemon juice, olive oil, pepper, chicken, mushroom, wheat berry, butter, rosemary, thyme, shallots, garlic, basil
dish_1561577947	32	9	23	28.1%	71.9%	8	22	Olive oil, basil, arugula, blueberries, vinegar, mustard, walnuts, white wine, salt, rosemary, oregano, cream, mushroom, wheat berry, chard,

Dish ID	Total original frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames	Number of algorithms wrongly predicting the dish	Number of ingredients per dish	List of ingredients per dish
								pepper, chicken, shallots, garlic, butter, lemon juice, thyme
dish_1561661377	102	13	89	12.7%	87.3%	8	14	Garlic, chard, brown rice, green beans, chicken, salt, carrot, Caesar salad, parsley, chive, rosemary, basil, lemon juice, olive oil
dish_1562009934	28	15	13	53.6%	46.4%	8	16	Quinoa, mixed greens, garlic, parsley, mustard, lemon juice, brown rice, arugula, vinegar, olives, shallots, pears, salt, goat cheese, thyme, olive oil
dish_1562618000	28	13	15	46.4%	53.6%	8	16	Vinegar, olive oil, garlic, mustard greens, pepper, salt, radishes, lemon juice, thyme, brown rice, parsley, basil, arugula, chicken thighs, chickpeas, broccoli
dish_1562790855	146	21	125	14.4%	85.6%	8	21	Radishes, fish, cherry tomatoes, shallots, onions, mustard, parsley, garlic, basil, salt, pepper, pork, lemon juice, brown rice, country rice, cucumbers, olive oil, vinegar, bell peppers, broccoli, green onions
dish_1563478751	32	1	31	3.1%	96.9%	8	12	Cream, mushroom, spinach (raw), olive oil, pasta, beef, wine, garlic, sour cream, onions, thyme, salt
dish_1563909550	29	25	4	86.2%	13.8%	8	11	Cucumbers, mustard, mustard greens, olive oil, garlic, green beans, tomatoes, salt, fried rice, vinegar, spinach (raw)
dish_1563909580	28	13	15	46.4%	53.6%	8	12	Mustard greens, cucumbers, tomatoes, salt, mustard, garlic, fried rice, cheese pizza, vinegar, spinach (raw), green beans, olive oil
dish_1565030391	32	8	24	25.0%	75.0%	8	19	White rice, garlic, orange juice, onions, cucumbers, kale, green onions, lettuce, soy sauce, pepper, cherry tomatoes, beef, vinegar, olive oil, broccoli, lime, salt, chili, mixed greens
dish_1565123881	31	14	17	45.2%	54.8%	8	13	Caesar salad, olive oil, onions, cheese pizza, zucchini, spinach (cooked), millet, shallots, bok choy, salt, beef, chayote squash, vinegar
dish_1565810969	63	30	33	47.6%	52.4%	7	1	Spinach (raw)
dish_1565898230	31	10	21	32.3%	67.7%	7	27	Garlic, bell peppers, beef, cherry tomatoes, brown rice, ginger, olive oil, vinegar, spinach

Dish ID	Total original frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames	Number of algorithms wrongly predicting the dish	Number of ingredients per dish	List of ingredients per dish
								(cooked), lime, shallots, bok choy, salmon, millet, vinaigrette, jalapenos, spinach (raw), green beans, feta cheese, cucumbers, lettuce, cilantro, lemon juice, onions, salt, chili, olives
dish_1565986761	343	29	314	8.5%	91.5%	8	22	Cherry tomatoes, fish, chive, ground turkey, cream, chard, onions, lemon juice, parsley, olive oil, shallots, thyme, brown rice, salt, white rice, wheat berry, kale, mushroom, celery, carrot, garlic, eggs
dish_1566414342	34	5	29	14.7%	85.3%	7	19	Garlic, pepper, mushroom, oregano, cream, wheat berry, butter, basil, salt, shallots, white wine, chicken, quinoa, arugula, thyme, olive oil, rosemary, lemon juice, roasted potatoes
dish_1566414412	32	8	24	25.0%	75.0%	8	27	Shallots, olive oil, garlic, lemon juice, basil, cream, wheat berry, mushroom, arugula, cherry tomatoes, quinoa, chicken, pepper, bell peppers, white wine, lettuce, feta cheese, roasted potatoes, onions, butter, thyme, rosemary, cucumbers, olives, oregano, vinaigrette, salt
dish_1566502573	31	7	24	22.6%	77.4%	8	28	Chive, bok choy, chicken, white rice, pork, arugula, spinach (raw), brown rice, chard, mustard, olive oil, garlic, cucumbers, sugar, rosemary, pepper, sun dried tomatoes, lemon juice, mustard greens, parsley, vinegar, corn on the cob, basil, onions, carrot, soy sauce, salt, chickpeas
dish_1566587182	28	7	21	25.0%	75.0%	8	17	Pepper, millet, avocado, spinach (raw), vinegar, olive oil, onions, bell peppers, salt, garlic, cherry tomatoes, chicken, jalapenos, mustard, celery root, mixed greens, tomatoes
dish_1566590007	33	8	25	24.2%	75.8%	8	13	Bell peppers, garlic, tomatoes, salt, onions, olive oil, pizza, pepper, tofu, jalapenos, spinach (raw), chicken, millet
dish_1566590056	31	8	23	25.8%	74.2%	8	19	Tomatoes, pepper, millet, vinegar, tofu, jalapenos, mustard, olive oil, bell peppers, cherry

Dish ID	Total original frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames	Number of algorithms wrongly predicting the dish	Number of ingredients per dish	List of ingredients per dish
								tomatoes, chicken, chard, spinach (raw), pizza, cucumbers, onions, garlic, salt, figs
dish_1566851616	31	5	26	16.1%	83.9%	8	4	Caesar salad, broccoli, cheese pizza, olive oil
dish_1568305257	34	7	27	20.6%	79.4%	7	10	Turkey bacon, salt, bell peppers, mustard, olive oil, cucumbers, vinegar, scrambled eggs, garlic, radishes
dish_1568401302	31	12	19	38.7%	61.3%	8	7	Fried rice, salt, squash, carrot, avocado, olive oil, tuna salad
Eggs-based group (median number of ingredients per dish: 5, IQR: 3–6)								
dish_1561999624	36	2	34	5.6%	94.4%	8	1	Scrambled eggs
dish_1561999706	36	11	25	30.6%	69.4%	8	2	Scrambled eggs, sweet potato
dish_1562691064	28	13	15	46.4%	53.6%	8	7	Berries, fried rice, olive oil, pineapple, scrambled eggs, roasted potatoes, broccoli
dish_1563551220	29	13	16	44.8%	55.2%	8	9	Cream cheese, berries, greek yogurt, milk, chia seeds, bagels, egg whites, olive oil, sweet potato
dish_1563984242	30	12	18	40.0%	60.0%	8	5	Sweet potato, egg whites, pineapple, olive oil, cantaloupe
dish_1563984296	29	12	17	41.4%	58.6%	8	6	Egg whites, olive oil, salsa, cantaloupe, sweet potato, pineapple
dish_1566316726	30	17	13	56.7%	43.3%	8	3	Egg whites, olive oil, sweet potato
dish_1566838378	36	9	27	25.0%	75.0%	8	4	Scrambled eggs, watermelon, berries, pineapple
dish_1566838407	29	6	23	20.7%	79.3%	8	6	Pineapple, scrambled eggs, sweet potato, berries, olive oil, watermelon
Chicken-based group (median number of ingredients per dish: 4, IQR: 3–5)								
dish_1550706583	114	87	27	76.3%	23.7%	7	1	Chicken
dish_1550706705	115	55	60	47.8%	52.2%	7	3	Chicken, cucumbers, cauliflower
dish_1550873434	119	119	0	100.0%	0.0%	7	1	Chicken
dish_1550873668	117	59	58	50.4%	49.6%	8	3	Avocado, chicken, cheese
dish_1563389600	35	17	18	48.6%	51.4%	8	2	Grilled chicken, cherry tomatoes
dish_1565811061	34	18	16	52.9%	47.1%	8	4	Chicken, carrot, spinach (raw), broccoli
dish_1565811091	92	55	37	59.8%	40.2%	7	5	Broccoli, spinach (raw), carrot, chicken, goat cheese

Dish ID	Total original frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames	Number of algorithms wrongly predicting the dish	Number of ingredients per dish	List of ingredients per dish
dish_1565811139	29	10	19	34.5%	65.5%	7	6	Carrot, goat cheese, olive oil, broccoli, spinach (raw), chicken
dish_1565974409	30	14	16	46.7%	53.3%	7	2	Chicken apple sausage, bacon
dish_1566246513	37	27	10	73.0%	27.0%	7	3	Feta cheese, mixed greens, chicken
dish_1566246626	37	26	11	70.3%	29.7%	8	6	Feta cheese, broccoli, mixed greens, chicken, olives, Caesar dressing
dish_1566328776	35	11	24	31.4%	68.6%	7	3	Chicken, cherry tomatoes, pizza
dish_1566328805	31	11	20	35.5%	64.5%	8	4	Cherry tomatoes, pizza, chicken, pineapple
dish_1566328831	34	10	24	29.4%	70.6%	8	5	Pizza, cherry tomatoes, chicken, pineapple, olives
dish_1566850031	36	10	26	27.8%	72.2%	8	6	Olives, carrot, chicken, Caesar dressing, cherry tomatoes, onions
dish_1568147009	38	18	20	47.4%	52.6%	8	4	Broccoli, steak, mixed greens, chicken
dish_1568147044	36	18	18	50.0%	50.0%	8	5	Broccoli, steak, mixed greens, chicken, olive oil
Western-inspired breakfast foods group (median number of ingredients per dish: 2, IQR: 1–3)								
dish_1557937079	819	127	692	15.5%	84.5%	8	1	Bacon
dish_1558372948	32	23	9	71.9%	28.1%	8	1	Almonds
dish_1558373159	32	4	28	12.5%	87.5%	8	3	Sausage, APPLES with peel, almonds
dish_1558375886	41	5	36	12.2%	87.8%	8	3	Almonds, sausage, grapes
dish_1558544663	33	17	16	51.5%	48.5%	8	1	Oatmeal
dish_1558549806	35	9	26	25.7%	74.3%	7	3	Almonds, white rice, spinach (raw)
dish_1560203424	28	11	17	39.3%	60.7%	8	2	Pepperoni pizza, brownies
dish_1563305513	35	15	20	42.9%	57.1%	7	1	Cheese pizza
dish_1566316681	87	15	72	17.2%	82.8%	8	2	Sweet potato, olive oil
Corrected-portion-sizes group (median number of ingredients per dish: 3, IQR: 2–3)								
dish_1551382179	116	76	40	65.5%	34.5%	8	3	Asparagus, white rice, oatmeal
dish_1551567508	114	114	0	100.0%	0.0%	8	1	Olives
dish_1551567573	115	74	41	64.3%	35.7%	8	3	Olives, sausage, ham
All incorrectly predicted dishes								

Dish ID	Total original frames	Left frames	Removed frames	Percentage of left frames	Percentage of removed frames	Number of algorithms wrongly predicting the dish	Number of ingredients per dish	List of ingredients per dish
Minimum	24.0	1.0	0.0	3.1%	0.0%	7.0	1.0	—
Q1	29.0	8.8	16.0	23.8%	49.9%	8.0	3.0	—
Median	32.0	12.5	23.0	39.0%	61.0%	8.0	6.0	—
Q3	37.0	18.3	27.0	50.1%	76.2%	8.0	14.5	—
Maximum	819.0	127.0	692.0	100.0%	96.9%	8.0	28.0	—
Mean	61.2	21.9	39.3	38.9%	61.1%	7.8	8.9	—
SD	104.6	27.5	89.7	22.3%	22.3%	0.4	7.8	—

Table C6. Performance metrics for single target variables, algorithms, and available datasets, as well as median metrics across datasets, after frame filtering. Nutrition5k test set (n = 664)

Dataset and algorithm ¹	Mass (g)			Energy content (kcal)			Protein content (g)			Fat content (g)			Carbohydrates content (g)		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
US FCDB-no correction															
<i>IncV3_2+1</i>	312.07	44.79	23.81	507.75	76.28	30.58	11.37	6.61	42.06	47.25	6.86	50.96	29.70	9.17	48.88
<i>IncV3_2+2</i>	311.49	42.92	22.82	507.46	74.66	29.93	10.71	5.82	37.01	47.28	6.61	49.13	29.54	8.64	46.06
<i>R101_2+1</i>	311.02	40.93	21.76	505.64	71.92	28.83	8.97	4.88	31.06	46.87	6.05	44.94	29.03	7.27	38.74
<i>R101_2+2</i>	311.27	42.77	22.74	505.88	72.00	28.86	9.48	5.16	32.82	46.97	6.13	45.58	29.02	7.21	38.40
<i>R50_2+1</i>	311.07	42.06	22.36	506.08	73.08	29.29	9.44	5.29	33.65	46.93	6.27	46.62	29.02	7.07	37.70
<i>R50_2+2</i>	311.24	42.51	22.60	506.28	73.65	29.52	9.75	5.19	33.05	46.97	6.07	45.11	28.93	6.98	37.20
<i>ViT-B-16_2+1</i>	311.22	42.50	22.59	508.11	76.20	30.55	9.76	5.11	32.53	47.03	6.12	45.51	28.93	6.59	35.13
<i>ViT-B-16_2+2</i>	311.04	42.74	22.72	506.91	76.45	30.65	10.00	5.53	35.18	47.00	6.47	48.11	29.33	7.99	42.57
US FCDB-correction															
<i>IncV3_2+1</i>	48.61	31.88	18.11	78.07	49.77	22.54	10.91	6.47	41.96	7.37	4.76	43.76	11.64	7.67	44.98
<i>IncV3_2+2</i>	48.54	32.77	18.62	74.66	48.55	21.98	10.77	6.70	43.51	6.81	4.28	39.34	12.13	8.35	48.98
<i>R101_2+1</i>	41.48	27.51	15.63	68.26	42.39	19.19	8.24	4.75	30.83	6.06	3.69	33.93	8.22	5.17	30.31
<i>R101_2+2</i>	41.39	27.47	15.60	67.67	42.13	19.08	8.32	4.67	30.30	5.67	3.44	31.62	8.53	5.24	30.70
<i>R50_2+1</i>	42.13	27.84	15.82	71.43	43.41	19.65	8.60	4.94	32.04	5.72	3.49	32.09	8.61	5.44	31.91
<i>R50_2+2</i>	42.35	28.01	15.91	68.76	43.36	19.63	8.32	4.68	30.36	5.61	3.41	31.34	8.52	5.28	30.97
<i>ViT-B-16_2+1</i>	45.46	30.52	17.33	78.72	47.47	21.49	8.49	4.81	31.20	5.99	3.63	33.32	7.85	4.81	28.21
<i>ViT-B-16_2+2</i>	43.95	29.55	16.79	77.97	47.71	21.60	7.99	4.43	28.72	5.67	3.36	30.92	7.67	4.60	26.99
IT FCDB-no correction															
<i>IncV3_2+1</i>	456.00	61.38	29.91	664.55	92.51	35.32	10.73	6.09	39.99	65.82	8.40	54.85	13.39	7.59	51.87
<i>IncV3_2+2</i>	455.66	61.48	29.96	664.56	92.13	35.18	11.81	6.93	45.56	66.05	8.31	54.25	14.92	8.94	61.11
<i>R101_2+1</i>	455.01	58.02	28.28	663.01	86.38	32.99	9.30	4.82	31.67	65.65	7.81	50.96	11.25	5.32	36.35
<i>R101_2+2</i>	454.46	57.55	28.05	662.40	88.11	33.65	9.49	5.05	33.21	65.67	7.54	49.23	11.92	5.99	40.98
<i>R50_2+1</i>	455.37	59.15	28.83	663.44	86.67	33.10	9.63	4.77	31.31	65.71	7.38	48.20	11.52	5.79	39.59
<i>R50_2+2</i>	455.32	59.24	28.87	662.48	87.05	33.24	9.46	4.78	31.44	65.57	7.46	48.72	11.34	5.61	38.37
<i>ViT-B-16_2+1</i>	454.54	58.00	28.27	663.35	87.31	33.34	9.21	4.67	30.71	65.65	7.27	47.48	10.15	4.74	32.39
<i>ViT-B-16_2+2</i>	455.02	58.43	28.48	663.38	87.19	33.29	9.24	4.45	29.22	65.63	7.14	46.61	10.02	4.62	31.59
IT FCDB-correction															
<i>IncV3_2+1</i>	47.04	31.34	17.79	91.16	52.78	23.56	9.92	5.89	39.71	8.65	4.76	40.63	12.77	7.56	53.17
<i>IncV3_2+2</i>	48.92	31.95	18.13	88.91	52.62	23.49	10.63	6.51	43.83	8.35	4.74	40.45	13.54	8.46	59.50
<i>R101_2+1</i>	43.01	28.72	16.30	83.17	48.09	21.47	7.27	4.61	31.03	7.10	3.76	32.11	9.33	5.20	36.54
<i>R101_2+2</i>	41.56	27.13	15.40	86.80	47.30	21.12	9.05	5.12	34.46	8.13	4.17	35.60	11.44	6.81	47.87
<i>R50_2+1</i>	41.92	27.58	15.65	83.69	48.52	21.66	7.81	4.70	31.67	7.23	3.88	33.10	10.37	5.45	38.33
<i>R50_2+2</i>	43.44	28.54	16.19	84.65	49.37	22.04	7.41	4.34	29.24	7.16	3.81	32.56	9.74	5.00	35.19

Dataset and algorithm ¹	Mass (g)			Energy content (kcal)			Protein content (g)			Fat content (g)			Carbohydrates content (g)		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
<i>ViT-B-16_2+1</i>	44.52	29.46	16.72	82.59	48.50	21.65	7.47	4.46	30.04	6.53	3.85	32.92	8.37	4.35	30.58
<i>ViT-B-16_2+2</i>	45.60	30.28	17.18	86.35	50.44	22.52	6.88	4.03	27.13	6.85	3.63	31.04	8.37	4.19	29.43
Overall median															
<i>IncV3_2+1</i>	180.34	38.33	20.96	299.45	64.53	27.07	10.82	6.28	40.98	27.95	5.81	47.36	13.08	7.63	50.37
<i>IncV3_2+2</i>	180.20	37.85	20.72	298.19	63.64	26.71	10.74	6.61	43.67	27.82	5.67	44.79	14.23	8.55	54.24
<i>R101_2+1</i>	177.01	34.82	19.03	294.40	60.01	25.15	8.61	4.79	31.05	26.99	4.90	39.43	10.29	5.26	36.45
<i>R101_2+2</i>	176.41	35.12	19.17	296.34	59.65	24.99	9.26	5.08	33.01	27.55	5.15	40.59	11.68	6.40	39.69
<i>R50_2+1</i>	176.60	34.95	19.09	294.89	60.80	25.48	9.02	4.85	31.86	27.08	5.07	39.86	10.95	5.62	38.02
<i>R50_2+2</i>	177.34	35.52	19.40	295.47	61.51	25.78	8.89	4.73	30.90	27.07	4.94	38.83	10.54	5.45	36.19
<i>ViT-B-16_2+1</i>	178.34	36.51	19.96	295.35	62.35	26.10	8.85	4.74	30.95	26.78	4.99	39.41	9.26	4.78	31.49
<i>ViT-B-16_2+2</i>	178.32	36.51	19.95	296.63	63.45	26.58	8.62	4.44	28.97	26.93	5.05	38.82	9.20	4.61	30.51

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum performance metrics (i.e., the minimum error) for each target variable; similarly values with an orange cell background indicate the maximum performance MAPE (i.e., the maximum error) for each target variable as commented in the text. Abbreviations: FCDB, Food Composition Database

Table C7. Sensitivity analysis: percentages of perfect agreement of pairs of predicted and computed energy contents under the 4-task and 5-task deep learning algorithms, before and after frame filtering. Nutrition5k test set (n = 676 and n = 664, respectively)

BEFORE FRAME FILTERING				AFTER FRAME FILTERING		
Dataset and algorithm ¹	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content
US FCDB-no correction						
<i>IncV3_2+1</i>	0.666	0.648	0.910	0.643	0.628	0.895
<i>IncV3_2+2</i>	0.670	0.586	0.679	0.590	0.581	0.878
<i>R101_2+1</i>	0.663	0.703	0.821	0.643	0.687	0.789
<i>R101_2+2</i>	0.698	0.667	0.898	0.690	0.651	0.896
<i>R50_2+1</i>	0.716	0.741	0.858	0.697	0.721	0.843
<i>R50_2+2</i>	0.728	0.723	0.891	0.708	0.699	0.880
<i>ViT-B-16_2+1</i>	0.809	0.775	0.892	0.803	0.764	0.870
<i>ViT-B-16_2+2</i>	0.827	0.601	0.593	0.614	0.610	0.893
US FCDB-correction						
<i>IncV3_2+1</i>	0.660	0.660	0.833	0.652	0.652	0.837
<i>IncV3_2+2</i>	0.614	0.604	0.902	0.608	0.593	0.898
<i>R101_2+1</i>	0.706	0.660	0.855	0.693	0.633	0.834
<i>R101_2+2</i>	0.670	0.691	0.882	0.658	0.682	0.886
<i>R50_2+1</i>	0.722	0.698	0.849	0.714	0.690	0.834
<i>R50_2+2</i>	0.719	0.695	0.905	0.702	0.682	0.901
<i>ViT-B-16_2+1</i>	0.788	0.780	0.879	0.788	0.780	0.878
<i>ViT-B-16_2+2</i>	0.812	0.775	0.864	0.813	0.771	0.858
IT FCDB-no correction						
<i>IncV3_2+1</i>	0.661	0.667	0.939	0.669	0.670	0.940
<i>IncV3_2+2</i>	0.643	0.638	0.828	0.640	0.625	0.819
<i>R101_2+1</i>	0.706	0.744	0.885	0.690	0.721	0.870
<i>R101_2+2</i>	0.695	0.649	0.814	0.690	0.642	0.813
<i>R50_2+1</i>	0.700	0.709	0.842	0.682	0.697	0.813
<i>R50_2+2</i>	0.710	0.707	0.867	0.699	0.696	0.861
<i>ViT-B-16_2+1</i>	0.769	0.784	0.911	0.759	0.785	0.904
<i>ViT-B-16_2+2</i>	0.812	0.802	0.917	0.810	0.794	0.925
IT FCDB-correction						
<i>IncV3_2+1</i>	0.484	0.614	0.714	0.474	0.610	0.697
<i>IncV3_2+2</i>	0.611	0.601	0.852	0.623	0.610	0.846
<i>R101_2+1</i>	0.683	0.741	0.836	0.679	0.747	0.840
<i>R101_2+2</i>	0.652	0.632	0.814	0.631	0.623	0.810

BEFORE FRAME FILTERING				AFTER FRAME FILTERING		
Dataset and algorithm ¹	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content
<i>R50_2+1</i>	0.709	0.703	0.855	0.708	0.700	0.839
<i>R50_2+2</i>	0.710	0.706	0.867	0.712	0.696	0.870
<i>ViT-B-16_2+1</i>	0.765	0.768	0.920	0.767	0.765	0.904
<i>ViT-B-16_2+2</i>	0.738	0.737	0.917	0.736	0.745	0.913

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum and maximum performance metrics for each target variable. Abbreviations: FCDB, Food Composition Database.

Table C8. Sensitivity analysis: unweighted Cohen’s kappa coefficients of pairs of predicted and computed energy contents under the 4-task and 5-task deep learning algorithms, before and after frame filtering. Nutrition5k test set (n = 676 and n = 664, respectively)

BEFORE FRAME FILTERING				AFTER FRAME FILTERING		
Dataset and algorithm ¹	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content
US FCDB-no correction						
<i>IncV3_2+1</i>	0.554*	0.531*	0.880*	0.524*	0.504*	0.859*
<i>IncV3_2+2</i>	0.560*	0.448*	0.572*	0.454*	0.442*	0.837*
<i>R101_2+1</i>	0.550*	0.604*	0.761*	0.524*	0.582*	0.719*
<i>R101_2+2</i>	0.598*	0.556*	0.864*	0.586*	0.534*	0.861*
<i>R50_2+1</i>	0.621*	0.655*	0.811*	0.596*	0.629*	0.791*
<i>R50_2+2</i>	0.637*	0.631*	0.854*	0.61*	0.598*	0.839*
<i>ViT-B-16_2+1</i>	0.746*	0.700*	0.856*	0.737*	0.685*	0.827*
<i>ViT-B-16_2+2</i>	0.769*	0.467*	0.458*	0.486*	0.480*	0.857*
US FCDB-correction						
<i>IncV3_2+1</i>	0.546*	0.546*	0.777*	0.536*	0.536*	0.783*
<i>IncV3_2+2</i>	0.485*	0.471*	0.870*	0.478*	0.458*	0.863*
<i>R101_2+1</i>	0.607*	0.546*	0.807*	0.590*	0.510*	0.779*
<i>R101_2+2</i>	0.560*	0.588*	0.842*	0.544*	0.576*	0.847*
<i>R50_2+1</i>	0.629*	0.598*	0.799*	0.618*	0.586*	0.779*
<i>R50_2+2</i>	0.625*	0.594*	0.874*	0.602*	0.576*	0.867*
<i>ViT-B-16_2+1</i>	0.718*	0.706*	0.838*	0.717*	0.707*	0.837*
<i>ViT-B-16_2+2</i>	0.750*	0.700*	0.819*	0.751*	0.695*	0.811*
IT FCDB-no correction						
<i>IncV3_2+1</i>	0.548*	0.556*	0.919*	0.558*	0.560*	0.920*
<i>IncV3_2+2</i>	0.525*	0.517*	0.771*	0.520*	0.500*	0.759*
<i>R101_2+1</i>	0.607*	0.659*	0.846*	0.586*	0.629*	0.827*
<i>R101_2+2</i>	0.594*	0.533*	0.751*	0.586*	0.522*	0.751*
<i>R50_2+1</i>	0.600*	0.611*	0.789*	0.576*	0.596*	0.751*
<i>R50_2+2</i>	0.613*	0.609*	0.822*	0.598*	0.594*	0.815*
<i>ViT-B-16_2+1</i>	0.692*	0.712*	0.882*	0.679*	0.713*	0.871*
<i>ViT-B-16_2+2</i>	0.750*	0.736*	0.89*	0.747*	0.725*	0.900*
IT FCDB-correction						

Dataset and algorithm ¹	BEFORE FRAME FILTERING			AFTER FRAME FILTERING		
	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content	5-Task Computed vs. 4-Task Computed Energy Content	5-Task Predicted vs. 4-Task Computed Energy Content	5-Task Predicted vs. 5-Task Computed Energy Content
<i>IncV3_2+1</i>	0.312*	0.485*	0.619*	0.299*	0.480*	0.596*
<i>IncV3_2+2</i>	0.481*	0.467*	0.803*	0.498*	0.480*	0.795*
<i>R101_2+1</i>	0.578*	0.655*	0.781*	0.572*	0.663*	0.787*
<i>R101_2+2</i>	0.536*	0.509*	0.751*	0.508*	0.498*	0.747*
<i>R50_2+1</i>	0.611*	0.604*	0.807*	0.610*	0.600*	0.785*
<i>R50_2+2</i>	0.613*	0.607*	0.822*	0.616*	0.594*	0.827*
<i>ViT-B-16_2+1</i>	0.686*	0.690*	0.893*	0.689*	0.687*	0.871*
<i>ViT-B-16_2+2</i>	0.651*	0.649*	0.890*	0.649*	0.661*	0.884*

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum and maximum performance metrics for each target variable. Abbreviations: FCDB, Food Composition Database.

Table C9. Sensitivity analysis: performance metrics for predicted and computed energy contents under the 4-task and 5-task deep learning algorithms, before and after frame filtering. Nutrition5k test set (n = 676 and n = 664, respectively)

Target variable and algorithm ¹	BEFORE FRAME FILTERING								
	5-Task Predicted Energy Content			5-Task Computed Energy Content			4-Task Computed Energy Content		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Mass (g)									
<i>IncV3_2+1</i>	183.41	41.50	22.57	183.41	41.50	22.57	183.62	41.83	22.75
<i>IncV3_2+2</i>	182.73	40.11	21.84	183.33	41.80	22.74	184.39	41.93	22.80
<i>R101_2+1</i>	180.22	37.69	20.49	180.22	37.69	20.49	180.13	37.25	20.24
<i>R101_2+2</i>	179.19	37.74	20.49	179.19	37.74	20.49	180.50	37.60	20.45
<i>R50_2+1</i>	179.75	38.00	20.64	179.75	38.00	20.64	180.69	38.87	21.12
<i>R50_2+2</i>	180.42	38.48	20.90	180.42	38.48	20.90	180.25	38.87	21.12
<i>ViT-B-16_2+1</i>	180.12	38.53	20.95	180.12	38.53	20.95	180.46	38.49	20.92
<i>ViT-B-16_2+2</i>	180.50	38.58	20.97	180.53	38.77	21.07	179.78	38.42	20.89
Energy content (kcal)									
<i>IncV3_2+1</i>	302.71	69.19	28.68	311.86	76.27	31.75	312.49	83.51	34.71
<i>IncV3_2+2</i>	301.16	67.90	28.17	305.45	70.92	29.44	320.05	89.55	37.28
<i>R101_2+1</i>	296.36	63.66	26.36	295.58	65.49	27.27	299.84	68.94	28.54
<i>R101_2+2</i>	298.33	63.75	26.39	302.29	67.08	27.85	304.97	72.73	30.22
<i>R50_2+1</i>	297.25	64.70	26.79	300.51	68.42	28.34	300.98	70.01	28.99
<i>R50_2+2</i>	297.43	65.13	26.97	298.15	65.37	27.07	302.14	70.90	29.38
<i>ViT-B-16_2+1</i>	297.73	65.50	27.12	298.99	69.63	28.95	297.70	67.85	28.08
<i>ViT-B-16_2+2</i>	299.41	66.49	27.55	301.23	67.69	28.05	297.23	67.16	27.78
Protein content (g)									
<i>IncV3_2+1</i>	11.52	6.71	43.77	11.52	6.71	43.77	10.85	6.61	43.32
<i>IncV3_2+2</i>	11.41	7.05	46.61	11.90	7.17	46.61	11.24	6.97	45.64
<i>R101_2+1</i>	9.40	5.21	33.76	9.40	5.21	33.76	9.72	5.32	34.70
<i>R101_2+2</i>	9.90	5.46	35.62	9.90	5.46	35.62	10.19	5.73	37.06
<i>R50_2+1</i>	9.83	5.30	34.74	9.83	5.30	34.74	9.61	5.43	35.44
<i>R50_2+2</i>	9.71	5.17	33.77	9.71	5.17	33.77	9.71	5.36	35.00

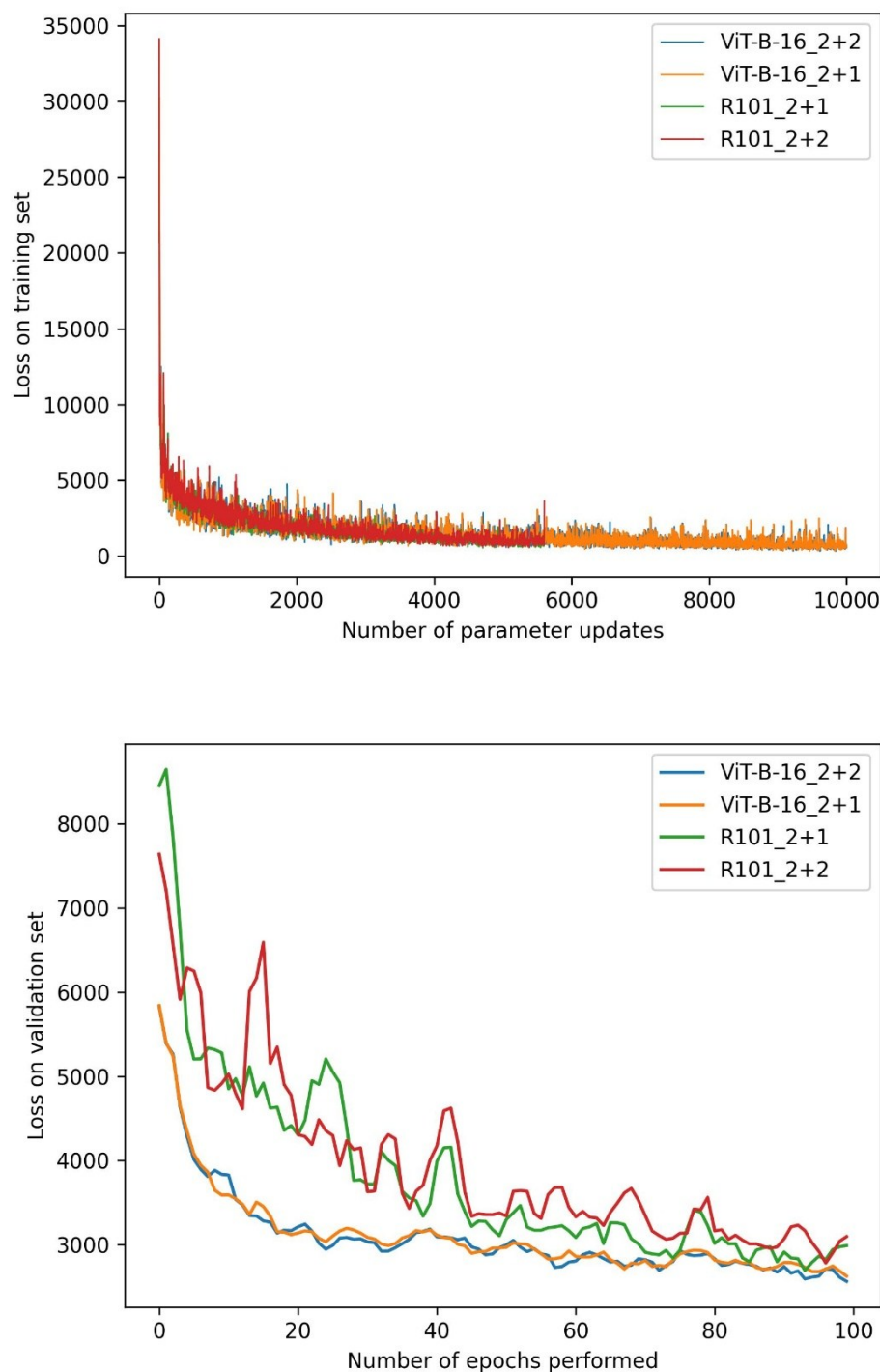
<i>ViT-B-16_2+1</i>	9.49	5.10	33.27	9.49	5.10	33.27	9.02	4.76	31.10
<i>ViT-B-16_2+2</i>	9.29	4.80	31.32	9.29	4.80	31.32	8.92	4.62	30.14
Fat content (g)									
<i>IncV3_2+1</i>	27.95	6.03	48.56	27.95	6.03	48.56	28.55	6.88	53.73
<i>IncV3_2+2</i>	27.72	5.81	45.33	27.91	5.97	46.47	29.39	7.45	58.34
<i>R101_2+1</i>	26.93	5.10	40.80	26.93	5.10	40.80	27.13	5.28	41.44
<i>R101_2+2</i>	27.47	5.35	41.63	27.47	5.35	41.63	28.03	5.86	45.87
<i>R50_2+1</i>	27.10	5.29	41.02	27.10	5.29	41.02	27.29	5.56	43.10
<i>R50_2+2</i>	27.04	5.12	39.75	27.04	5.12	39.75	27.39	5.54	43.05
<i>ViT-B-16_2+1</i>	26.82	5.16	40.52	26.82	5.16	40.52	26.68	5.06	40.16
<i>ViT-B-16_2+2</i>	27.02	5.27	39.97	26.99	4.99	38.89	26.68	4.96	38.89
Carbohydrates content (g)									
<i>IncV3_2+1</i>	13.80	8.00	51.23	13.80	8.00	51.23	14.05	8.29	52.34
<i>IncV3_2+2</i>	14.89	8.72	54.76	14.89	9.04	56.58	15.16	9.25	57.54
<i>R101_2+1</i>	11.00	5.63	37.96	11.00	5.63	37.96	11.12	5.97	38.39
<i>R101_2+2</i>	12.27	6.76	40.55	12.27	6.76	40.55	12.81	7.37	44.31
<i>R50_2+1</i>	11.67	6.01	39.13	11.67	6.01	39.13	11.85	5.99	39.67
<i>R50_2+2</i>	11.28	5.79	37.55	11.28	5.79	37.55	11.17	5.91	38.32
<i>ViT-B-16_2+1</i>	10.29	5.19	33.54	10.29	5.19	33.54	10.34	5.09	32.71
<i>ViT-B-16_2+2</i>	10.20	5.01	32.62	10.20	5.01	32.62	10.16	4.96	31.76
Overall median									
<i>IncV3_2+1</i>	27.95	8.00	43.77	27.95	8.00	43.77	28.55	8.29	43.32
<i>IncV3_2+2</i>	27.72	8.72	45.33	27.91	9.04	46.47	29.39	9.25	45.64
<i>R101_2+1</i>	26.93	5.63	33.76	26.93	5.63	33.76	27.13	5.97	34.70
<i>R101_2+2</i>	27.47	6.76	35.62	27.47	6.76	35.62	28.03	7.37	37.06
<i>R50_2+1</i>	27.10	6.01	34.74	27.10	6.01	34.74	27.29	5.99	35.44
<i>R50_2+2</i>	27.04	5.79	33.77	27.04	5.79	33.77	27.39	5.91	35.00
<i>ViT-B-16_2+1</i>	26.82	5.19	33.27	26.82	5.19	33.27	26.68	5.09	31.10
<i>ViT-B-16_2+2</i>	27.02	5.27	31.32	26.99	5.01	31.32	26.68	4.96	30.14
AFTER FRAME FILTERING									

Target variable and algorithm ¹	5-Task Predicted Energy Content			5-Task Computed Energy Content			4-Task Computed Energy Content		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Mass (g)									
<i>IncV3_2+1</i>	180.34	38.33	20.96	180.34	38.33	20.96	180.89	38.76	21.19
<i>IncV3_2+2</i>	180.20	37.85	20.72	180.20	37.85	20.72	181.56	38.87	21.25
<i>R101_2+1</i>	177.01	34.82	19.03	177.01	34.82	19.03	177.57	34.33	18.76
<i>R101_2+2</i>	176.41	35.12	19.17	176.41	35.12	19.17	178.19	34.86	19.07
<i>R50_2+1</i>	176.60	34.95	19.09	176.60	34.95	19.09	178.23	36.03	19.69
<i>R50_2+2</i>	177.34	35.52	19.40	177.34	35.52	19.40	177.87	36.16	19.76
<i>ViT-B-16_2+1</i>	178.34	36.51	19.96	178.34	36.51	19.96	178.17	36.04	19.70
<i>ViT-B-16_2+2</i>	178.32	36.51	19.95	178.32	36.51	19.95	177.76	36.10	19.74
Energy content (kcal)									
<i>IncV3_2+1</i>	299.45	64.53	27.07	309.15	71.75	30.24	309.69	79.25	33.35
<i>IncV3_2+2</i>	298.19	63.64	26.71	301.20	65.70	27.60	316.92	84.99	35.83
<i>R101_2+1</i>	294.40	60.01	25.15	293.81	62.15	26.05	297.87	65.39	27.39
<i>R101_2+2</i>	296.34	59.65	24.99	300.25	62.91	26.43	303.09	69.08	29.05
<i>R50_2+1</i>	294.89	60.80	25.48	298.12	64.45	27.01	299.20	66.40	27.82
<i>R50_2+2</i>	295.47	61.51	25.78	295.87	61.58	25.80	300.69	67.50	28.30
<i>ViT-B-16_2+1</i>	295.35	62.35	26.10	296.36	66.19	27.89	294.92	64.13	26.85
<i>ViT-B-16_2+2</i>	296.63	63.45	26.58	298.23	64.01	26.83	294.25	63.46	26.70
Protein content (g)									
<i>IncV3_2+1</i>	10.82	6.28	40.98	10.82	6.28	40.98	10.07	6.14	40.37
<i>IncV3_2+2</i>	10.74	6.61	43.67	10.74	6.61	43.67	10.46	6.50	42.55
<i>R101_2+1</i>	8.61	4.79	31.05	8.61	4.79	31.05	8.98	4.90	32.01
<i>R101_2+2</i>	9.26	5.08	33.01	9.26	5.08	33.01	9.40	5.28	34.19
<i>R50_2+1</i>	9.02	4.85	31.86	9.02	4.85	31.86	8.82	5.02	32.80
<i>R50_2+2</i>	8.89	4.73	30.90	8.89	4.73	30.90	8.92	4.92	32.12
<i>ViT-B-16_2+1</i>	8.85	4.74	30.95	8.85	4.74	30.95	8.30	4.37	28.51
<i>ViT-B-16_2+2</i>	8.62	4.44	28.97	8.62	4.44	28.97	8.21	4.24	27.69
Fat content (g)									

<i>IncV3_2+1</i>	27.95	5.81	47.36	27.95	5.81	47.36	28.51	6.68	52.84
<i>IncV3_2+2</i>	27.82	5.67	44.79	27.82	5.67	44.79	29.32	7.22	57.30
<i>R101_2+1</i>	26.99	4.90	39.43	26.99	4.90	39.43	27.14	5.08	40.18
<i>R101_2+2</i>	27.55	5.15	40.59	27.55	5.15	40.59	28.09	5.68	45.02
<i>R50_2+1</i>	27.08	5.07	39.86	27.08	5.07	39.86	27.33	5.36	42.09
<i>R50_2+2</i>	27.07	4.94	38.83	27.07	4.94	38.83	27.43	5.35	42.08
<i>ViT-B-16_2+1</i>	26.78	4.99	39.41	26.78	4.99	39.41	26.62	4.85	38.75
<i>ViT-B-16_2+2</i>	26.93	5.05	38.82	26.93	5.05	38.82	26.61	4.73	37.25
Carbohydrates content (g)									
<i>IncV3_2+1</i>	13.08	7.63	50.37	13.08	7.63	50.37	13.40	7.92	51.43
<i>IncV3_2+2</i>	14.23	8.55	54.24	14.23	8.55	54.24	14.58	8.94	57.06
<i>R101_2+1</i>	10.29	5.26	36.45	10.29	5.26	36.45	10.44	5.64	37.31
<i>R101_2+2</i>	11.68	6.40	39.69	11.68	6.40	39.69	12.19	7.05	43.60
<i>R50_2+1</i>	10.95	5.62	38.02	10.95	5.62	38.02	11.14	5.65	38.65
<i>R50_2+2</i>	10.54	5.45	36.19	10.54	5.45	36.19	10.44	5.57	37.27
<i>ViT-B-16_2+1</i>	9.26	4.78	31.49	9.26	4.78	31.49	9.34	4.67	30.77
<i>ViT-B-16_2+2</i>	9.20	4.61	30.51	9.20	4.61	30.51	9.15	4.57	29.76
Overall median									
<i>IncV3_2+1</i>	27.95	7.63	40.98	27.95	7.63	40.98	28.51	7.92	40.37
<i>IncV3_2+2</i>	27.82	8.55	43.67	27.82	8.55	43.67	29.32	8.94	42.55
<i>R101_2+1</i>	26.99	5.26	31.05	26.99	5.26	31.05	27.14	5.64	32.01
<i>R101_2+2</i>	27.55	6.40	33.01	27.55	6.40	33.01	28.09	7.05	34.19
<i>R50_2+1</i>	27.08	5.62	31.86	27.08	5.62	31.86	27.33	5.65	32.80
<i>R50_2+2</i>	27.07	5.45	30.90	27.07	5.45	30.90	27.43	5.57	32.12
<i>ViT-B-16_2+1</i>	26.78	4.99	30.95	26.78	4.99	30.95	26.62	4.85	28.51
<i>ViT-B-16_2+2</i>	26.93	5.05	28.97	26.93	5.05	28.97	26.61	4.73	27.69

¹US FCDB-no correction was directly obtained by using the original file from the Nutrition5k project; US FCDB-correction was obtained from US FCDB-no correction by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB-no correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB; IT FCDB-correction was obtained after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum performance metrics (i.e., the minimum error) for each target variable. Abbreviations: FCDB, Food Composition Database.

Figure C1. Representative training and validation loss curves supporting the choice of fixed training epochs. Rolling mean (window sizes of 3 and 5, respectively) was applied to smooth the curves for visualization purposes¹



¹ViT-B-16 was trained with a reduced batch size (half that of other models) due to higher memory requirements (see the Methods section for details). Consequently, the number of iterations per epoch is doubled, resulting in a greater number of loss values shown for this architecture in upper panel. See Table 6.1 for algorithm name abbreviations.

Figure C2. Examples of food images, observed and predicted mass and nutritional composition for the different combinations of algorithms and available datasets

Salad-based group

dish_1560800988

		Predicted values									
		IncV3 2+1	IncV3 2+2	R101 2+1	R101 2+2	R50 2+1	R50 2+2	VIT-B-16 2+1	VIT-B-16 2+2		
Target Variable	Observed values										
US FCDB-no correction	Mass (g)	230.00	254.24	282.10	296.78	293.88	278.58	284.74	233.33	282.10	282.10
	Energy (kcal)	314.87	269.64	338.03	336.49	324.79	334.26	333.08	211.46	338.03	338.03
	Protein (g)	11.73	18.70	24.24	24.28	24.14	24.88	23.57	12.56	24.24	24.24
	Fat (g)	5.12	13.79	17.92	17.71	15.96	17.76	16.47	11.76	17.92	17.92
	Carbohydrates (g)	61.25	19.60	22.07	23.97	23.46	22.59	23.60	16.41	22.07	22.07
US FCDB-correction	Mass (g)	230.00	258.65	273.19	272.21	278.91	267.49	274.02	229.97	222.88	222.88
	Energy (kcal)	314.87	260.21	295.56	295.46	295.99	296.19	303.07	195.79	195.40	195.40
	Protein (g)	11.73	17.04	22.25	20.35	21.27	21.90	22.27	11.22	12.15	12.15
	Fat (g)	5.12	12.27	13.63	13.26	14.79	14.70	14.74	10.32	10.68	10.68
	Carbohydrates (g)	61.25	16.78	20.32	23.16	21.47	23.15	22.15	17.04	16.60	16.60
IT FCDB-no correction	Mass (g)	230.00	264.75	273.86	280.58	278.89	268.77	283.66	235.65	227.80	227.80
	Energy (kcal)	141.74	299.30	294.66	303.60	317.44	296.76	330.57	222.26	220.50	220.50
	Protein (g)	7.35	20.76	19.91	22.07	22.85	19.58	22.52	13.34	12.38	12.38
	Fat (g)	4.18	16.35	14.06	14.70	13.94	13.00	15.14	11.24	11.17	11.17
	Carbohydrates (g)	15.32	15.17	16.29	18.10	20.15	19.82	23.03	15.61	15.97	15.97
IT FCDB-correction	Mass (g)	230.00	231.01	236.78	275.69	273.51	261.29	267.57	225.76	226.53	226.53
	Energy (kcal)	141.74	233.66	255.36	302.32	276.48	298.49	309.90	208.35	215.49	215.49
	Protein (g)	7.35	13.56	16.43	23.85	19.27	20.79	21.51	11.98	13.49	13.49
	Fat (g)	4.18	10.60	12.40	14.45	12.77	12.80	14.06	10.92	10.51	10.51
	Carbohydrates (g)	15.32	9.91	14.02	21.06	19.03	20.18	20.73	15.54	14.96	14.96

Eggs-based group

dish_1568126726

		Predicted values									
		IncV3 2+1	IncV3 2+2	R101 2+1	R101 2+2	R50 2+1	R50 2+2	VIT-B-16 2+1	VIT-B-16 2+2		
Target Variable	Observed values										
US FCDB-no correction	Mass (g)	685.00	564.43	567.74	566.43	553.44	562.59	563.74	567.79	567.74	567.74
	Energy (kcal)	409.52	350.34	389.07	386.34	382.87	371.69	379.00	342.15	389.07	389.07
	Protein (g)	57.49	33.28	40.91	48.49	43.28	44.06	49.37	42.14	40.91	40.91
	Fat (g)	4.10	11.46	10.37	8.22	9.03	8.21	7.76	5.31	10.37	10.37
	Carbohydrates (g)	25.37	27.33	28.54	27.37	28.31	27.04	25.78	19.18	28.54	28.54
US FCDB-correction	Mass (g)	685.00	498.32	490.20	556.82	537.37	539.19	534.89	522.98	538.44	538.44
	Energy (kcal)	409.52	349.19	357.59	371.43	380.49	348.97	360.39	341.55	342.95	342.95
	Protein (g)	57.49	31.46	31.95	43.27	45.81	46.48	44.01	41.75	46.19	46.19
	Fat (g)	4.10	9.24	9.58	11.12	9.70	6.21	7.34	4.52	9.70	9.70
	Carbohydrates (g)	25.37	26.85	30.93	27.33	24.24	24.73	25.25	22.76	20.74	20.74
IT FCDB-no correction	Mass (g)	685.00	487.25	466.91	555.74	575.91	513.10	545.14	556.57	516.75	516.75
	Energy (kcal)	378.34	283.91	304.15	335.74	377.29	317.96	337.64	325.48	302.26	302.26
	Protein (g)	61.67	28.92	31.74	48.21	49.57	42.01	45.39	38.18	45.49	45.49
	Fat (g)	3.61	7.32	8.03	7.37	8.25	5.59	6.68	5.07	5.04	5.04
	Carbohydrates (g)	25.63	26.32	28.84	17.58	23.30	20.71	23.05	22.29	19.13	19.13
IT FCDB-correction	Mass (g)	685.00	500.87	434.76	532.07	554.56	536.21	514.99	552.20	519.37	519.37
	Energy (kcal)	378.34	297.01	286.90	328.10	364.95	336.43	356.44	325.71	307.40	307.40
	Protein (g)	61.67	29.48	20.52	46.61	38.28	48.89	46.34	48.28	46.96	46.96
	Fat (g)	3.61	3.55	8.22	7.26	9.63	5.95	8.99	8.08	5.08	5.08
	Carbohydrates (g)	25.63	23.49	25.63	23.46	21.72	18.70	19.74	19.65	20.90	20.90

Chicken-based group

dish_1565811061

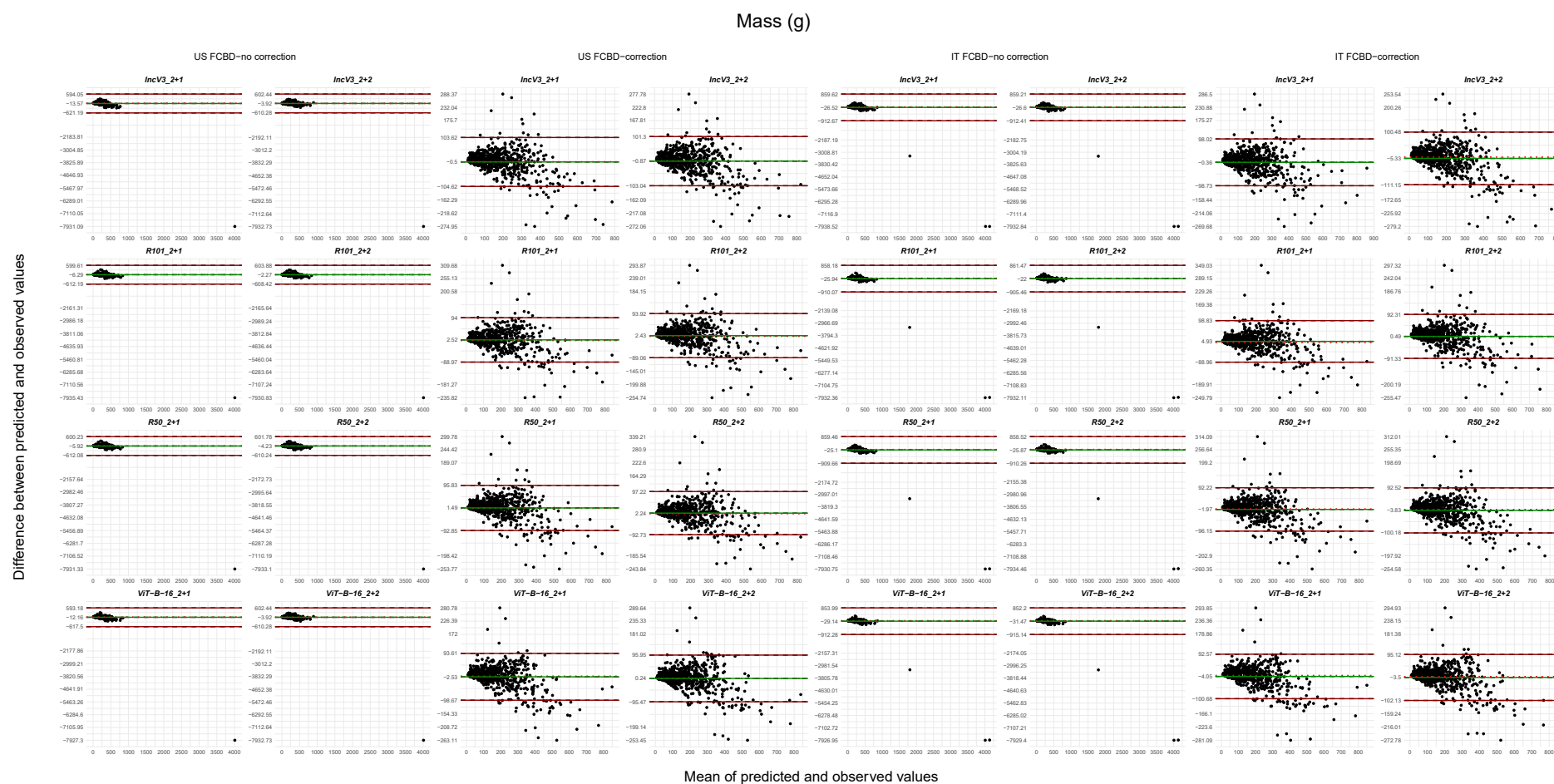
		Predicted values									
		IncV3 2+1	IncV3 2+2	R101 2+1	R101 2+2	R50 2+1	R50 2+2	VIT-B-16 2+1	VIT-B-16 2+2		
Target Variable	Observed values										
US FCDB-no correction	Mass (g)	324.00	254.24	282.10	296.78	293.88	278.58	284.74	233.33	282.10	282.10
	Energy (kcal)	380.32	269.64	338.03	336.49	324.79	334.26	333.08	211.46	338.03	338.03
	Protein (g)	65.80	18.70	24.24	24.28	24.14	24.88	23.57	12.56	24.24	24.24
	Fat (g)	7.76	13.79	17.92	17.71	15.96	17.76	16.47	11.76	17.92	17.92
	Carbohydrates (g)	9.06	16.78	20.32	23.16	21.47	23.15	22.15	17.04	16.60	16.60
US FCDB-correction	Mass (g)	324.00	258.65	273.19	272.21	278.91	267.49	274.02	229.97	222.88	222.88
	Energy (kcal)	380.32	260.21	295.56	295.46	295.99	296.19	303.07	195.79	195.40	195.40
	Protein (g)	65.80	17.04	22.25	20.35	21.27	21.90	22.27	11.22	12.15	12.15
	Fat (g)	7.76	12.27	13.63	13.26	14.79	14.70	14.74	10.32	10.68	10.68
	Carbohydrates (g)	9.06	16.78	20.32	23.16	21.47	23.15	22.15	17.04	16.60	16.60
IT FCDB-no correction	Mass (g)	324.00	264.75	273.86	280.58	278.89	268.77	283.66	235.65	227.80	227.80
	Energy (kcal)	370.49	299.30	294.66	303.60	317.44	296.76	330.57	222.26	220.50	220.50
	Protein (g)	59.95	20.76	19.91	22.07	22.85	19.58	22.52	13.34	12.38	12.38
	Fat (g)	11.42	16.35	14.06	14.70	13.94	13.00	15.14	11.24	11.17	11.17
	Carbohydrates (g)	5.78	15.17	16.29	18.10	20.15	19.82	23.03	15.61	15.97	15.97
IT FCDB-correction	Mass (g)	324.00	231.01	236.78	275.69	273.51	261.29	267.57	225.76	226.53	226.53
	Energy (kcal)	370.49	233.66	255.36	302.32	276.48	298.49	309.90	208.35	215.49	215.49
	Protein (g)	59.95	13.56	16.43	23.85	19.27	20.79	21.51	11.98	13.49	13.49
	Fat (g)	11.42	10.60	12.40	14.45	12.77	12.80	14.06	10.92	10.51	10.51
	Carbohydrates (g)	5.78	9.91	14.02	21.06	19.03	20.18	20.73	15.54	14.96	14.96

Western-inspired breakfast foods group

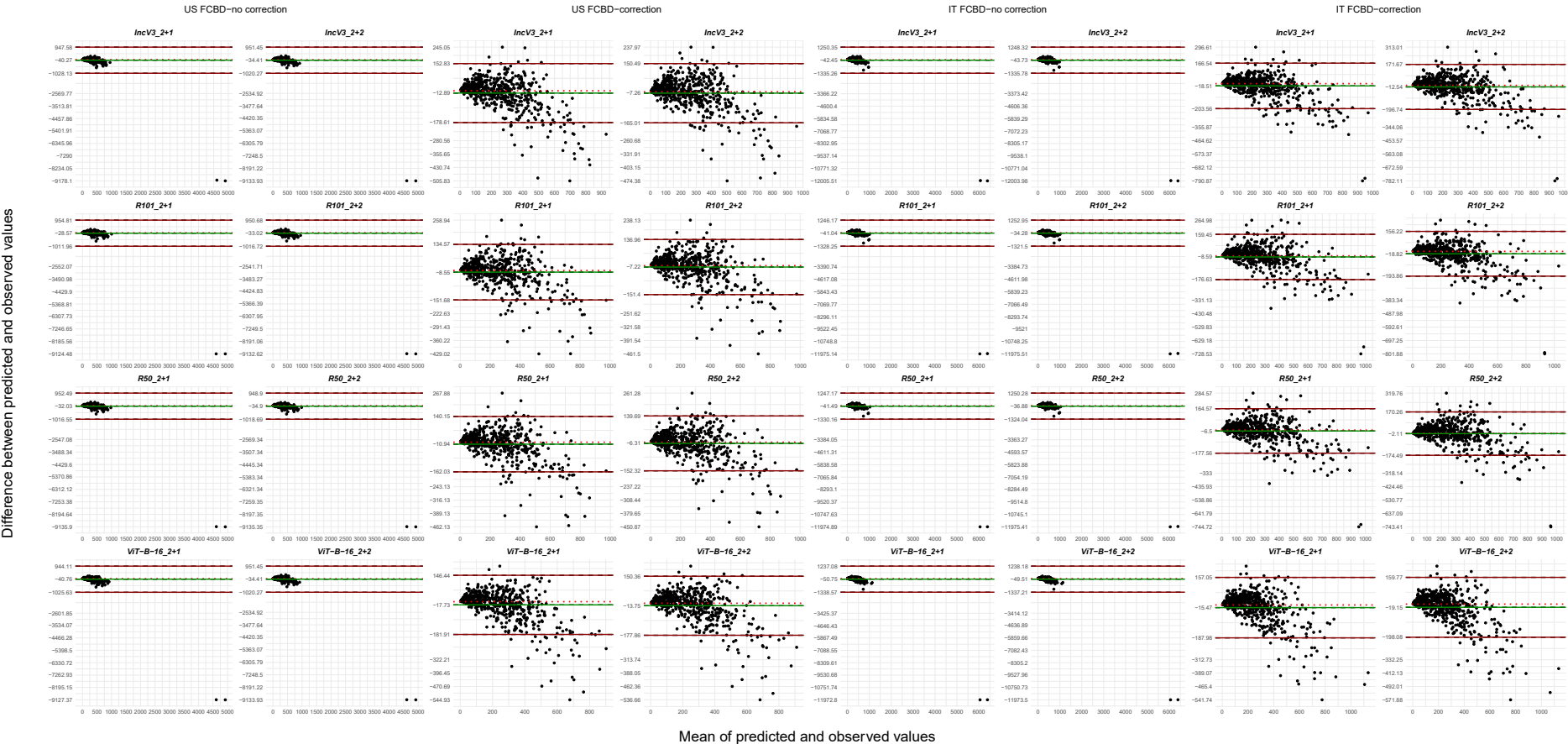
dish_1558373159

		Predicted values									
		IncV3 2+1	IncV3 2+2	R101 2+1	R101 2+2	R50 2+1	R50 2+2	VIT-B-16 2+1	VIT-B-16 2+2		
Target Variable	Observed values										
US FCDB-no correction	Mass (g)	334.00	299.99	294.60	293.87	304.22	279.94	309.69	270.63	294.60	294.60
	Energy (kcal)	1013.34	626.22	675.22	749.47	698.57	721.79	743.24	534.35	675.22	675.22
	Protein (g)	60.63	29.43	26.63	32.89	28.53	30.58	30.12	22.92	26.63	26.63
	Fat (g)	79.12	41.23	50.83	58.14	49.69	54.31	52.70	36.02	50.83	50.83
	Carbohydrates (g)	20.51	42.35	38.31	45.25	40.07	39.59	44.08	31.98	38.31	38.31
US FCDB-correction	Mass (g)	334.00	290.53	284.26	300.50	285.97	296.19	283.88	259.13	278.87	278.87
	Energy (kcal)	1013.34	626.63	671.40	717.57	721.89	709.27	725.37	511.85	512.49	512.49
	Protein (g)	60.63	25.47	37.30	28.50	29.00	31.44	30.25	22.25	22.88	22.88
	Fat (g)	79.12	38.74	39.91	50.31	53.17	49.83	52.09	35.97	35.18	35.18
	Carbohydrates (g)	20.51	34.26	34.85	30.10	38.52	41.36	30.47	32.98	34.29	34.29
IT FCDB-no correction	Mass (g)	334.00	289.92	309.59	301.47	313.34	304.50	298.77	267.05	259.39	259.39
	Energy (kcal)	1046.32	603.00	674.84	763.60	760.34	758.49	805.20	505.92	523.11	523.11
	Protein (g)	42.67	26.82	37.88	30.05	28.94	26.56	30.65	17.41	17.36	17.36
	Fat (g)	84.93	44.88	43.66	61.32	54.43	55.66	61.51	37.84	37.84	37.84
	Carbohydrates (g)	19.67	23.44	20.00	24.54	25.18	28.81	26.75	24.16	24.16	24.16
IT FCDB-correction	Mass (g)	334.00	282.24	286.94	301.95	296.81	290.04	273.07	262.90	258.00	258.00
	Energy (kcal)	1046.32	632.28	622.93	760.49	760.16	736.67	773.59	504.58	474.44	474.44
	Protein (g)	42.67	24.86	35.47	35.27	31.38	30.82	29.97	18.33	17.05	17.05
	Fat (g)	84.93	45.30	38.89	61.55	54.40	55.45	61.27	36.70	33.05	33.05
	Carbohydrates (g)										

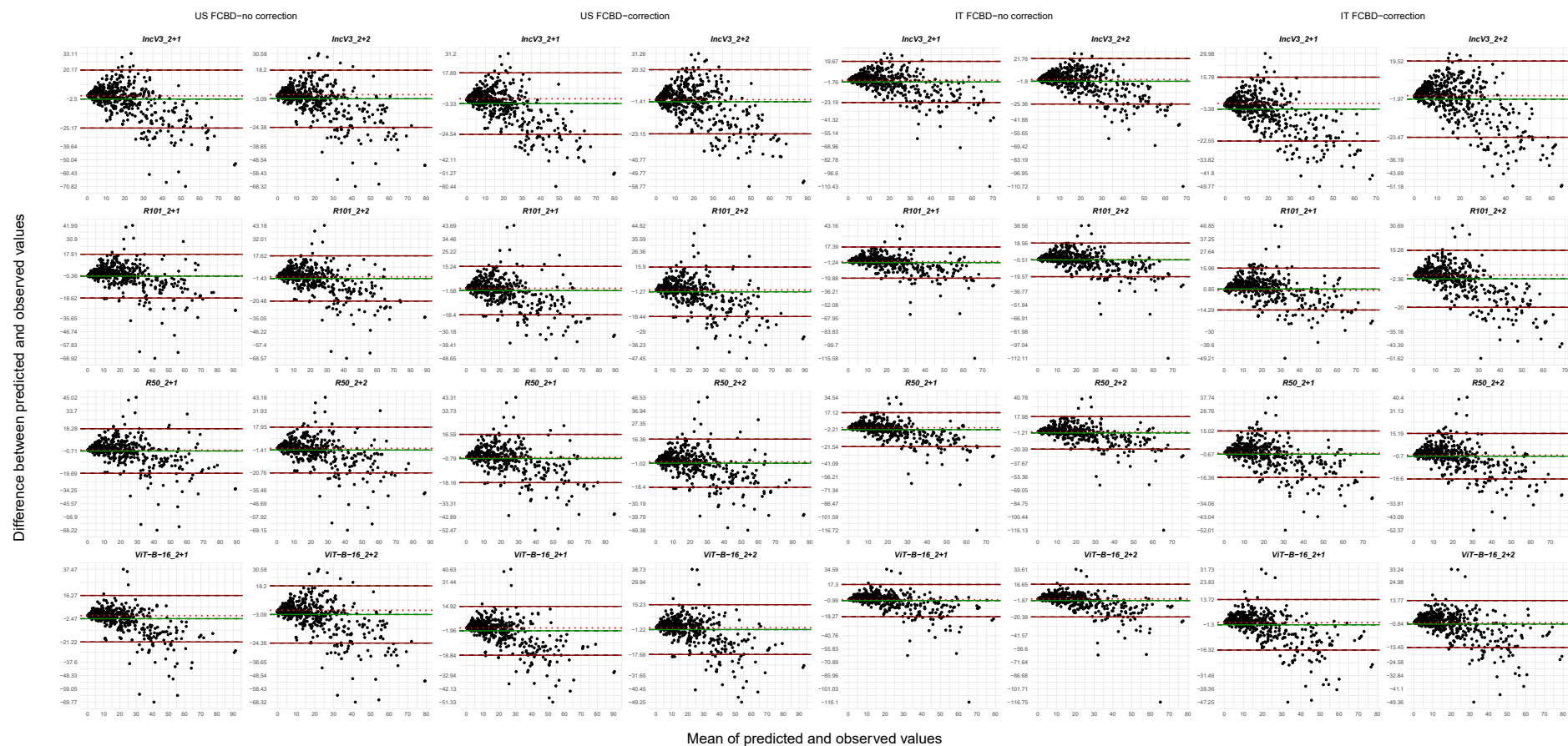
Figures C3-C7. Bland-Altman plots representing the raw absolute difference between predicted and observed values on the test set (y-axis) versus the mean of the predicted and observed values for each target variable (x-axis), with corresponding 95% limits of agreement. On the y-axis, the dotted line indicates the reference value of 0. Each panel represents mass, energy, or macronutrients content, and information is organized by algorithm and dataset in 32 plots. Nutrition5k test set (n = 676)



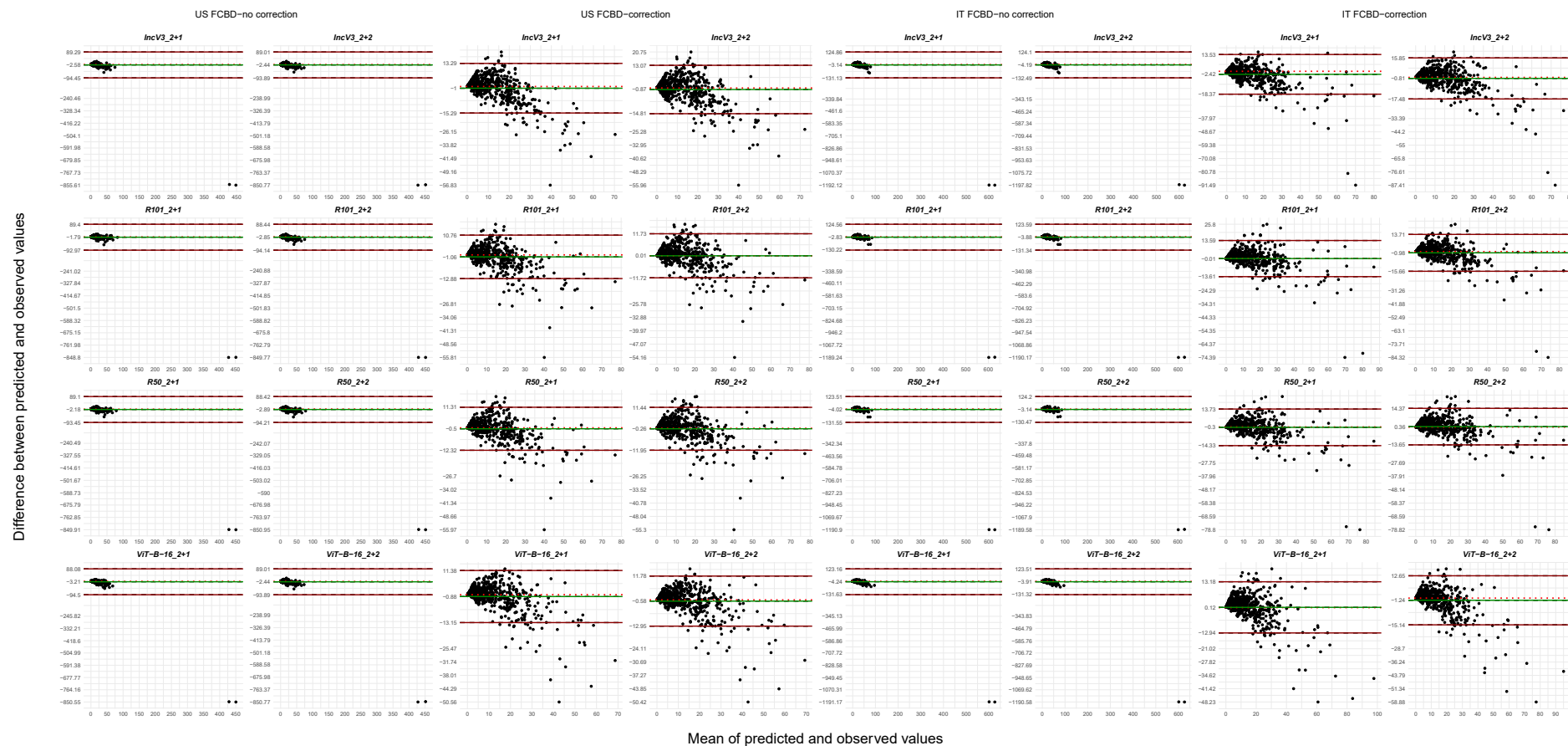
Energy content (kcal)



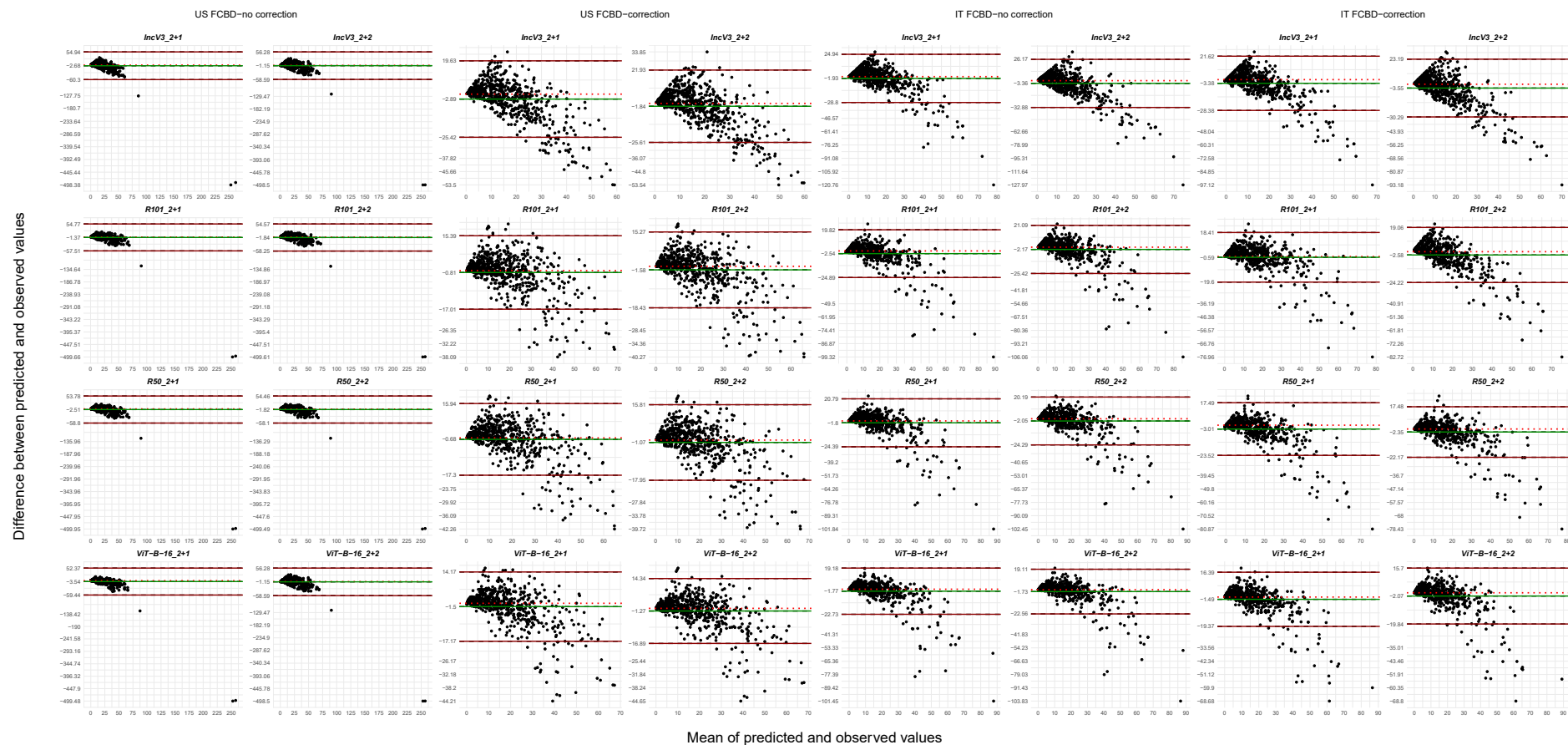
Protein content (g)



Fat content (g)



Carbohydrates content (g)



Appendix D: Supplementary Materials Chapter 7

Table D1. Median and interquartile range of the number of observed ingredients and number of predicted ingredients per dish by dataset and algorithm, before and after frame filtering (n = 676)

Observed values		
<i>Median (IQR)</i>		
3 (1—8)		
Predicted values		
	Before frame filtering	After frame filtering
US FCDB—correction	<i>Median (IQR)</i>	<i>Median (IQR)</i>
<i>IncV3_2+2</i>	8 (2–24.25)	8 (2–22)
<i>R101_2+2</i>	3 (1–10)	3 (1–9)
<i>ViT-B-16_2+2</i>	3 (1–8)	3 (1–9)
IT FCDB—correction		
<i>IncV3_2+2</i>	9 (2–24)	7 (2–25)
<i>R101_2+2</i>	3 (1—9)	3 (1—9)
<i>ViT-B-16_2+2</i>	3 (1–9)	3 (1–10)

Abbreviation: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Table D2. Descriptive statistics on observed and predicted values for mass, energy, and macronutrients content for dishes included in the test set from Nutrition5k, before and after automated frame filtering, matching with US- and Italian-FCDB-specific nutritional values. Nutrition5k test set (n = 676)

Target variable and datasets ¹	Before frame filtering		After frame filtering	
	US FCDB-correction Median (Q1–Q3)	IT FCDB-correction Median (Q1–Q3)	US FCDB-correction Median (Q1–Q3)	IT FCDB-correction Median (Q1–Q3)
Mass (g)				
Observed values	142.0 (70.0–248.5)	142.0 (70.0–248.5)	142.0 (70.0–249.0)	142.0 (70.0–249.0)
Predicted values				
<i>IncV3_2+2</i>	147.7 (75.3–248.7)	148.8 (74.7–243.5)	151.6 (78.1–258.4)	148.0 (76.1–258.6)
<i>R101_2+2</i>	144.1 (71.0–242.9)	144.7 (71.7–243.7)	150.8 (73.1–252.2)	147.6 (73.5–249.4)
<i>ViT-B-16_2+2</i>	146.6 (75.4–245.2)	140.7 (71.8–232.3)	144.1 (73.9–240.2)	141.3 (72.3–242.2)
Energy content (kcal)				
Observed values	160.0 (61.3–339.6)	165.6 (60.4–329.1)	160.0 (61.2–339.7)	165.6 (60.3–329.8)
Predicted values				
<i>IncV3_2+2</i>	166.7 (68.2–322.5)	168.0 (66.3–315.2)	176.5 (74.0–339.5)	176.1 (67.2–329.4)
<i>R101_2+2</i>	160.2 (66.0–315.4)	172.9 (67.5–322.8)	170.8 (66.3–320.8)	184.7 (68.1–333.3)
<i>ViT-B-16_2+2</i>	167.1 (69.1–296.4)	176.2 (68.7–296.8)	162.7 (67.2–301.8)	172.2 (70.5–298.0)
Protein content (g)				
Observed values	8.5 (1.6–22.6)	7.9 (1.6–21.8)	8.5 (1.6–22.7)	7.9 (1.6–21.8)
Predicted values				
<i>IncV3_2+2</i>	8.8 (2.0–20.9)	8.5 (2.0–19.9)	9.0 (2.2–21.0)	9.4 (2.3–21.6)
<i>R101_2+2</i>	8.4 (1.7–20.3)	8.8 (1.9–20.3)	8.9 (1.9–21.6)	8.8 (2.0–21.4)
<i>ViT-B-16_2+2</i>	8.9 (1.8–20.0)	8.7 (1.9–19.2)	8.9 (1.9–20.5)	9.0 (2.0–20.4)
Fat content (g)				
Observed values	6.6 (0.6–17.4)	7.3 (0.4–17.2)	6.6 (0.6–17.4)	7.4 (0.4–17.2)
Predicted values				
<i>IncV3_2+2</i>	7.2 (1.4–17.2)	6.7 (1.0–16.4)	7.4 (1.6–17.2)	7.4 (1.3–17.9)
<i>R101_2+2</i>	7.0 (1.4–16.4)	8 (1.3–16.7)	7.3 (1.3–17.0)	8.3 (1.6–18.4)
<i>ViT-B-16_2+2</i>	7.6 (1.5–16.1)	7.7 (1.2–16.0)	6.9 (1.2–15.4)	7.9 (1.5–16.2)
Carbohydrates content (g)				
Observed values	13.0 (4.4–25.4)	9.0 (2.2–20.5)	13.0 (4.4–25.4)	9.0 (2.2–20.5)
Predicted values				
<i>IncV3_2+2</i>	14.5 (6.8–21.7)	11.3 (4.1–18.7)	15.7 (7.4–24.4)	11.7 (4.3–20.1)
<i>R101_2+2</i>	13.4 (5.5–22.6)	10.4 (3.0–20.0)	13.8 (5.5–24.1)	10.1 (3.2–20.4)
<i>ViT-B-16_2+2</i>	13.9 (6.4–22.4)	9.8 (3.3–18.5)	13.5 (6.0–22.0)	9.6 (3.4–18.3)

¹US FCDB–correction was directly obtained by using the original file from the Nutrition5k project and carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB–correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB and after correcting portion sizes for selected ingredients in dishes. Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Table D3. Unweighted Cohen’s kappa coefficients obtained by cross-classifying dishes based on quartiles of observed and predicted values, before and after frame filtering on training and test sets. Nutrition5k test set (n = 676)

Target variable and dataset ¹	Before frame filtering			After frame filtering			Δ Kappa ² (%)		
	IncV3_2+2	R101_2+2	ViT-B-16_2+2	IncV3_2+2	R101_2+2	ViT-B-16_2+2	IncV3_2+2	R101_2+2	ViT-B-16_2+2
Mass (g)									
US FCBD—correction	0.716*	0.769*	0.750*	0.726*	0.777*	0.777*	1.397	1.040	3.600
IT FCBD—correction	0.726*	0.767*	0.761*	0.716*	0.783*	0.769*	-1.377	2.086	1.051
Energy content (kcal)									
US FCBD—correction	0.732*	0.753*	0.755*	0.722*	0.757*	0.771*	-1.366	0.531	2.119
IT FCBD—correction	0.722*	0.740*	0.716*	0.720*	0.728*	0.714*	-0.277	-1.622	-0.279
Protein content (g)									
US FCBD—correction	0.607*	0.714*	0.716*	0.621*	0.728*	0.734*	2.306	1.961	2.514
IT FCBD—correction	0.647*	0.736*	0.714*	0.627*	0.732*	0.714*	-3.091	-0.543	0.000
Fat content (g)									
US FCBD—correction	0.633*	0.698*	0.712*	0.639*	0.706*	0.714*	0.948	1.146	0.281
IT FCBD—correction	0.609*	0.712*	0.734*	0.627*	0.742*	0.716*	2.956	4.213	-2.452
Carbohydrates content (g)									
US FCBD—correction	0.440*	0.611*	0.619*	0.442*	0.647*	0.619*	0.455	5.892	0.000
IT FCBD—correction	0.499*	0.722*	0.718*	0.509*	0.690*	0.686*	2.004	-4.432	-4.457

¹US FCDB—correction was directly obtained by using the original file from the Nutrition5k project, and by carrying out correction of portion sizes for selected ingredients in dishes; IT FCDB—correction was obtained by substituting the nutritional composition from the US FCDB with that from the IT FCDB and this included imputing missing-name ingredients, trace values, and missing values for food items in the Italian FCDB, and after correcting portion sizes for selected ingredients in dishes. Values in bold typeface with a light blue cell background indicate the minimum and maximum Cohen’s kappa coefficients for each target variable. The asterisk indicates that the corresponding Cohen’s kappa coefficient was different from zero at the 0.05 level.; ²Calculated as $100 \times (K_{\text{after frame filtering}} - K_{\text{before frame filtering}} / K_{\text{before frame filtering}})\%$. Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Table D4. Performance for ingredients prediction as measured by the F1-score, stratified by frame filtering and algorithm¹, in the US FCDB-correction dataset

Ingredient	Before frame filtering			After frame filtering			Comparison ($\Delta\%$) ³		
	IncV3_2+2	R101_2+2	ViT-B-16_2+2	IncV3_2+2	R101_2+2	ViT-B-16_2+2	IncV3_2+2	R101_2+2	ViT-B-16_2+2
<i>Almonds</i>	0.80	0.84¹	0.88	0.84	0.84	0.85	5.68	0.00	-2.95
<i>Apple</i>	0.30	0.52	0.63	0.33	0.63	0.62	9.52	19.92	-1.23
<i>Apples with peel</i>	0.36	0.71	0.71	0.36	0.80	0.77	0.00	12.00	7.69
<i>Artichokes</i>	NaN_W	0.40	0.40	NaN_W	0.80	0.50	-	100.00	25.00
<i>Arugula</i>	0.53	0.65	0.57	0.55	0.56	0.60	3.11	-13.93	5.13
<i>Asparagus</i>	0.41	0.90	0.86	0.41	0.75	0.80	0.37	-16.67	-6.67
<i>Avocado</i>	0.17	0.32	0.47	0.15	0.43	0.43	-14.81	35.71	-8.93
<i>Baby carrots</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Bacon</i>	0.63	0.93	0.88	0.50	0.91	0.89	-21.00	-2.86	1.35
<i>Bagels</i>	0.17	0.60	0.80	0.36	0.67	0.80	118.18	11.11	0.00
<i>Balsamic vinegar</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Banana</i>	0.33	0.71	0.83	0.40	0.83	0.83	20.00	16.67	0.00
<i>Banana with peel</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Basil</i>	0.34	0.47	0.42	0.37	0.55	0.45	8.20	16.71	8.39
<i>Bean seed</i>	NaN_W	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	-	-	-
<i>Beef</i>	0.27	0.74	0.79	0.29	0.80	0.70	7.88	8.33	-10.44
<i>Beets</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Bell peppers</i>	0.26	0.39	0.50	0.23	0.44	0.49	-8.40	13.02	-1.45
<i>Berries</i>	0.60	0.91	0.79	0.63	0.93	0.82	4.39	2.13	4.00
<i>Biscuits</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Black beans</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Blackberries</i>	0.33	0.43	0.33	0.57	0.50	0.33	71.43	15.00	0.00
<i>Blue cheese</i>	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	NaN_R	-	↑	-
<i>Blueberries</i>	0.49	0.42	0.36	0.44	0.36	0.36	-9.76	-14.88	0.00
<i>Bok choy</i>	0.25	0.43	0.56	0.27	0.40	0.53	7.32	-7.06	-6.08
<i>Bread</i>	0.10	0.86	1.00	0.40	1.00	1.00	320.00	16.67	0.00
<i>Broccoli</i>	0.37	0.77	0.84	0.37	0.81	0.87	1.39	5.79	3.01

<i>Brown rice</i>	0.35	0.35	0.42	0.38	0.38	0.42	6.54	8.30	-1.79
<i>Brown sugar</i>	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	NaN_R	-	↑	-
<i>Brownies</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Brussels sprouts</i>	0.31	0.92	0.94	0.29	0.94	0.94	-7.20	2.04	0.00
<i>Bulgur</i>	NaN_W	NaN_W	0.29	NaN_W	NaN_W	0.25	-	-	-12.50
<i>Butter</i>	0.15	0.29	0.59	0.25	0.40	0.59	62.50	40.00	0.00
<i>Buttermilk</i>	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	NaN_R	-	↑	-
<i>Cabbage</i>	0.09	0.62	0.67	0.12	0.44	0.67	28.00	-27.78	0.00
<i>Caesar dressing</i>	0.20	0.40	0.50	0.13	0.50	0.50	-33.33	25.00	0.00
<i>Caesar salad</i>	0.48	0.96	0.91	0.55	0.98	0.94	16.09	2.11	4.17
<i>Cantaloupe</i>	0.46	0.99	0.94	0.37	0.99	0.91	-19.05	0.00	-3.13
<i>Carrot</i>	0.40	0.63	0.70	0.42	0.72	0.64	6.19	15.34	-7.53
<i>Cauliflower</i>	0.44	0.85	0.95	0.48	0.83	0.91	7.57	-1.93	-3.71
<i>Celery</i>	0.17	0.18	0.17	0.17	0.18	0.17	0.00	0.00	0.00
<i>Celery root</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cereal</i>	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	-	-	↑
<i>Chard</i>	0.46	0.59	0.59	0.52	0.59	0.54	12.81	-0.49	-7.68
<i>Chayote squash</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cheese</i>	0.12	0.67	0.55	0.25	0.67	0.62	106.25	0.00	12.82
<i>Cheese pizza</i>	0.45	0.82	0.79	0.44	0.81	0.78	-4.12	-1.87	-1.93
<i>Cherry tomatoes</i>	0.39	0.57	0.61	0.40	0.57	0.59	2.18	1.23	-4.19
<i>Chia seeds</i>	NaN_W	NaN_W	0.25	NaN_W	NaN_W	0.25	-	-	0.00
<i>Chicken</i>	0.52	0.64	0.71	0.51	0.63	0.67	-0.26	-2.30	-6.25
<i>Chicken apple sausage</i>	0.22	0.57	0.73	0.20	1.00	0.67	-10.00	75.00	-8.33
<i>Chicken breast</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Chicken salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Chicken thighs</i>	0.06	0.27	0.20	0.07	NaN_W	0.29	13.33	↓	42.86
<i>Chickpeas</i>	NaN_W	NaN_W	NaN_W	NaN_W	0.14	NaN_W	-	↑	-
<i>Chilaquiles</i>	NaN_W	1.00	NaN_W	NaN_W	NaN_W	NaN_W	-	↓	-
<i>Chili</i>	0.15	0.15	NaN_W	0.16	0.12	0.11	6.86	-20.59	↑

Appendix

<i>Chive</i>	0.31	0.57	0.65	0.38	0.75	0.63	22.78	30.39	-2.61
<i>Cilantro</i>	0.18	0.12	0.13	0.19	0.09	0.14	4.31	-26.09	6.90
<i>Cod</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Cookies</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Corn</i>	0.40	0.57	0.57	0.44	0.62	0.67	11.11	7.69	16.67
<i>Corn on the cob</i>	0.33	0.89	0.94	0.38	0.94	0.96	16.11	5.32	2.37
<i>Cottage cheese</i>	NaN_W	0.67	0.67	NaN_W	NaN_W	0.67	-	↓	0.00
<i>Country rice</i>	NaN_W	0.31	NaN_W	NaN_W	0.15	0.11	-	-50.00	↑
<i>Couscous</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cranberries</i>	0.09	0.18	0.32	0.10	0.12	0.29	8.47	-35.29	-9.52
<i>Cream</i>	0.23	0.43	0.36	0.33	0.43	0.43	44.44	0.00	20.00
<i>Cream cheese</i>	NaN_W	0.50	0.75	0.29	0.57	0.75	↑	14.29	0.00
<i>Croutons</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cucumbers</i>	0.44	0.58	0.70	0.47	0.67	0.67	5.93	15.72	-4.09
<i>Egg whites</i>	0.72	0.88	0.90	0.87	0.90	0.88	20.99	2.50	-1.92
<i>Eggplant</i>	0.05	NaN_W	NaN_W	0.04	NaN_W	NaN_W	-14.89	-	-
<i>Eggs</i>	0.11	0.50	0.22	0.10	0.50	0.33	-10.00	0.00	50.00
<i>Feta cheese</i>	NaN_W	0.18	0.15	NaN_W	0.31	0.38	-	69.23	143.75
<i>Figs</i>	0.15	0.10	NaN_W	0.05	0.25	NaN_W	-66.25	150.00	-
<i>Fish</i>	0.23	0.39	0.44	0.24	0.46	0.28	6.94	19.17	-36.46
<i>Flour</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Fried rice</i>	NaN_W	0.67	0.67	NaN_W	0.67	0.40	-	0.00	-40.00
<i>Frozen yogurt</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Fruit salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Garden salad</i>	NaN_W	0.50	NaN_W	NaN_W	0.50	NaN_W	-	0.00	-
<i>Garlic</i>	0.70	0.77	0.80	0.73	0.81	0.77	4.47	4.63	-3.68
<i>Ginger</i>	0.17	0.13	NaN_W	0.31	0.27	NaN_W	76.92	113.33	-
<i>Goat cheese</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Granola</i>	0.38	0.48	0.47	0.67	0.55	0.47	77.78	14.55	0.00
<i>Grapefruit juice</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Grapes</i>	0.64	0.83	0.90	0.49	0.81	0.95	-23.38	-2.13	5.00

<i>Greek salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_W	NaN_R	-	↓	-
<i>Greek yogurt</i>	NaN_W	NaN_W	NaN_W	0.25	NaN_W	NaN_W	↑	-	-
<i>Green beans</i>	0.27	0.48	0.71	0.32	0.61	0.76	18.73	26.53	6.25
<i>Green onions</i>	0.16	NaN_W	0.09	0.19	0.09	0.23	23.30	↑	153.85
<i>Grilled chicken</i>	0.60	0.80	0.80	0.44	0.80	0.67	-25.93	0.00	-16.67
<i>Ground turkey</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Ham</i>	0.50	0.96	1.00	0.48	0.80	1.00	-3.03	-16.36	0.00
<i>Hash browns</i>	NaN_W	0.67	0.57	NaN_W	0.67	0.67	-	0.00	16.67
<i>Hominy</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Honeydew melons</i>	0.63	0.94	0.94	0.57	0.94	0.94	-10.51	0.00	0.35
<i>Ice cream cones</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Jalapenos</i>	0.31	0.45	0.43	0.33	0.38	0.52	8.33	-15.16	22.20
<i>Jicama</i>	NaN_W	NaN_W	NaN_W	NaN_R	NaN_W	NaN_W	↑	-	-
<i>Kale</i>	0.21	0.38	0.45	0.20	0.49	0.20	-8.40	30.61	-57.07
<i>Ketchup</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Kimchi</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Kiwi</i>	0.57	1.00	1.00	0.31	1.00	1.00	-45.56	0.00	0.00
<i>Lemon</i>	0.48	1.00	1.00	0.64	1.00	1.00	31.82	0.00	0.00
<i>Lemon juice</i>	0.54	0.63	0.66	0.59	0.65	0.60	10.48	2.87	-8.52
<i>Lentils</i>	NaN_W	0.67	NaN_W	NaN_W	1.00	NaN_W	-	50.00	-
<i>Lettuce</i>	0.30	0.32	0.40	0.28	0.46	0.35	-6.29	45.14	-13.04
<i>Lime</i>	0.23	0.37	0.46	0.25	0.32	0.33	6.82	-12.50	-27.78
<i>Mandarin oranges</i>	0.50	0.63	0.83	0.47	0.44	0.83	-5.88	-28.89	0.00
<i>Mangos</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Mayonnaise</i>	NaN_W	0.50	0.67	NaN_W	0.67	0.67	-	33.33	0.00
<i>Milk</i>	NaN_W	NaN_W	NaN_W	0.25	NaN_W	NaN_W	↑	-	-
<i>Millet</i>	0.30	0.46	0.50	0.27	0.33	0.39	-10.64	-29.25	-21.74
<i>Mixed greens</i>	0.51	0.58	0.55	0.50	0.56	0.58	-3.36	-4.10	6.28
<i>Mozzarella cheese</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Mushroom</i>	0.28	0.62	0.65	0.29	0.59	0.69	1.95	-5.57	6.01

<i>Mustard</i>	0.68	0.72	0.68	0.67	0.70	0.70	-2.00	-3.15	2.78
<i>Mustard greens</i>	0.25	0.30	0.19	0.20	0.08	0.19	-17.92	-73.50	-3.13
<i>Noodles</i>	NaN_W	1.00	1.00	0.17	1.00	1.00	↑	0.00	0.00
<i>Nopales</i>	NaN_W	NaN_W	NaN_W	NaN_R	NaN_W	NaN_W	↑	-	-
<i>Nuts</i>	0.91	0.95	1.00	1.00	1.00	1.00	10.00	5.00	0.00
<i>Oatmeal</i>	0.61	0.89	0.92	0.53	0.92	0.92	-12.38	3.85	0.00
<i>Olive oil</i>	0.76	0.87	0.88	0.79	0.88	0.85	3.93	1.26	-3.18
<i>Olives</i>	0.49	0.66	0.72	0.39	0.69	0.73	-19.39	5.56	1.41
<i>Onions</i>	0.57	0.67	0.70	0.58	0.70	0.73	2.64	3.39	5.20
<i>Orange</i>	0.49	0.91	0.94	0.34	0.88	0.94	-30.26	-2.94	0.00
<i>Orange juice</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Orange with peel</i>	NaN_W	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	↑	-	-
<i>Oregano</i>	0.15	0.29	0.59	0.27	0.40	0.59	73.33	40.00	0.00
<i>Parmesan cheese</i>	0.07	0.11	NaN_W	0.07	NaN_W	NaN_W	0.00	↓	-
<i>Parsley</i>	0.54	0.65	0.64	0.56	0.64	0.65	3.84	-1.39	2.20
<i>Parsnips</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pasta</i>	NaN_W	0.40	0.50	NaN_W	0.50	0.50	-	25.00	0.00
<i>Pasta salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pears</i>	0.75	0.75	0.67	0.75	0.75	0.60	0.00	0.00	-10.00
<i>Pecans</i>	NaN_W	NaN_W	0.50	NaN_W	NaN_W	0.40	-	-	-20.00
<i>Pepper</i>	0.48	0.63	0.63	0.49	0.60	0.66	3.40	-3.70	4.40
<i>Pepperoni</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pepperoni pizza</i>	NaN_W	NaN_W	0.29	NaN_W	NaN_W	0.50	-	-	75.00
<i>Pesto</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Pickles</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pilaf</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Pineapple</i>	0.40	0.73	0.75	0.36	0.68	0.71	-9.64	-6.80	-4.60
<i>Pizza</i>	0.16	0.27	0.47	0.16	0.32	0.43	0.81	20.46	-8.71
<i>Plate only²</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Pork</i>	0.32	0.48	0.67	0.34	0.54	0.63	6.48	11.83	-5.88
<i>Potato chips</i>	0.38	1.00	1.00	0.30	1.00	1.00	-20.00	0.00	0.00

Potatoes	0.47	0.86	0.81	0.43	0.90	0.79	-10.00	5.56	-2.63
Pumpkin seeds	0.24	NaN_W	0.44	0.50	0.22	0.44	112.50	↑	0.00
Quinoa	0.14	0.13	0.26	0.17	0.13	0.08	17.02	-3.23	-70.19
Radishes	0.17	0.24	0.27	0.13	0.10	0.26	-22.95	-59.52	-5.38
Raisins	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
Raspberries	0.27	0.32	0.30	0.38	0.34	0.30	41.70	5.71	0.00
Rice noodles	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
Roast chicken	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
Roasted potatoes	0.16	0.42	0.46	0.16	0.39	0.44	1.79	-7.53	-3.70
Rosemary	0.43	0.49	0.52	0.41	0.51	0.53	-4.74	3.28	2.45
Salmon	0.15	0.10	0.22	0.11	0.20	0.17	-27.82	110.00	-25.00
Salsa	0.75	1.00	1.00	0.38	0.80	1.00	-50.00	-20.00	0.00
Salt	0.76	0.88	0.91	0.79	0.91	0.90	3.90	2.95	-1.07
Sandwiches	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
Sausage	0.43	0.76	0.74	0.43	0.79	0.74	-0.95	4.32	0.00
Scrambled eggs	0.67	0.89	0.91	0.64	0.95	0.93	-5.36	6.98	2.38
Shallots	0.43	0.59	0.61	0.50	0.64	0.56	14.94	9.04	-8.20
Shrimp	0.27	1.00	1.00	0.21	1.00	1.00	-22.41	0.00	0.00
Snow peas	NaN_W	0.50	0.50	NaN_W	0.80	0.67	-	60.00	33.33
Sour cream	NaN_W	NaN_W	NaN_W	NaN_W	0.33	0.67	-	↑	↑
Soy sauce	0.14	0.17	0.31	0.13	0.19	0.23	-6.70	9.52	-25.00
Spinach cooked	0.20	0.55	0.52	0.21	0.41	0.44	5.50	-24.14	-13.89
Spinach raw	0.46	0.61	0.64	0.48	0.66	0.64	3.88	7.15	0.46
Squash	0.13	0.13	0.16	0.14	0.05	0.21	3.64	-64.39	29.31
Steak	0.11	0.33	0.30	0.25	0.29	0.40	125.00	-14.29	33.33
Strawberries	0.13	0.52	0.50	0.17	0.59	0.53	30.43	12.75	5.26
Succotash	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
Sugar	NaN_W	0.33	0.50	NaN_W	0.40	0.36	-	20.00	-27.27
Sun dried tomatoes	NaN_W	0.43	NaN_W	NaN_W	NaN_W	NaN_W	-	↓	-
Sunflower seeds	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-

<i>Sweet potato</i>	0.54	0.81	0.82	0.51	0.79	0.79	-4.97	-2.26	-2.94
<i>Syrup</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Tatsoi</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Thyme</i>	0.42	0.49	0.64	0.46	0.55	0.66	9.58	13.19	2.98
<i>Toast</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Tofu</i>	0.25	0.63	0.73	0.25	0.63	0.67	2.41	0.00	-9.09
<i>Tomatillo</i>	NaN_W	NaN_R	NaN_W	NaN_W	NaN_R	NaN_W	-	-	-
<i>Tomatoes</i>	0.25	0.54	0.56	0.24	0.54	0.55	-2.96	0.16	-2.27
<i>Tortilla</i>	0.39	0.93	0.93	0.39	0.93	1.00	-0.46	0.00	7.14
<i>Tortilla chips</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Tuna</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Tuna salad</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Turkey bacon</i>	NaN_W	0.40	0.50	0.11	0.80	0.86	↑	100.00	71.43
<i>Turnips</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Vegetable oil</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Vinaigrette</i>	0.47	0.52	0.43	0.55	0.51	0.53	17.55	-0.36	24.44
<i>Vinegar</i>	0.66	0.82	0.77	0.68	0.82	0.75	2.23	0.04	-2.52
<i>Waffles^l</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Walnuts</i>	0.37	0.52	0.43	0.37	0.43	0.30	0.00	-17.12	-29.92
<i>Watermelon</i>	0.44	0.93	0.87	0.33	0.93	0.90	-26.25	0.00	3.45
<i>Wheat berry</i>	0.43	0.49	0.52	0.46	0.56	0.58	7.43	13.03	10.85
<i>Wheat bread</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>White beans</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_W	NaN_R	-	↓	-
<i>White rice</i>	0.34	0.46	0.62	0.37	0.59	0.62	7.85	27.82	0.97
<i>White wine</i>	0.15	0.29	0.59	0.25	0.40	0.59	62.50	40.00	0.00
<i>Wild rice</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Wine</i>	NaN_W	NaN_W	NaN_W	NaN_W	0.33	0.40	-	↑	↑
<i>Yam</i>	0.32	0.68	0.60	0.33	0.67	0.67	1.57	-2.38	11.11
<i>Yogurt^l</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_W	NaN_R	-	↓	-
<i>Zucchini</i>	0.19	0.52	0.55	0.18	0.34	0.34	-7.59	-33.19	-37.50

¹Ingredients were categorized based on the following colors: the orange color indicates that either before or after frame filtering all the F1 scores were >0.80, the yellow color indicates that either before or after frame filtering 2 out of 3 F1 scores were >0.80, and the green color indicates that either before or after frame filtering only 1 F1 score was >0.80.

²The “Plate only” ingredient was treated as if the plate itself were an ingredient to be recognized by the algorithm. ³The following symbols were used to indicate changes in the F1 score before and after automated frame filtering for ingredients with one or more NaN_R or NaN_W values: “↓” indicates a worst condition compared to before filtering, “_” indicates no change, and “↑” indicates an improvement relative to the before-filtering condition. Abbreviation: FCDB, Food Composition Database; IncV3, InceptionV3; NaN_R: Not a Number (NaN), but right prediction (_R) of an absent ingredient in the test set; NaN_W: Not a Number (NaN), but wrong prediction (_W) of an ingredient as specified in

Figure D13; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Table D5. Performance for ingredients prediction as measured by the F1-score, stratified by frame filtering and algorithm¹, in the IT FCDB–correction dataset

Ingredient	Before frame filtering			After frame filtering			Comparison ($\Delta\%$) ³		
	IncV3_2+2	R101_2+2	ViT-B-16_2+2	IncV3_2+2	R101_2+2	ViT-B-16_2+2	IncV3_2+2	R101_2+2	ViT-B-16_2+2
<i>Almonds</i>	0.83¹	0.84	0.86	0.83	0.86	0.86	0.00	3.41	0.37
<i>Apple</i>	0.31	0.59	0.61	0.40	0.68	0.58	28.61	14.41	-5.45
<i>Apples with peel</i>	0.36	0.77	0.83	0.38	0.83	0.71	7.69	8.33	-14.29
<i>Artichokes</i>	NaN_W	0.80	0.50	NaN_W	0.80	0.80	-	0.00	60.00
<i>Arugula</i>	0.55	0.64	0.62	0.54	0.58	0.61	-1.49	-9.43	-2.04
<i>Asparagus</i>	0.37	0.86	0.86	0.33	0.86	0.78	-10.42	0.00	-8.70
<i>Avocado</i>	0.07	0.38	0.50	0.06	0.38	0.46	-15.63	0.00	-7.69
<i>Baby carrots</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Bacon</i>	0.52	0.89	0.91	0.61	0.91	0.88	16.78	1.33	-3.10
<i>Bagels</i>	0.18	0.60	0.80	0.22	0.60	0.80	22.22	0.00	0.00
<i>Balsamic vinegar</i>	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	-	-	↑
<i>Banana</i>	0.25	0.83	0.83	0.25	0.67	0.83	0.00	-20.00	0.00
<i>Banana with peel</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Basil</i>	0.33	0.52	0.44	0.33	0.53	0.51	0.18	1.67	14.29
<i>Bean seed</i>	NaN_W	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	-	-	-
<i>Beef</i>	0.19	0.75	0.71	0.20	0.73	0.81	4.11	-2.22	13.90
<i>Beets</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Bell peppers</i>	0.22	0.42	0.51	0.22	0.37	0.52	0.85	-12.56	1.01
<i>Berries</i>	0.58	0.86	0.86	0.60	0.88	0.85	3.25	1.67	-0.32
<i>Biscuits</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Black beans</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Blackberries</i>	0.44	0.50	0.33	0.48	0.38	0.57	8.62	-23.81	71.43
<i>Blue cheese</i>	NaN_R	NaN_W	NaN_R	NaN_R	NaN_W	NaN_R	-	-	-
<i>Blueberries</i>	0.53	0.43	0.37	0.42	0.41	0.35	-20.85	-2.89	-4.20
<i>Bok choy</i>	0.24	0.49	0.63	0.24	0.46	0.56	0.97	-5.80	-11.11
<i>Bread</i>	0.31	1.00	1.00	0.60	1.00	1.00	95.00	0.00	0.00
<i>Broccoli</i>	0.36	0.79	0.86	0.38	0.81	0.86	4.83	2.10	-0.22

Appendix

<i>Brown rice</i>	0.32	0.39	0.41	0.37	0.26	0.34	17.56	-33.45	-15.12
<i>Brown sugar</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Brownies</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Brussels sprouts</i>	0.33	0.95	0.98	0.22	0.90	0.96	-32.16	-5.93	-2.17
<i>Bulgur</i>	NaN_W	NaN_W	0.29	NaN_W	NaN_W	0.46	-	-	61.54
<i>Butter</i>	0.14	0.40	0.59	0.30	0.40	0.67	110.00	0.00	13.33
<i>Buttermilk</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Cabbage</i>	0.15	0.46	0.67	0.03	0.44	0.60	-77.01	-3.70	-10.00
<i>Caesar dressing</i>	0.31	0.50	0.50	NaN_W	0.50	0.33	↓	0.00	-33.33
<i>Caesar salad</i>	0.56	0.94	0.89	0.52	1.00	0.87	-7.67	6.25	-2.36
<i>Cantaloupe</i>	0.42	0.99	0.89	0.47	0.97	0.85	12.26	-1.51	-5.29
<i>Carrot</i>	0.39	0.65	0.66	0.40	0.68	0.67	4.01	4.61	1.88
<i>Cauliflower</i>	0.44	0.85	0.91	0.44	0.86	0.91	-0.53	1.10	-0.63
<i>Celery</i>	NaN_W	0.17	0.17	NaN_W	0.33	0.17	-	100.00	0.00
<i>Celery root</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cereal</i>	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	-	-	↑
<i>Chard</i>	0.46	0.63	0.58	0.50	0.56	0.60	8.80	-12.21	3.08
<i>Chayote squash</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cheese</i>	0.21	0.67	0.67	0.09	0.67	0.67	-56.06	0.00	0.00
<i>Cheese pizza</i>	0.46	0.83	0.83	0.39	0.80	0.78	-15.54	-4.00	-5.26
<i>Cherry tomatoes</i>	0.37	0.60	0.60	0.40	0.57	0.57	7.60	-5.71	-4.85
<i>Chia seeds</i>	0.17	NaN_W	NaN_W	NaN_W	NaN_W	0.44	↓	-	↑
<i>Chicken</i>	0.49	0.66	0.72	0.46	0.61	0.71	-4.30	-6.73	-2.16
<i>Chicken apple sausage</i>	0.43	1.00	0.89	0.26	1.00	0.89	-39.13	0.00	0.00
<i>Chicken breast</i>	NaN_W	NaN_W	NaN_W	NaN_W	0.17	NaN_W	-	↑	-
<i>Chicken salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Chicken thighs</i>	0.07	0.27	0.18	0.09	NaN_W	0.43	23.91	↓	135.71
<i>Chickpeas</i>	NaN_W	0.12	0.14	NaN_W	NaN_W	NaN_W	.	↓	↓
<i>Chilaquiles</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	0.67	-	-	↑
<i>Chili</i>	0.17	0.13	NaN_W	0.16	0.13	0.10	-8.22	0.00	↑

Appendix

<i>Chive</i>	0.29	0.67	0.69	0.30	0.59	0.67	2.96	-12.07	-3.92
<i>Cilantro</i>	0.16	0.12	0.14	0.17	0.10	0.11	0.82	-19.05	-17.14
<i>Cod¹</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Cookies</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Corn</i>	0.38	0.62	0.53	0.20	0.57	0.57	-48.78	-7.14	7.14
<i>Corn on the cob</i>	0.36	0.89	0.94	0.43	0.92	0.96	19.15	2.58	2.37
<i>Cottage cheese</i>	NaN_W	0.67	0.67	0.67	NaN_W	NaN_W	↑	↓	↓
<i>Country rice</i>	NaN_W	NaN_W	NaN_W	0.15	0.13	NaN_W	↑	↑	-
<i>Couscous</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Cranberries</i>	0.08	0.14	0.33	0.14	0.18	0.14	68.18	31.82	-58.62
<i>Cream</i>	0.19	0.23	0.37	0.31	0.48	0.47	64.06	109.20	26.00
<i>Cream cheese</i>	NaN_W	0.57	0.75	NaN_W	0.57	0.75	-	0.00	0.00
<i>Croutons</i>	NaN_W	1.00	NaN_W	NaN_W	0.67	NaN_W	-	-33.33	-
<i>Cucumbers</i>	0.42	0.63	0.67	0.48	0.61	0.64	14.48	-2.72	-4.40
<i>Egg whites</i>	0.84	0.86	0.83	0.73	0.86	0.88	-13.29	0.00	6.15
<i>Eggplant</i>	NaN_W	NaN_W	NaN_W	0.04	0.11	0.17	↑	↑	↑
<i>Eggs</i>	0.13	0.50	0.40	0.13	0.50	0.32	0.00	0.00	-21.05
<i>Feta cheese</i>	NaN_W	NaN_W	0.29	NaN_W	NaN_W	0.35	-	-	23.53
<i>Figs</i>	0.06	NaN_W	0.25	0.33	NaN_W	0.25	433.33	-	0.00
<i>Fish</i>	0.26	0.44	0.32	0.23	0.47	0.32	-10.54	5.88	0.00
<i>Flour</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Fried rice</i>	NaN_W	0.67	0.67	NaN_W	0.67	0.67	-	0.00	0.00
<i>Frozen yogurt</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Fruit salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Garden salad</i>	NaN_W	0.50	NaN_W	NaN_W	0.50	0.50	-	0.00	↑
<i>Garlic</i>	0.70	0.77	0.78	0.71	0.78	0.78	2.60	1.30	0.53
<i>Ginger</i>	0.15	0.14	NaN_W	0.20	0.17	NaN_W	30.86	16.67	-
<i>Goat cheese</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Granola</i>	0.50	0.56	0.38	0.61	0.44	0.56	21.74	-20.00	48.15
<i>Grapefruit juice</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Grapes</i>	0.51	0.90	0.97	0.62	0.95	0.82	21.31	5.00	-16.03

<i>Greek salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Greek yogurt</i>	0.20	NaN_W	NaN_W	NaN_W	NaN_W	0.25	↓	-	↑
<i>Green beans</i>	0.25	0.75	0.73	0.28	0.64	0.72	13.51	-15.15	-1.60
<i>Green onions</i>	0.16	0.09	0.15	0.19	NaN_W	0.14	17.00	↓	-3.57
<i>Grilled chicken</i>	0.60	0.57	0.67	0.57	0.50	0.57	-4.76	-12.50	-14.29
<i>Ground turkey</i>	NaN_W	NaN_W	NaN_W	NaN_W	0.20	NaN_W	-	↑	-
<i>Ham</i>	0.62	0.96	1.00	0.62	0.95	1.00	0.86	-0.43	0.00
<i>Hash browns</i>	NaN_W	0.67	0.67	NaN_W	0.40	0.67	-	-40.00	0.00
<i>Hominy</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Honeydew melons</i>	0.48	0.94	0.97	0.61	0.91	0.97	27.78	-3.19	0.18
<i>Ice cream cones</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Jalapenos</i>	0.29	0.39	0.46	0.31	0.44	0.51	5.59	13.13	10.46
<i>Jicama</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Kale</i>	0.21	0.38	0.48	0.22	0.45	0.30	2.72	20.43	-37.45
<i>Ketchup</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Kimchi</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Kiwi</i>	0.42	1.00	1.00	0.38	1.00	1.00	-8.57	0.00	0.00
<i>Lemon</i>	0.64	1.00	1.00	0.75	1.00	1.00	17.86	0.00	0.00
<i>Lemon juice</i>	0.55	0.61	0.63	0.56	0.66	0.61	0.47	8.04	-2.93
<i>Lentils</i>	NaN_W	0.67	0.67	NaN_W	0.67	NaN_W	-	0.00	↓
<i>Lettuce</i>	0.30	0.27	0.32	0.30	0.39	0.43	0.29	47.32	35.87
<i>Lime</i>	0.27	0.31	0.34	0.25	0.29	0.39	-6.08	-5.92	11.81
<i>Mandarin oranges</i>	0.40	0.83	0.73	0.47	0.73	0.83	17.65	-12.73	14.58
<i>Mangos</i>	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	NaN_R	-	↑	-
<i>Mayonnaise</i>	NaN_W	0.50	0.67	NaN_W	0.57	0.67	-	14.29	0.00
<i>Milk</i>	0.18	NaN_W	NaN_W	NaN_W	NaN_W	0.25	↓	-	↑
<i>Millet</i>	0.23	0.35	0.41	0.25	0.33	0.36	8.65	-6.12	-12.73
<i>Mixed greens</i>	0.51	0.58	0.62	0.54	0.56	0.59	5.65	-3.46	-3.55
<i>Mozzarella cheese</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Mushroom</i>	0.28	0.60	0.60	0.29	0.64	0.69	1.86	6.47	14.43
<i>Mustard</i>	0.67	0.72	0.67	0.71	0.69	0.69	7.03	-4.51	3.45

<i>Mustard greens</i>	0.26	0.33	0.17	0.28	0.26	0.19	10.38	-23.08	8.02
<i>Noodles</i>	NaN_W	1.00	1.00	NaN_W	1.00	1.00	-	0.00	0.00
<i>Nopales</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Nuts</i>	0.95	1.00	0.91	0.91	1.00	0.95	-4.55	0.00	4.76
<i>Oatmeal</i>	0.53	0.86	0.89	0.56	0.92	0.92	4.65	7.69	3.85
<i>Olive oil</i>	0.78	0.86	0.86	0.80	0.86	0.86	2.06	-0.29	-0.28
<i>Olives</i>	0.43	0.67	0.69	0.44	0.72	0.68	1.75	7.46	-2.75
<i>Onions</i>	0.55	0.69	0.72	0.56	0.64	0.72	1.19	-6.37	0.23
<i>Orange</i>	0.41	0.88	0.91	0.44	0.91	0.94	7.94	3.90	3.53
<i>Orange juice</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Orange with peel</i>	NaN_R	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	↓	-	-
<i>Oregano</i>	0.14	0.40	0.59	0.32	0.40	0.67	121.05	0.00	13.33
<i>Parmesan cheese</i>	0.15	0.13	NaN_W	0.08	0.11	NaN_W	-48.04	-15.79	-
<i>Parsley</i>	0.56	0.67	0.61	0.57	0.67	0.64	1.45	-1.09	5.15
<i>Parsnips</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pasta</i>	NaN_W	0.50	NaN_W	NaN_W	NaN_W	0.29	-	↓	↑
<i>Pasta salad</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pears</i>	0.67	0.60	0.67	0.67	0.60	0.75	0.00	0.00	12.50
<i>Pecans</i>	NaN_W	NaN_W	0.67	NaN_W	0.22	0.50	-	↑	-25.00
<i>Pepper</i>	0.49	0.60	0.65	0.50	0.63	0.59	2.59	5.35	-9.15
<i>Pepperoni</i>	NaN_R	NaN_R	NaN_W	NaN_R	NaN_R	NaN_R	-	-	↑
<i>Pepperoni pizza</i>	NaN_W	NaN_W	0.67	NaN_W	NaN_W	0.29	-	-	-57.14
<i>Pesto</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Pickles</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Pilaf</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Pineapple</i>	0.41	0.61	0.77	0.39	0.63	0.77	-6.26	2.58	-0.29
<i>Pizza</i>	0.20	0.37	0.48	0.11	0.40	0.55	-48.25	7.50	13.79
<i>Plate only²</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Pork</i>	0.33	0.46	0.71	0.34	0.60	0.62	2.83	30.69	-12.82
<i>Potato chips</i>	0.26	1.00	1.00	0.26	1.00	1.00	0.00	0.00	0.00
<i>Potatoes</i>	0.46	0.84	0.79	0.45	0.83	0.76	-1.33	-0.95	-4.14

<i>Pumpkin seeds</i>	0.38	NaN_W	NaN_W	0.40	NaN_W	0.33	5.00	-	↑
<i>Quinoa</i>	0.14	0.13	0.24	0.16	0.14	0.13	12.90	10.34	-48.44
<i>Radishes</i>	0.12	0.28	0.24	0.22	NaN_W	0.24	88.89	↓	-2.94
<i>Raisins</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Raspberries</i>	0.37	0.33	0.40	0.38	0.43	0.30	2.38	29.73	-24.24
<i>Rice noodles</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_W	-	-	↓
<i>Roast chicken</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Roasted potatoes</i>	0.15	0.41	0.40	0.16	0.36	0.41	6.67	-11.69	2.94
<i>Rosemary</i>	0.41	0.48	0.52	0.40	0.49	0.56	-2.23	1.54	9.19
<i>Salmon</i>	0.14	0.11	0.22	0.12	0.14	0.17	-14.91	28.57	-25.00
<i>Salsa</i>	0.35	1.00	1.00	0.55	1.00	1.00	54.55	0.00	0.00
<i>Salt</i>	0.77	0.90	0.90	0.79	0.87	0.91	3.06	-2.76	1.08
<i>Sandwiches</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Sausage</i>	0.45	0.68	0.72	0.47	0.77	0.73	3.13	12.43	1.31
<i>Scrambled eggs</i>	0.64	0.94	0.95	0.81	0.95	0.93	25.42	1.31	-1.09
<i>Shallots</i>	0.43	0.59	0.62	0.45	0.53	0.52	4.15	-10.76	-15.73
<i>Shrimp</i>	0.23	1.00	1.00	0.33	1.00	1.00	44.44	0.00	0.00
<i>Snow peas</i>	NaN_W	0.67	0.67	NaN_W	1.00	0.67	-	50.00	0.00
<i>Sour cream</i>	NaN_W	0.40	NaN_W	0.06	0.25	0.29	↑	-37.50	↑
<i>Soy sauce</i>	0.12	0.17	0.35	0.15	0.12	0.20	19.49	-32.35	-42.50
<i>Spinach cooked</i>	0.14	0.18	0.48	0.18	0.45	0.37	22.55	148.39	-23.28
<i>Spinach raw</i>	0.47	0.63	0.68	0.45	0.65	0.65	-3.18	3.84	-4.62
<i>Squash</i>	0.12	0.10	0.13	0.13	0.16	0.19	7.21	53.95	47.62
<i>Steak</i>	NaN_W	0.24	0.30	NaN_W	0.35	0.35	-	47.06	17.65
<i>Strawberries</i>	0.12	0.67	0.56	0.19	0.53	0.45	56.25	-20.00	-18.18
<i>Succotash</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Sugar</i>	0.20	0.33	0.60	NaN_W	0.20	0.50	↓	-40.00	-16.67
<i>Sun dried tomatoes</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Sunflower seeds</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Sweet potato</i>	0.50	0.80	0.78	0.53	0.73	0.79	6.02	-8.78	1.63

<i>Syrup</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Tatsoi</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Thyme</i>	0.42	0.59	0.60	0.42	0.53	0.60	-0.94	-9.63	0.43
<i>Toast</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Tofu</i>	0.26	0.56	0.63	0.29	0.54	0.63	11.11	-4.88	0.00
<i>Tomatillo</i>	NaN_W	NaN_R	NaN_W	NaN_W	NaN_R	NaN_W	-	-	-
<i>Tomatoes</i>	0.22	0.60	0.46	0.29	0.51	0.51	31.79	-14.73	10.64
<i>Tortilla</i>	0.34	0.74	0.93	0.39	0.78	0.93	12.26	5.56	0.00
<i>Tortilla chips</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Tuna</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Tuna salad</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Turkey bacon</i>	0.11	0.40	0.50	0.10	0.80	0.29	-10.00	100.00	-42.86
<i>Turnips</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Vegetable oil</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Vinaigrette</i>	0.41	0.44	0.44	0.52	0.42	0.52	27.54	-6.25	16.13
<i>Vinegar</i>	0.66	0.79	0.78	0.67	0.82	0.78	1.89	2.78	-0.34
<i>Waffles</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>Walnuts</i>	0.32	0.42	0.43	0.15	0.45	0.38	-52.56	6.07	-12.50
<i>Watermelon</i>	0.38	0.93	0.93	0.46	0.87	0.81	18.92	-6.67	-12.50
<i>Wheat berry</i>	0.43	0.54	0.51	0.42	0.51	0.52	-2.10	-6.11	0.96
<i>Wheat bread</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>White beans</i>	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	NaN_R	-	-	-
<i>White rice</i>	0.35	0.51	0.61	0.37	0.49	0.63	7.05	-2.98	4.05
<i>White wine</i>	0.14	0.40	0.59	0.30	0.40	0.67	110.00	0.00	13.33
<i>Wild rice</i>	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	NaN_W	-	-	-
<i>Wine</i>	NaN_W	0.40	NaN_W	NaN_W	NaN_W	0.33	-	↓	↑
<i>Yam</i>	0.33	0.59	0.63	0.37	0.67	0.62	9.86	12.82	-1.98
<i>Yogurt</i>	NaN_R	NaN_W	NaN_R	NaN_W	NaN_W	NaN_R	↓	-	-
<i>Zucchini</i>	0.18	0.42	0.31	0.20	0.29	0.58	12.94	-32.65	88.71

¹Ingredients were categorized based on the following colors: the orange color indicates that either before or after frame filtering all the F1 scores were >0.80; the yellow color indicates that either before or after frame filtering 2 out of 3 F1 scores were >0.80; and the green color indicates that either before or after frame filtering only 1 F1 score was >0.80.

²The “Plate only” ingredient was treated as if the plate itself were an ingredient to be recognized by the algorithm. ³The following symbols were used to indicate changes in the F1 score before and after automated frame filtering for ingredients with one or more NaN_R or NaN_W values: “↓” indicates a worst condition compared to before filtering, “—” indicates no change, and “↑” indicates an improvement relative to the before-filtering condition. Abbreviation: FCDB, Food Composition Database; IncV3, InceptionV3; NaN_R: Not a Number (NaN), but right prediction (_R) of an absent ingredient in the test set; NaN_W: Not a Number (NaN), but wrong prediction (_W) of an ingredient as specified in **Figure D14**; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Table D6. Performance metrics for mass, energy, and macronutrients prediction stratified by frame filtering, dataset, and algorithm¹

Before frame filtering	Mass (g)			Energy content (kcal)			Protein content (g)			Fat content (g)			Carbohydrates content (g)			
	FCDB	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
US FCBD–correction																
<i>IncV3_2+2</i>	58.51	36.65	20.68	90.12	53.92	24.07	10.33	5.90	38.29	7.14	4.07	36.79	11.07	7.15	40.90	
<i>R101_2+2</i>	55.25	32.84	18.52	87.25	49.65	22.17	9.51	4.95	32.12	6.51	3.53	31.87	9.00	5.38	30.77	
<i>ViT-B-16_2+2</i>	54.58	33.87	19.11	93.63	53.69	23.97	9.09	4.78	31.02	6.74	3.61	32.57	8.77	5.20	29.78	
IT FCBD–correction																
<i>IncV3_2+2</i>	58.48	35.96	20.26	101.50	58.68	25.80	9.72	5.45	36.68	8.23	4.36	36.68	12.34	6.90	47.13	
<i>R101_2+2</i>	53.26	31.25	17.61	95.91	52.50	23.08	8.52	4.48	30.12	7.32	3.64	30.63	9.80	4.79	32.69	
<i>ViT-B-16_2+2</i>	55.21	33.68	18.98	96.78	54.99	24.18	8.19	4.35	29.25	7.18	3.72	31.25	10.01	4.82	32.95	
After frame filtering	Mass (g)			Energy content (kcal)			Protein content (g)			Fat content (g)			Carbohydrates content (g)			
	FCDB	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
US FCDB –correction																
<i>IncV3_2+2</i>	57.64	36.87	20.80	83.89	53.00	23.66	10.21	5.77	37.43	6.42	3.90	35.17	10.42	6.89	39.45	
<i>R101_2+2</i>	51.50	32.06	18.08	77.51	46.38	20.71	8.87	4.65	30.16	5.79	3.31	29.91	8.28	4.98	28.49	
<i>ViT-B-16_2+2</i>	52.83	32.58	18.38	91.99	53.08	23.69	9.01	4.83	31.32	6.54	3.54	31.95	8.89	5.22	29.87	
IT FCDB –correction																
<i>IncV3_2+2</i>	57.13	36.49	20.57	96.24	57.14	25.12	8.98	5.26	35.42	7.94	4.24	35.68	11.99	6.83	46.62	
<i>R101_2+2</i>	50.17	30.98	17.46	89.09	51.13	22.48	7.80	4.25	28.62	7.01	3.49	29.36	9.95	5.06	34.60	
<i>ViT-B-16_2+2</i>	52.32	32.91	18.54	95.04	54.16	23.81	8.14	4.38	29.51	7.16	3.65	30.69	9.93	4.78	32.68	

¹Values in bold typeface with a light blue cell background indicate the minimum performance metrics (i.e., the minimum error) for each nutritional variable; similarly values with an orange cell background indicate the maximum MAPE (i.e., the maximum error) for each nutritional variable as commented in the text. Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Table D7. List of 67 mispredicted dishes across nutritional values and datasets, after frame filtering, as grouped by similarity in ingredient content. Nutrition5k test set ($n = 676$)

Dish ID	Number of ingredients per dish	List of ingredients per dish
Salad-based group (median number of ingredients per dish: 15, IQR: 10.75–19)		
dish_1560367952	9	Fish, spinach (raw), pizza, onions, country rice, olive oil, salt, garlic, green onions
dish_1560367980	10	Asparagus, salt, onions, country rice, olive oil, green onions, pizza, spinach (raw), fish, garlic
dish_1560368506	18	Brown rice, fish, shallots, honeydew melons, broccoli, lemon juice, parsley, pork, vinegar, cherry tomatoes, pepper, garlic, salt, country rice, basil, olive oil, onions, green onions
dish_1560368570	24	Honeydew melons, pepper, cherry tomatoes, lettuce, mixed greens, pork, mustard, olive oil, lemon juice, onions, carrot, broccoli, green onions, shallots, arugula, vinegar, brown rice, fish, pumpkin seeds, basil, parsley, country rice, salt, garlic
dish_1560800988	9	Pepper, cauliflower, chickpeas, salt, bulgur, olive oil, kale, lemon juice, parsley
dish_1560801020	16	Cauliflower, garlic, spinach (raw), parmesan cheese, wheat berry, chickpeas, pepper, chicken breast, cherry tomatoes, thyme, lemon juice, olive oil, parsley, kale, bulgur, salt
dish_1560801041	22	Pork, zucchini, arugula, chicken breast, cherry tomatoes, rosemary, lemon juice, thyme, olive oil, onions, wheat berry, parmesan cheese, pepper, spinach (raw), cauliflower, garlic, chickpeas, white rice, salt, bulgur, parsley, kale
dish_1561577848	17	Salt, white wine, cream, oregano, arugula, lemon juice, olive oil, pepper, chicken, mushroom, wheat berry, butter, rosemary, thyme, shallots, garlic, basil
dish_1561577947	22	Olive oil, basil, arugula, blueberries, vinegar, mustard, walnuts, white wine, salt, rosemary, oregano, cream, mushroom, wheat berry, chard, pepper, chicken, shallots, garlic, butter, lemon juice, thyme
dish_1561661377	14	Garlic, chard, brown rice, green beans, chicken, salt, carrot, Caesar salad, parsley, chive, rosemary, basil, lemon juice, olive oil
dish_1562009934	16	Quinoa, mixed greens, garlic, parsley, mustard, lemon juice, brown rice, arugula, vinegar, olives, shallots, pears, salt, goat cheese, thyme, olive oil
dish_1562618000	16	Vinegar, olive oil, garlic, mustard greens, pepper, salt, radishes, lemon juice, thyme, brown rice, parsley, basil, arugula, chicken thighs, chickpeas, broccoli
dish_1562790855	21	Radishes, fish, cherry tomatoes, shallots, onions, mustard, parsley, garlic, basil, salt, pepper, pork, lemon juice, brown rice, country rice, cucumbers, olive oil, vinegar, bell peppers, broccoli, green onions
dish_1563478751	12	Cream, mushroom, spinach (raw), olive oil, pasta, beef, wine, garlic, sour cream, onions, thyme, salt
dish_1563909550	11	Cucumbers, mustard, mustard greens, olive oil, garlic, green beans, tomatoes, salt, fried rice, vinegar, spinach (raw)
dish_1563909580	12	Mustard greens, cucumbers, tomatoes, salt, mustard, garlic, fried rice, cheese pizza, vinegar, spinach (raw), green beans, olive oil
dish_1565030391	19	White rice, garlic, orange juice, onions, cucumbers, kale, green onions, lettuce, soy sauce, pepper, cherry tomatoes, beef, vinegar, olive oil, broccoli, lime, salt, chili, mixed greens
dish_1565123881	13	Caesar salad, olive oil, onions, cheese pizza, zucchini, spinach (cooked), millet, shallots, bok choy, salt, beef, chayote squash, vinegar
dish_1565898230	27	Garlic, bell peppers, beef, cherry tomatoes, brown rice, ginger, olive oil, vinegar, spinach (cooked), lime, shallots, bok choy, salmon, millet, vinaigrette, jalapenos, spinach (raw), green beans, feta cheese, cucumbers, lettuce, cilantro, lemon juice, onions, salt, chili, olives

Dish ID	Number of ingredients per dish	List of ingredients per dish
dish_1566414342	19	Garlic, pepper, mushroom, oregano, cream, wheat berry, butter, basil, salt, shallots, white wine, chicken, quinoa, arugula, thyme, olive oil, rosemary, lemon juice, roasted potatoes
dish_1566414412	27	Shallots, olive oil, garlic, lemon juice, basil, cream, wheat berry, mushroom, arugula, cherry tomatoes, quinoa, chicken, pepper, bell peppers, white wine, lettuce, feta cheese, roasted potatoes, onions, butter, thyme, rosemary, cucumbers, olives, oregano, vinaigrette, salt
dish_1566502573	28	Chive, bok choy, chicken, white rice, pork, arugula, spinach (raw), brown rice, chard, mustard, olive oil, garlic, cucumbers, sugar, rosemary, pepper, sun dried tomatoes, lemon juice, mustard greens, parsley, vinegar, corn on the cob, basil, onions, carrot, soy sauce, salt, chickpeas
dish_1566587182	17	Pepper, millet, avocado, spinach (raw), vinegar, olive oil, onions, bell peppers, salt, garlic, cherry tomatoes, chicken, jalapenos, mustard, celery root, mixed greens, tomatoes
dish_1566590007	13	Bell peppers, garlic, tomatoes, salt, onions, olive oil, pizza, pepper, tofu, jalapenos, spinach (raw), chicken, millet
dish_1566590056	19	Tomatoes, pepper, millet, vinegar, tofu, jalapenos, mustard, olive oil, bell peppers, cherry tomatoes, chicken, chard, spinach (raw), pizza, cucumbers, onions, garlic, salt, figs
dish_1568305257	10	Turkey bacon, salt, bell peppers, mustard, olive oil, cucumbers, vinegar, scrambled eggs, garlic, radishes
dish_1568401302	7	Fried rice, salt, squash, carrot, avocado, olive oil, tuna salad
dish_1562703447	15	Salt, spinach (cooked), vinegar, millet, berries, beef, shallots, mixed greens, onions, olive oil, pizza, lemon juice, parsley, bok choy, apple
dish_1558630325	3	Apple, garden salad, almonds
dish_1558720236	4	Apple, carrot, cauliflower, almonds
dish_1563566939	10	Vinegar, blueberries, wild rice, pecans, chard, arugula, mustard, olive oil, garlic, salt
dish_1563566965	14	Salt, parsley, wild rice, blueberries, olive oil, arugula, chard, mustard, pecans, vinegar, mustard greens, chickpeas, garlic, pepper
Eggs-based group (median number of ingredients per dish: 5, IQR: 3.5–6.25)		
dish_1561999624	1	Scrambled eggs
dish_1561999706	2	Scrambled eggs, sweet potato
dish_1562691064	7	Berries, fried rice, olive oil, pineapple, scrambled eggs, roasted potatoes, broccoli
dish_1563551220	9	Cream cheese, berries, greek yogurt, milk, chia seeds, bagels, egg whites, olive oil, sweet potato
dish_1563984296	6	Egg whites, olive oil, salsa, cantaloupe, sweet potato, pineapple
dish_1566838378	4	Scrambled eggs, watermelon, berries, pineapple
dish_1566838407	6	Pineapple, scrambled eggs, sweet potato, berries, olive oil, watermelon
dish_1566316757	4	Sweet potato, egg whites, olive oil, salsa
Chicken-based group (median number of ingredients per dish: 4, IQR: 2.5–5.5)		
dish_1550873668	3	Avocado, chicken, cheese
dish_1563389600	2	Grilled chicken, cherry tomatoes
dish_1565811061	4	Chicken, carrot, spinach (raw), broccoli
dish_1565811139	6	Carrot, goat cheese, olive oil, broccoli, spinach (raw), chicken
dish_1565974409	2	Chicken apple sausage, bacon
dish_1566246626	6	Feta cheese, broccoli, mixed greens, chicken, olives, Caesar dressing
dish_1566328776	3	Chicken, cherry tomatoes, pizza
dish_1566328805	4	Cherry tomatoes, pizza, chicken, pineapple
dish_1566328831	5	Pizza, cherry tomatoes, chicken, pineapple, olives

Dish ID	Number of ingredients per dish	List of ingredients per dish
dish_1566850031	6	Olives, carrot, chicken, Caesar dressing, cherry tomatoes, onions
dish_1568147009	4	Broccoli, steak, mixed greens, chicken
dish_1568147044	5	Broccoli, steak, mixed greens, chicken, olive oil
dish_1566849987	2	Olives, carrot, chicken, cherry tomatoes, onions
dish_1568146942	2	Chicken, mixed greens
dish_1563389626	6	Salt, pepper, grilled chicken, carrot, olive oil, cherry tomatoes
Western-inspired breakfast foods group (median number of ingredients per dish: 1, IQR: 1–3)		
dish_1557937079	1	Bacon
dish_1558372948	1	Almonds
dish_1558373159	3	Sausage, APPLES with peel, almonds
dish_1558375886	3	Almonds, sausage, grapes
dish_1558544663	1	Oatmeal
dish_1563305513	1	Cheese pizza
dish_1563551194	8	Olive oil, sweet potato, egg whites, bagels, greek yogurt, chia seeds, milk, cream cheese
dish_1563898084	7	Bacon, milk, greek yogurt, blueberries, scrambled eggs, pineapple, chia seeds
dish_1566838351	3	Berries, watermelon, pineapple
dish_1563566909	1	Wild rice
dish_1566501575	1	Brownies ¹
dish_1566501594	1	Brownies ¹
Minimum	1.0	—
Q1	3.0	—
Median	6.0	—
Q3	12	—
Maximum	24.0	—
Mean	7.8	—
SD	6.6	—

¹We indicate with a lighter cell background those dishes identified as mispredicted in the current publication but not in the Bianco et al (104). ²The dishes labeled as “Brownies” (*dish_1566501575* and *dish_1566501594*) were originally identified as mispredicted in Bianco et al (104). However, manual inspection of frames identified a mismatch between the reported ingredients listed in the metadata and the visible ingredients. Therefore, these 2 dishes were excluded from the list of 68 mispredicted dishes.

Table D8. Characteristics of mispredicted dishes in the current application but not in Bianco et al (104) after frame filtering¹

Dishes	Observed ingredients	Predicted ingredients	Observed nutritional values	Predicted nutritional values
dish 1563551194 	Olive oil, sweet potato, egg whites, bagels, greek yogurt, chia seeds, milk, cream cheese	Olive oil (6), sweet potato (5), egg whites (1), bagels (0), greek yogurt (0), chia seeds (1), milk (0), cream cheese (0) 45 additional ingredients detected at least once, but not mentioned in the ground truth	Mass: 400.0g Energy: 500.2 kcal Protein: 27.0g Fat: 18.3g Carbohydrates: 57.5g	Mass: 271.4g Energy: 356.8kcal Protein: 22.8g Fat: 12.8g Carbohydrates: 35.5g
dish 1563898084 	Bacon, milk, greek yogurt, blueberries, scrambled eggs, pineapple, chia seeds	Bacon (5), milk (0), greek yogurt (0), blueberries (0), scrambled eggs (6), pineapple (5), chia seeds (0) 11 additional ingredients detected at least once, but not mentioned in the ground truth	Mass: 384.0g Energy: 440.2 kcal Protein: 23.9g Fat: 27.4g Carbohydrates: 25.2g	Mass: 276.8g Energy: 355.0kcal Protein: 19.2g Fat: 19.5g Carbohydrates: 23.6g
dish 1566316757 	Sweet potato, egg whites, olive oil, salsa	Sweet potato (6), egg whites (6), olive oil (6), salsa (6) 7 additional ingredients detected at least once, but not mentioned in the ground truth	Mass: 819.0g Energy: 450.2 kcal Protein: 61.2g Fat: 4.3g Carbohydrates: 37.6g	Mass: 648.7g Energy: 399.1 kcal Protein: 47.9g Fat: 5.4g Carbohydrates: 35.0g

dish 1566849987 	Olives, carrot, chicken, cherry tomatoes, onions	Olives (6), carrot (6), chicken (6), cherry tomatoes (6), onions (6) 6 additional ingredients detected at least once, but not mentioned in the ground truth	Mass: 540.0g Energy: 565.4 kcal Protein: 77.0g Fat: 20.3g Carbohydrates: 16.5g	Mass: 419.6g Energy: 474.4 kcal Protein: 56.8g Fat: 19.5g Carbohydrates: 12.8g
dish 1568146942 	Chicken, mixed greens	Chicken (6), mixed greens (3) 13 additional ingredients detected at least once, but not mentioned in the ground truth	Mass: 274.0g Energy: 342.4 kcal Protein: 60.3g Fat: 9.3g Carbohydrates: 2.5g	Mass: 384.2g Energy: 501.1 kcal Protein: 60.3g Fat: 23.4g Carbohydrates: 6.6g

¹Ingredients detection counts are calculated across datasets and algorithms. Predicted and observed nutritional values are reported as the median across datasets and algorithms (predicted values) and across datasets (observed values).

Table D9. Summary statistics of the distribution of the raw absolute differences in prediction errors (Δ MAPE, %) between the current application and Bianco et al. (104)

	Statistics	Δ MAPE mass	Δ MAPE calories	Δ MAPE protein	Δ MAPE fat	Δ MAPE carbohydrates
Overall	Minimum	-67.94	-77.57	-141.92	-149.24	-161.01
	1st quartile	-2.87	-3.25	-9.16	-9.27	-11.76
	Median	0.28	-0.09	-1.65	-1.14	-2.23
	3rd quartile	3.54	3.58	1.89	3.18	3.33
	Maximum	66.55	82.89	116.14	119.39	94.55
By dataset						
Dataset	Statistics	Δ MAPE mass	Δ MAPE calories	Δ MAPE protein	Δ MAPE fat	Δ MAPE carbohydrates
US FCBD—correction	Minimum	-67.94	-52.58	-109.22	-106.21	-130.05
	1st quartile	-2.72	-3.46	-8.01	-8.64	-8.38
	Median	0.35	-0.10	-1.16	-0.94	-0.93
	3rd quartile	3.52	3.91	2.58	3.49	4.47
	Maximum	66.55	75.92	116.14	119.39	62.98
IT FCBD—correction	Minimum	-64.07	-77.57	-141.92	-149.24	-161.01
	1st quartile	-3.01	-3.12	-10.82	-9.65	-16.82
	Median	0.21	-0.06	-2.18	-1.36	-4.07
	3rd quartile	3.60	3.39	1.32	2.67	1.86
	Maximum	65.82	82.89	106.37	94.79	94.55
By algorithm						
Algorithm	Statistics	Δ MAPE mass	Δ MAPE calories	Δ MAPE protein	Δ MAPE fat	Δ MAPE carbohydrates
IncV3_2+2	Minimum	-60.20	-52.58	-135.69	-125.08	-161.01
	1st quartile	-3.08	-3.57	-16.16	-13.25	-19.10
	Median	0.19	-0.24	-4.45	-1.89	-6.24

R101_2+2	3rd quartile	3.41	3.69	0.76	4.11	3.24
	Maximum	66.55	68.84	106.37	85.63	83.87
	Minimum	-65.99	-77.57	-141.92	-149.24	-158.37
	1st quartile	-3.16	-3.52	-7.80	-10.31	-16.01
	Median	0.35	0.06	-1.52	-1.69	-4.28
	3rd quartile	4.06	4.12	2.48	1.75	1.48
ViT-B-16_2+2	Maximum	65.82	82.89	116.14	119.39	85.99
	Minimum	-67.94	-33.39	-105.57	-64.38	-63.15
	1st quartile	-2.33	-2.81	-5.12	-4.58	-3.85
	Median	0.27	-0.11	-0.66	-0.45	0.04
	3rd quartile	3.20	3.16	2.78	3.55	5.47
	Maximum	42.74	49.24	85.12	90.90	94.55

By dataset and algorithm

Algorithm	Dataset	Statistics	Δ MAPE mass	Δ MAPE calories	Δ MAPE protein	Δ MAPE fat	Δ MAPE carbohydrates
IncV3_2+2	US FCBD— correction	Minimum	-60.20	-52.58	-109.22	-106.21	-130.05
		1st quartile	-3.39	-3.94	-16.35	-12.61	-16.39
		Median	0.09	-0.55	-3.62	-1.86	-5.69
		3rd quartile	3.52	3.36	0.99	3.42	3.37
		Maximum	66.55	68.84	105.56	85.63	62.98
	IT FCBD— correction	Minimum	-54.02	-52.50	-135.69	-125.08	-161.01
		1st quartile	-2.89	-3.07	-16.13	-13.80	-25.59
		Median	0.27	0.09	-5.31	-1.89	-6.84
		3rd quartile	3.31	3.85	0.35	4.86	2.77
		Maximum	42.76	61.78	106.37	83.61	83.87
R101_2+2	US FCBD— correction	Minimum	-65.99	-50.96	-90.23	-70.91	-63.90
		1st quartile	-2.78	-3.46	-5.96	-8.70	-6.09
		Median	0.61	0.13	-0.56	-1.16	-0.34
		3rd quartile	4.20	5.43	3.89	3.23	4.57
		Maximum	65.71	75.92	116.14	119.39	62.76
		Minimum	-55.93	-77.57	-141.92	-149.24	-158.37

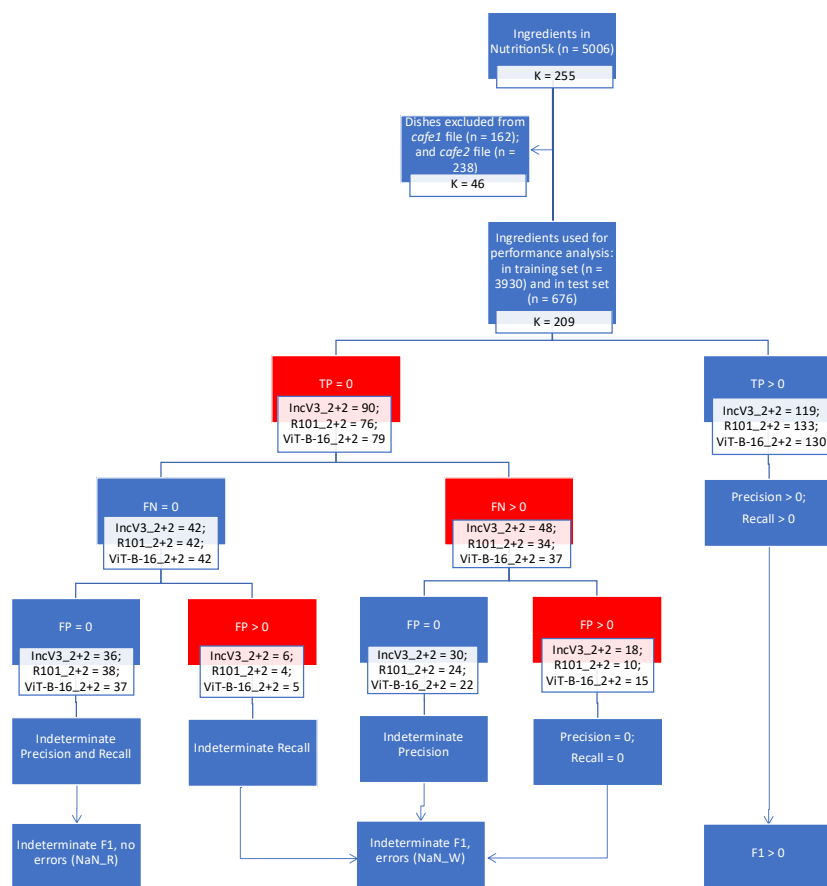
ViT-B-16_2+2	IT FCBD— correction	1st quartile	-3.44	-3.60	-9.62	-12.12	-26.42
		Median	0.05	-0.04	-2.18	-2.79	-10.78
		3rd quartile	3.93	3.43	0.48	0.35	-2.54
		Maximum	65.82	82.89	86.76	94.79	85.99
	US FCBD— correction	Minimum	-67.94	-31.16	-105.57	-64.38	-63.15
		1st quartile	-2.03	-2.94	-4.38	-5.19	-3.93
		Median	0.28	-0.05	-0.56	-0.56	0.18
		3rd quartile	3.04	3.55	2.55	4.17	5.46
		Maximum	42.74	40.24	75.66	90.90	49.23
	IT FCBD— correction	Minimum	-64.07	-33.39	-89.90	-59.10	-50.71
		1st quartile	-2.65	-2.75	-6.02	-4.28	-3.73
		Median	0.27	-0.15	-1.00	-0.32	-0.11
		3rd quartile	3.37	2.99	2.86	3.22	5.48
		Maximum	33.92	49.24	85.12	58.82	94.55

Abbreviations: FCDB, Food Composition Database; Inc V3, InceptionV3; MAPE, mean absolute percentage error; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

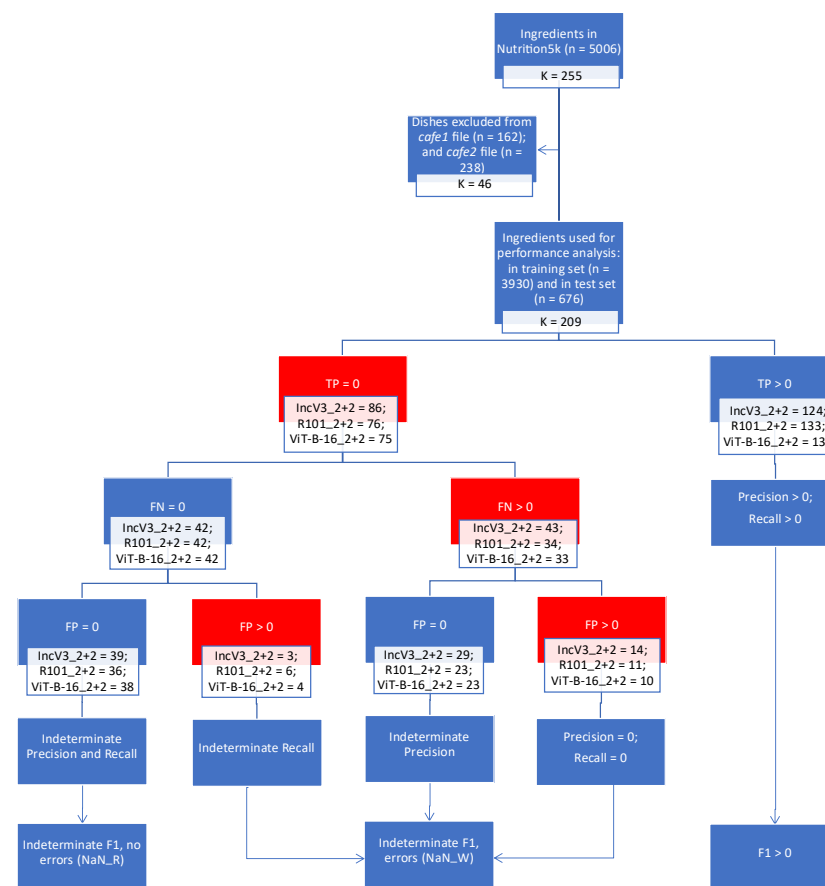
Figures D1-D2. Flowchart illustrating determinate and indeterminate F1 scores for a single ingredient from the test set, based on True Positives, False Negatives, and False Positives, before and after frame filtering, across the US and IT FCDBs, and according to the selected algorithms¹

US FCBD—correction

Before frame filtering

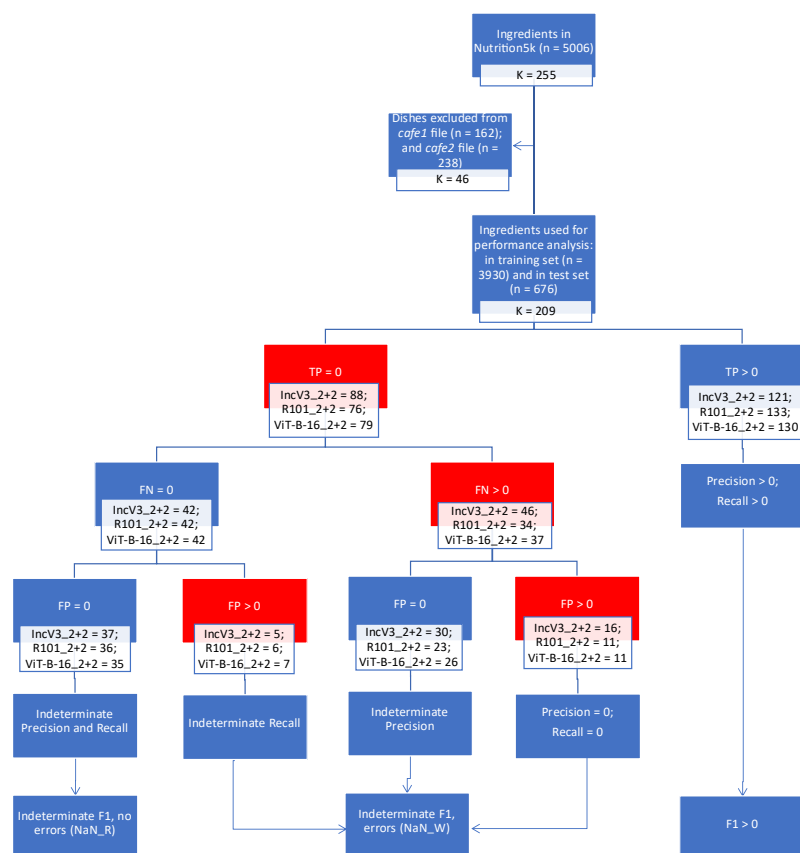


After frame filtering

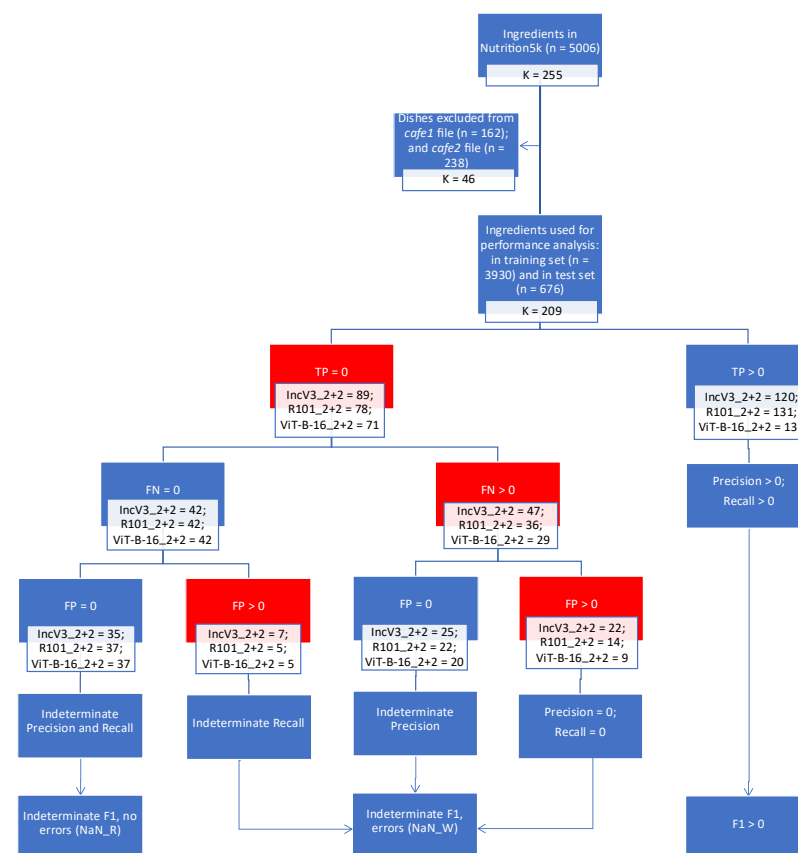


IT FCBD—correction

Before frame filtering

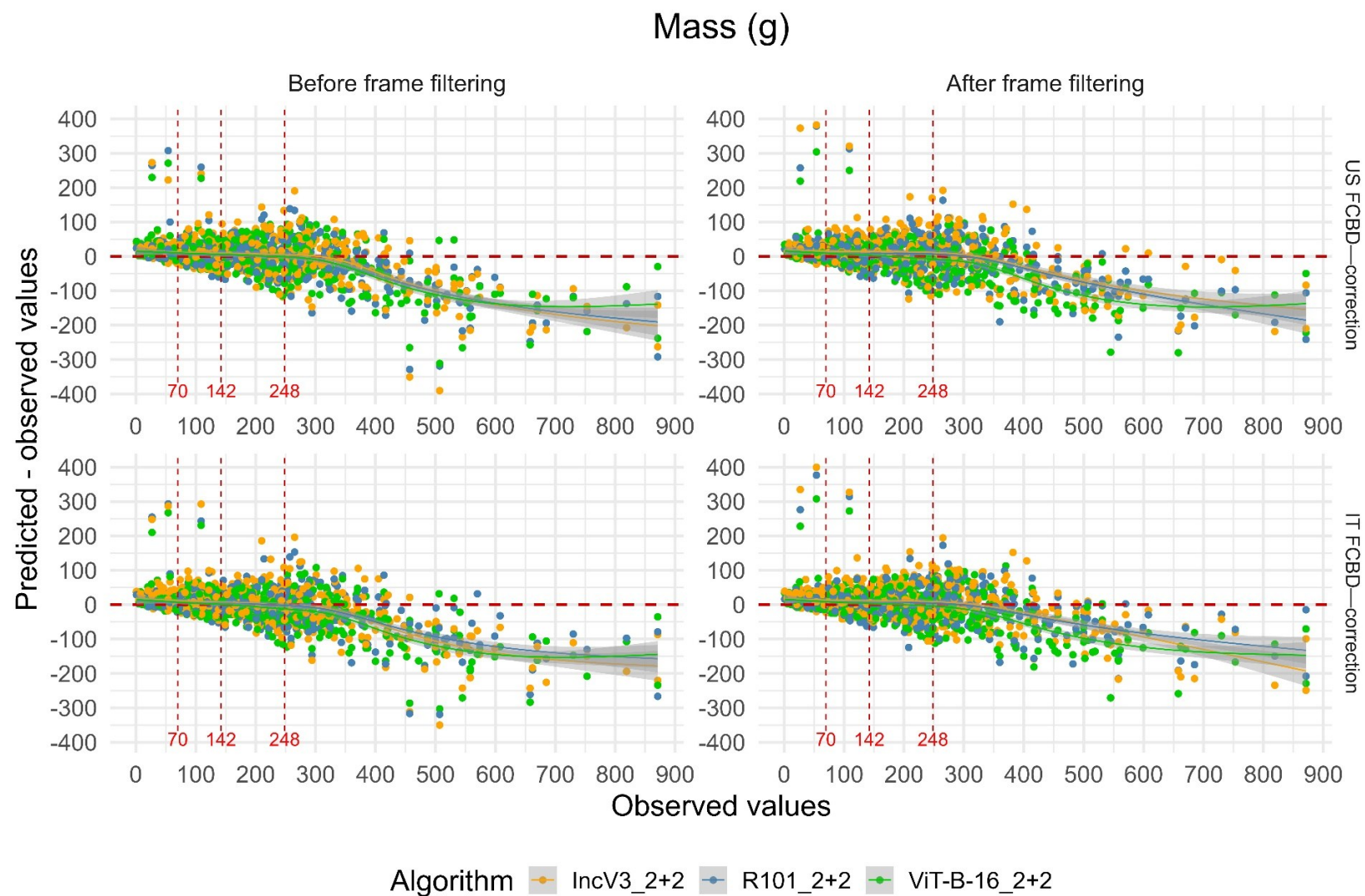


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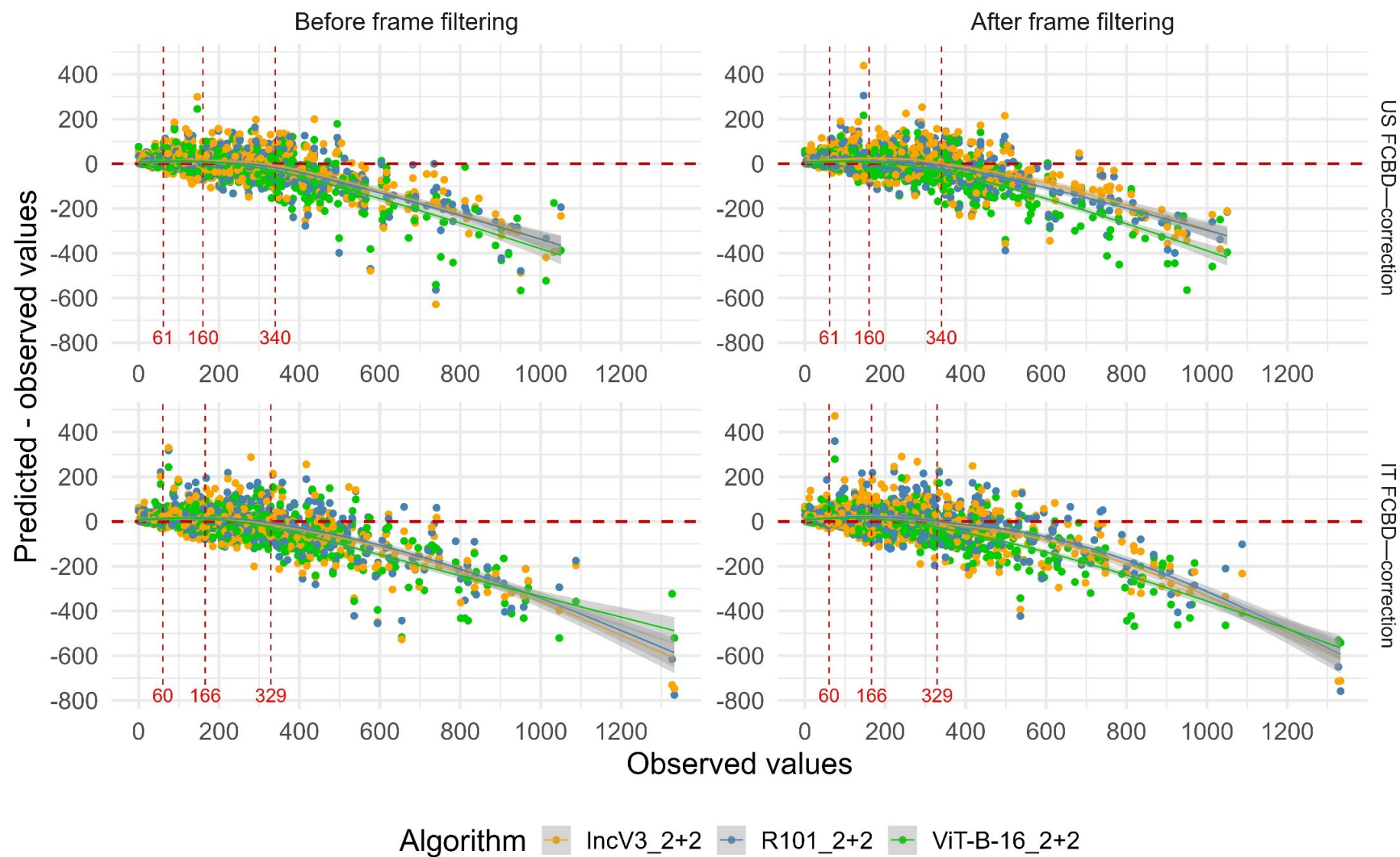


¹At successive steps, the number of ingredients was split into separate values according to the selected algorithms. Abbreviations: FCDB, Food Composition Database; FN, False Negatives; FP, False Positives; K, number of ingredients; IncV3, InceptionV3; n, number of dishes; NaN_R, Not a Number, but right prediction of an absent ingredient in the test set; NaN_W, Not a Number, but wrong prediction of an ingredient as specified in the current figures; R101, ResNet-101; TP, True Positives; ViT-B-16, Vision Transformer Base-16.

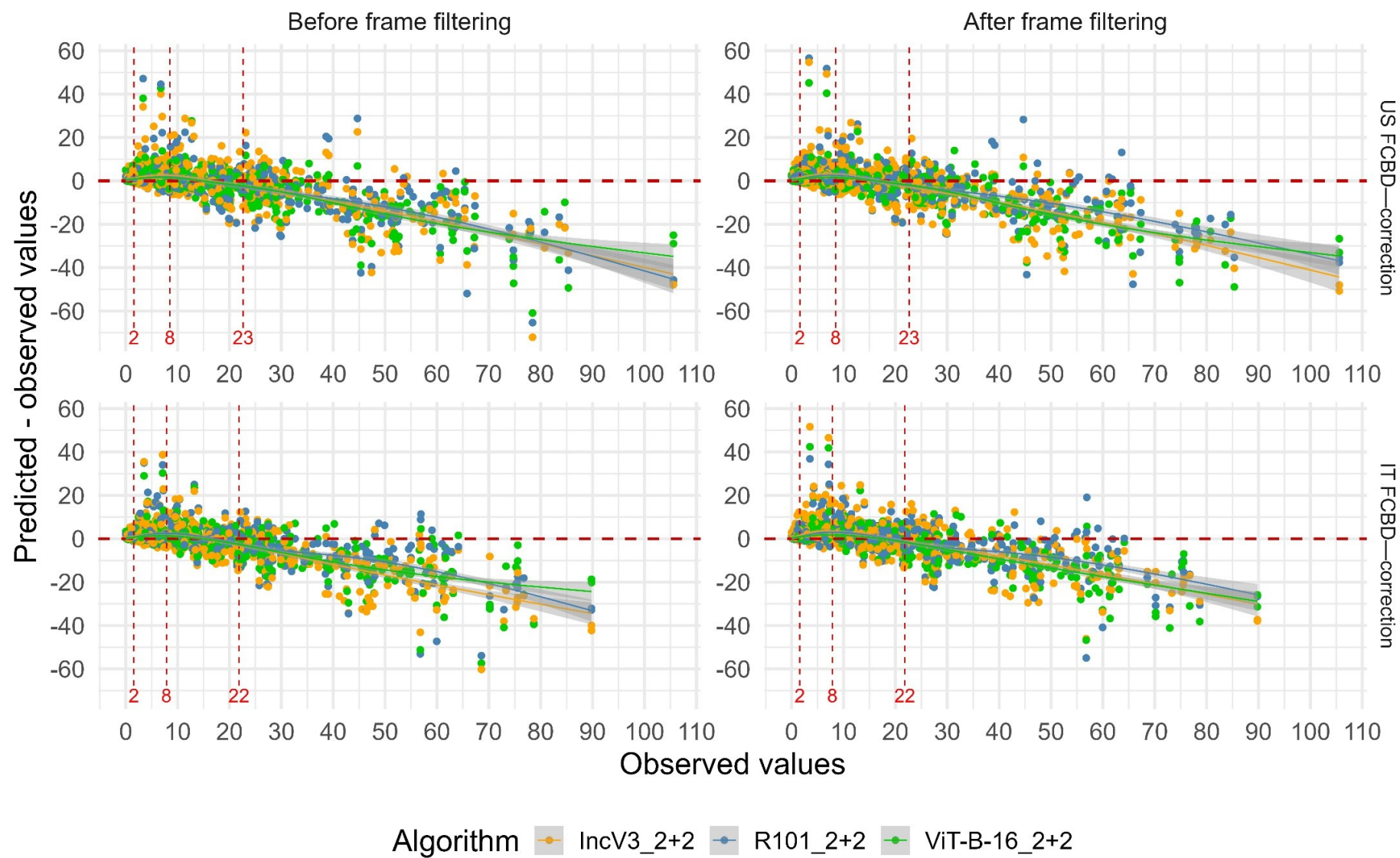
Figures D3-D7. Plots representing the raw absolute difference between predicted and observed number of ingredients on the test set (y-axis) versus the observed number of ingredients (x-axis). On the y-axis, the dotted line indicates the reference value of 0. Each panel represents mass, energy, or macronutrients content, and information is organized by dataset and frame filtering in 20 plots. Nutrition5k test set ($n = 676$)



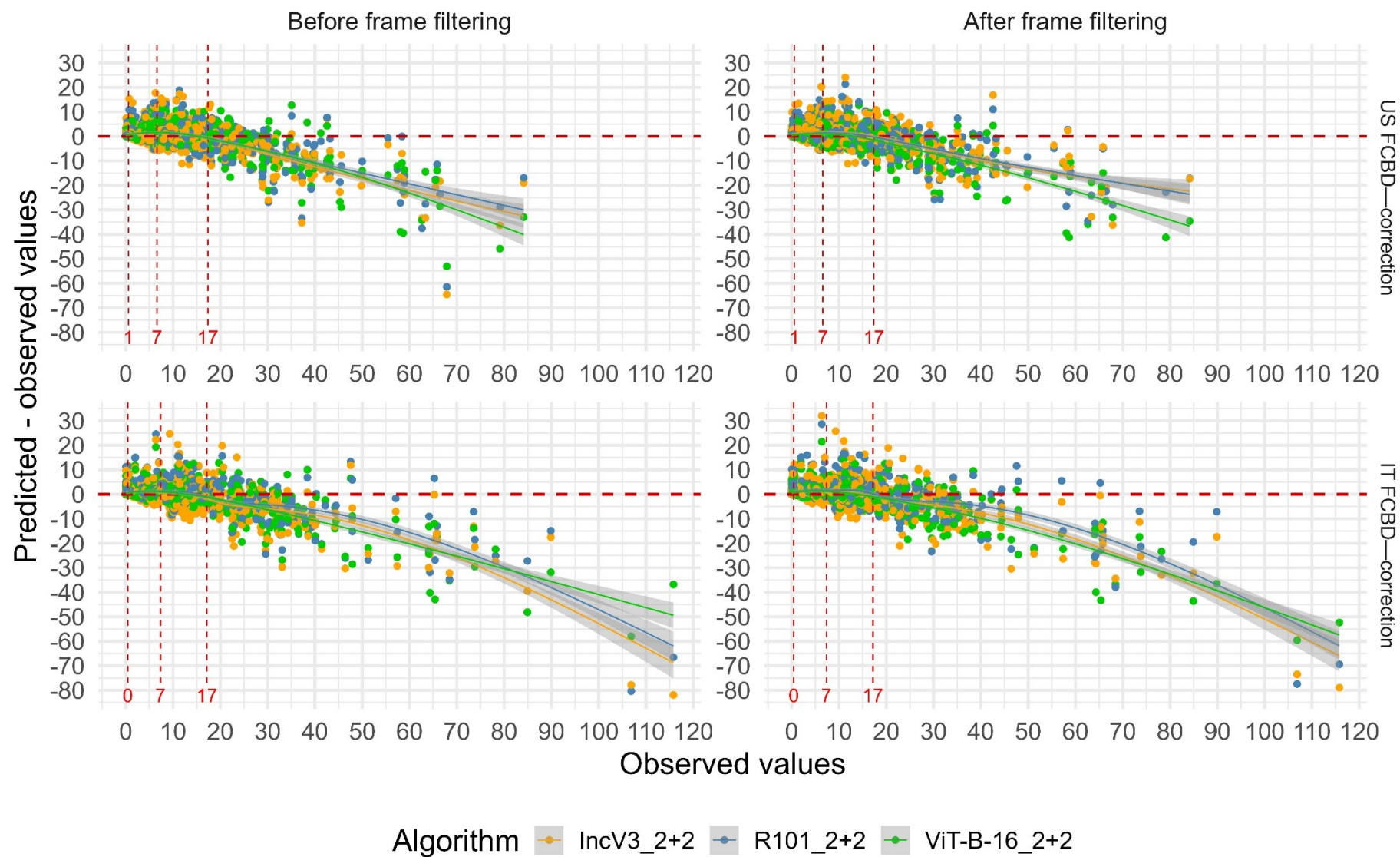
Energy content (kcal)



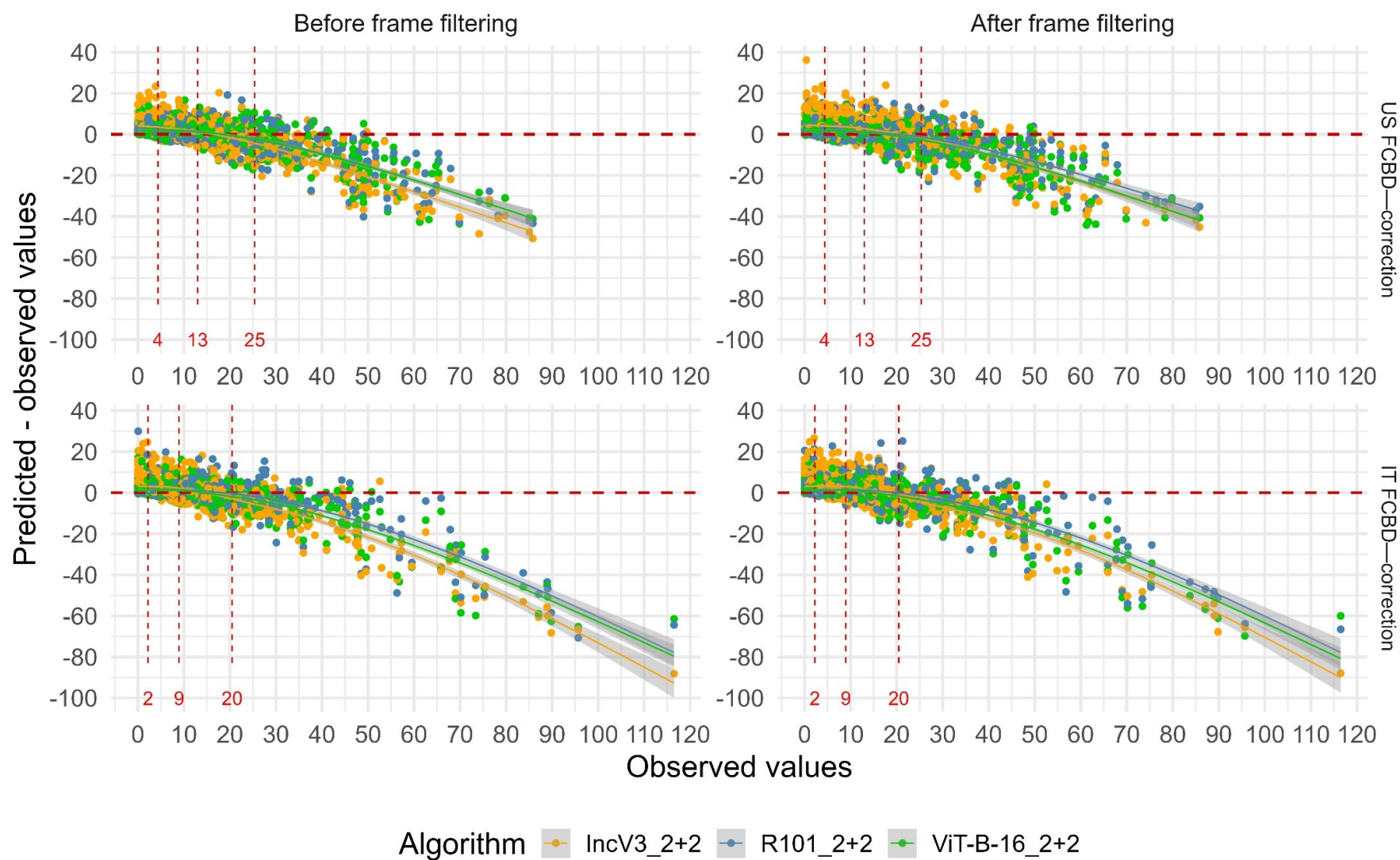
Protein content (g)



Fat content (g)

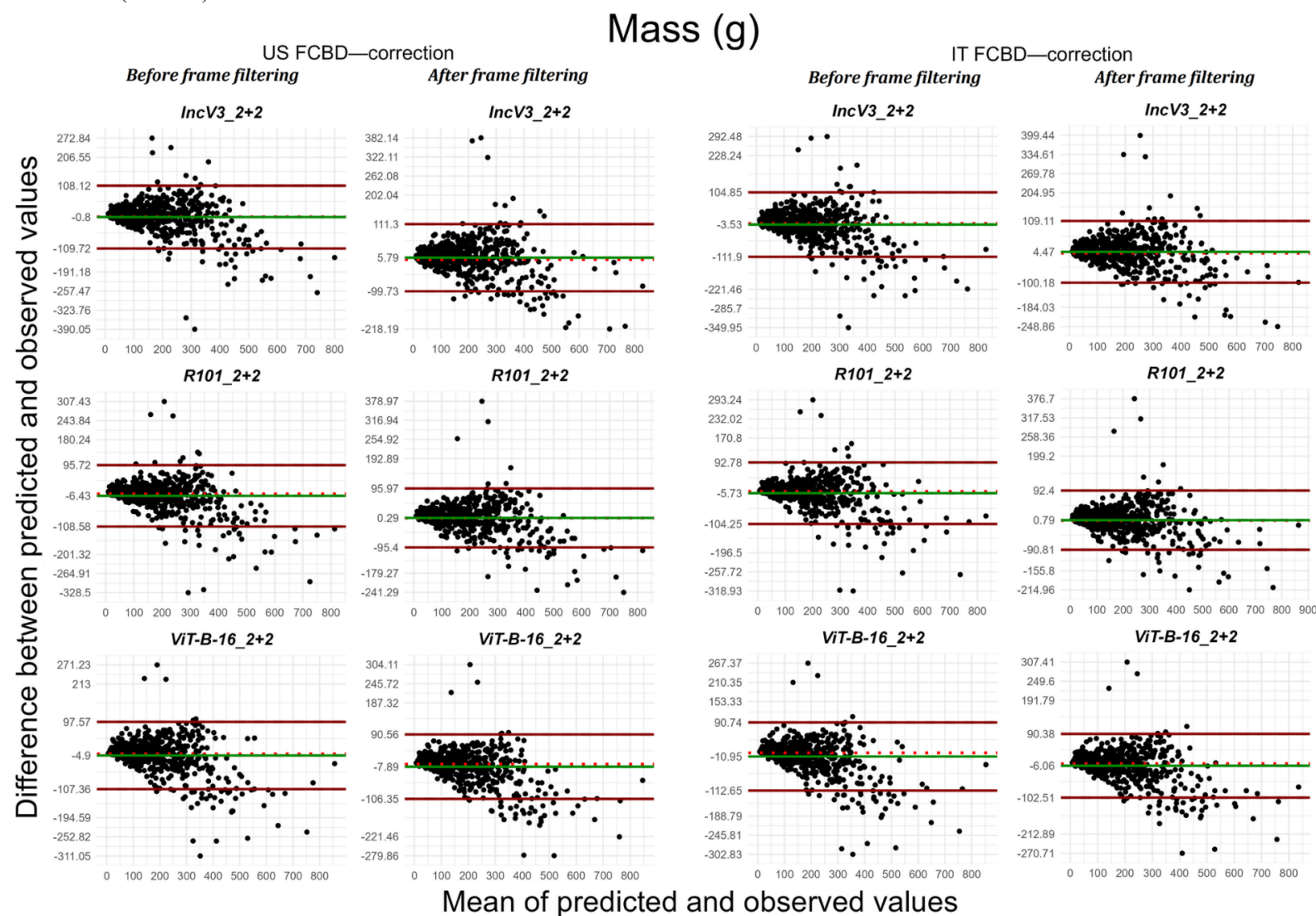


Carbohydrates content (g)

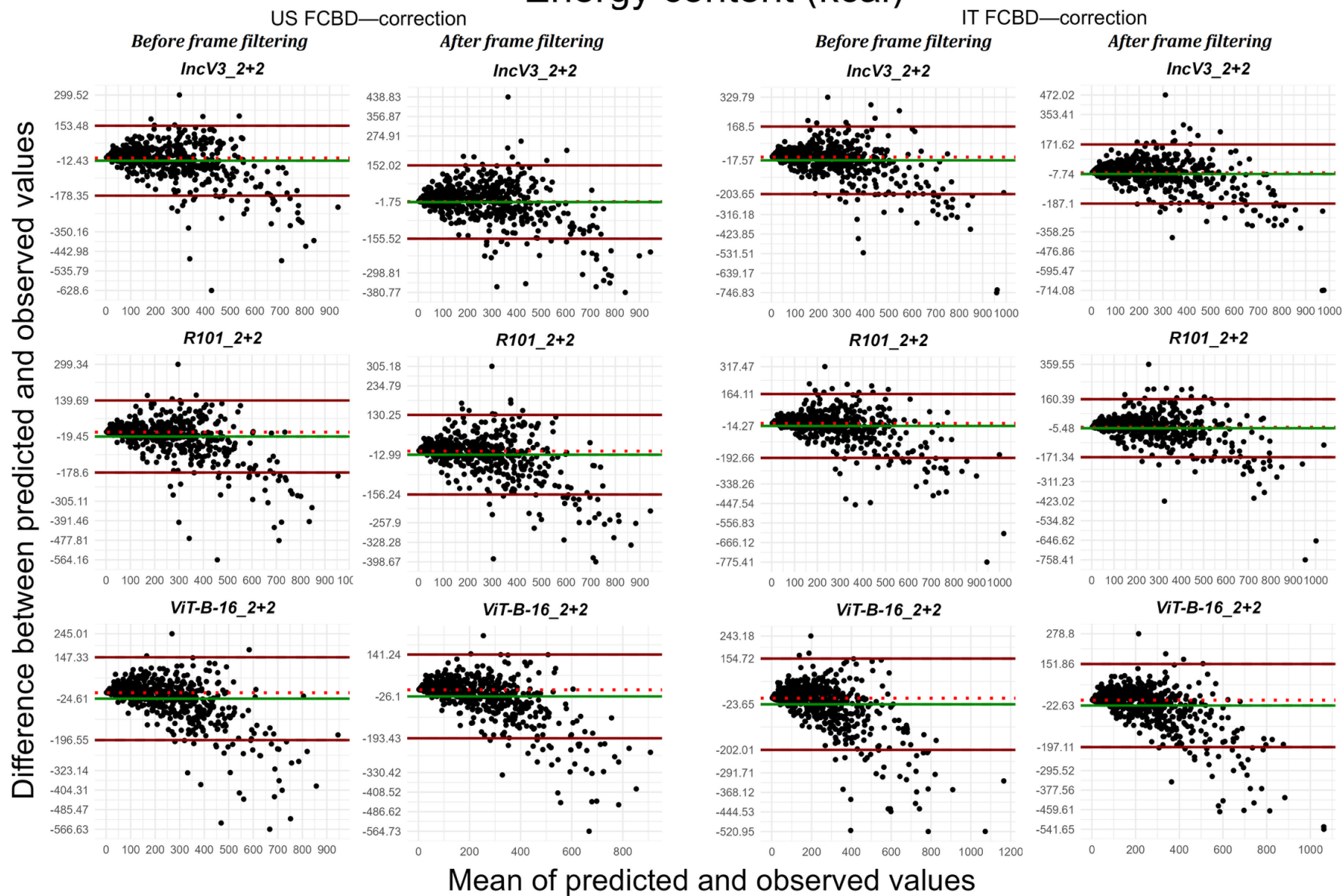


Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

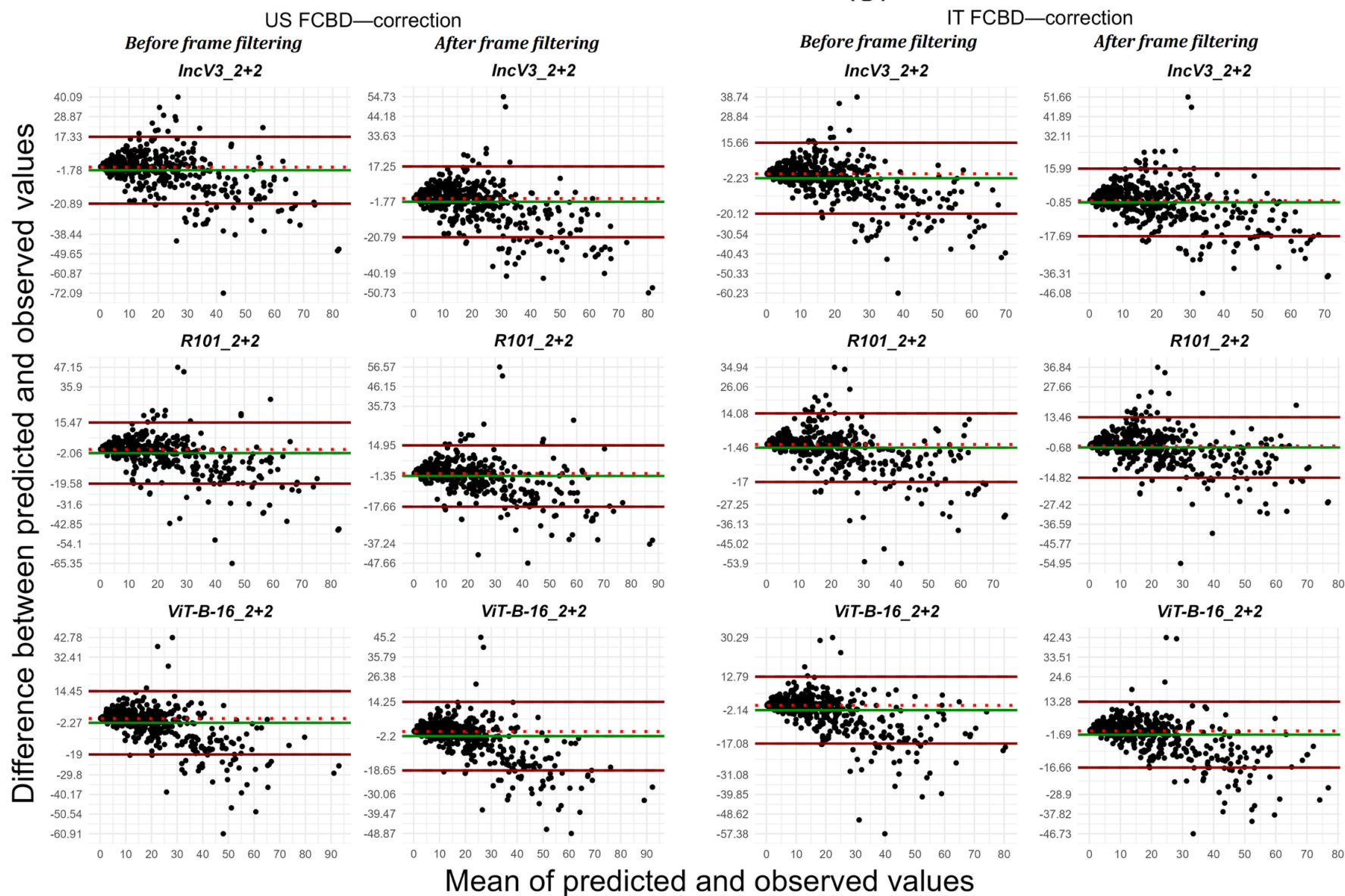
Figures D8-D12. Bland–Altman plots representing the raw absolute difference between predicted and observed values on the test set (y-axis) versus the mean of the predicted and observed values for each nutritional variable (x-axis), with corresponding 95% limits of agreement. On the y-axis, the dotted line indicates the reference value of 0. Each panel represents mass, energy, or macronutrients content, and information is organized by algorithm, frame filtering, and dataset in 60 plots. Nutrition5k test set ($n = 676$)



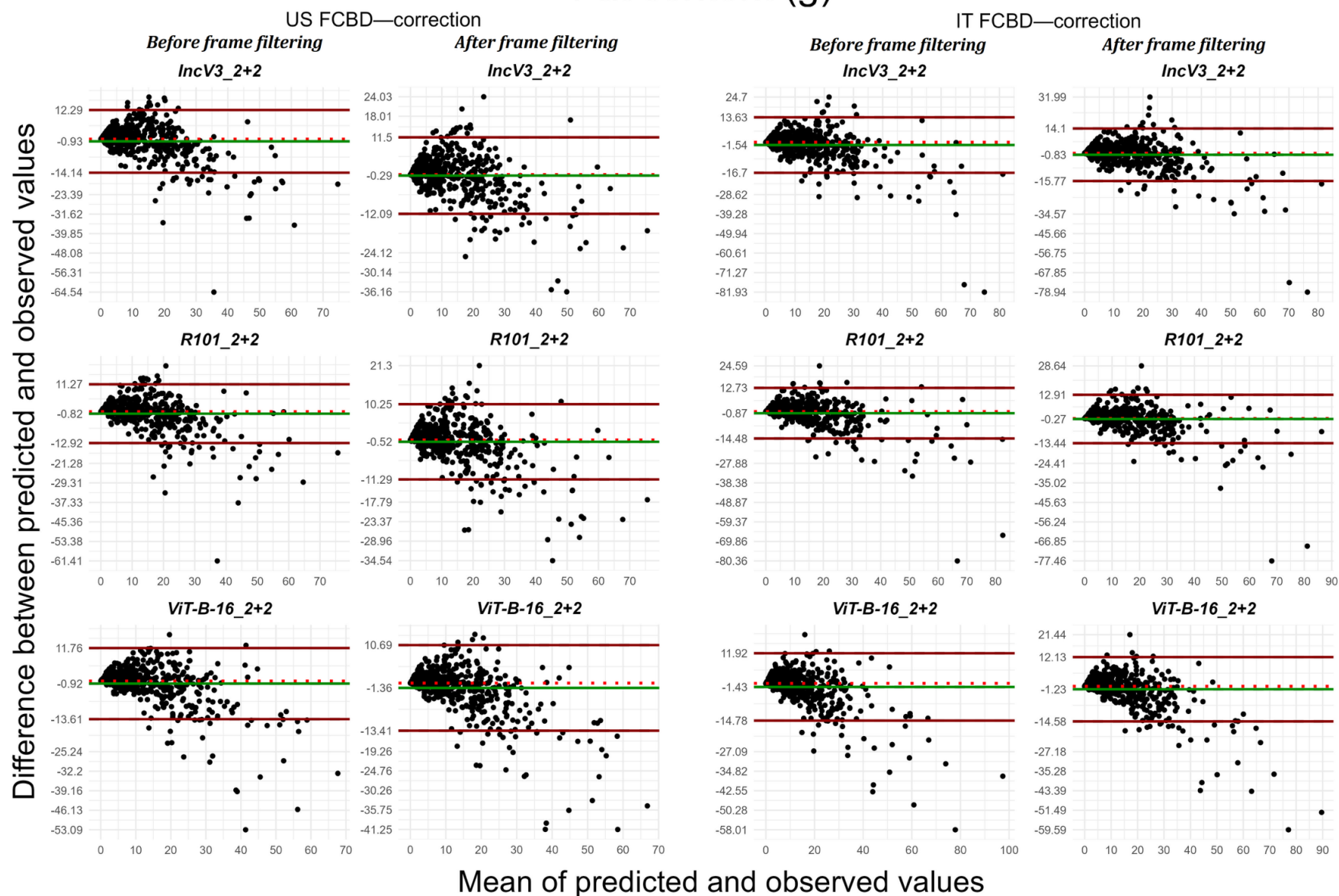
Energy content (kcal)



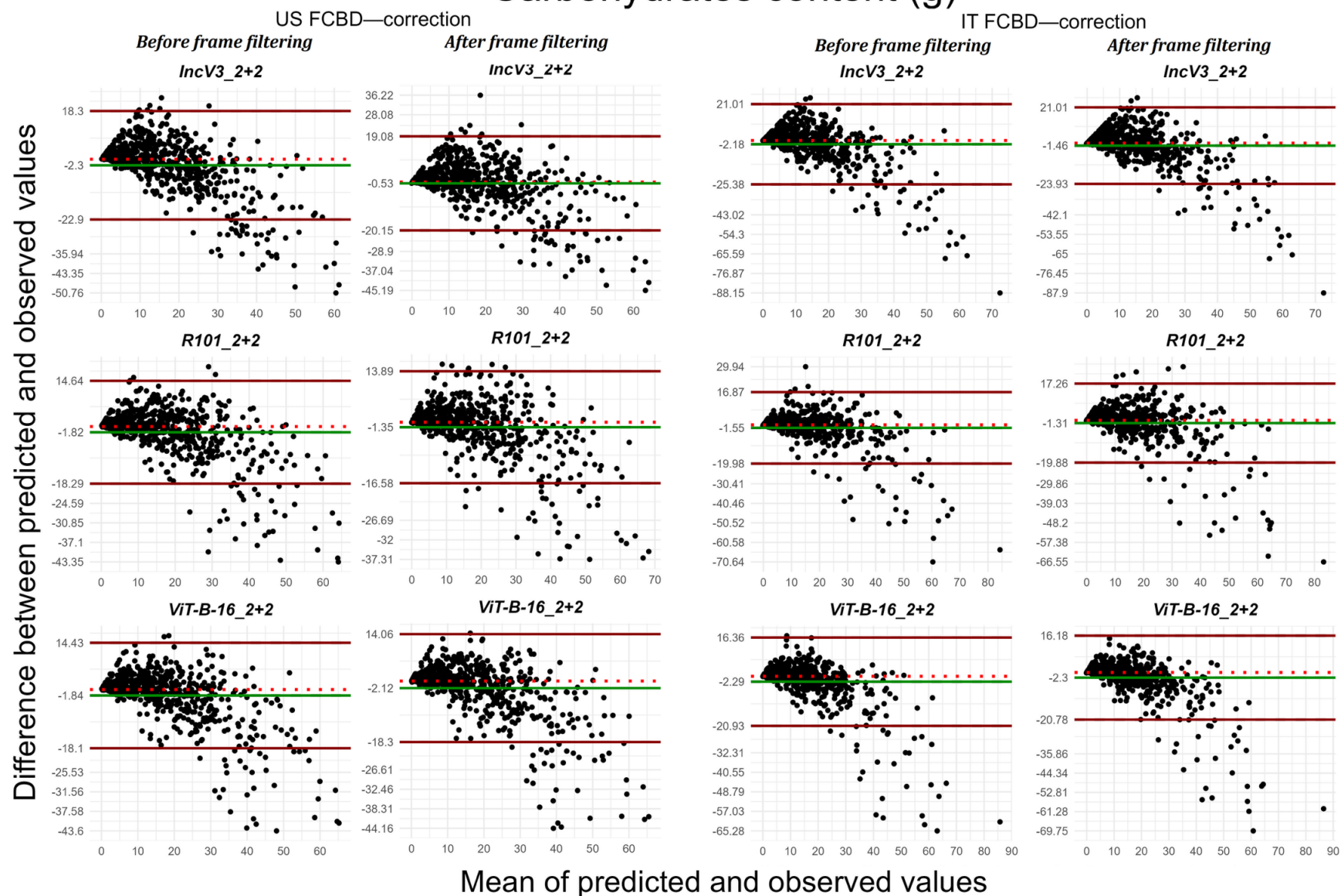
Protein content (g)



Fat content (g)

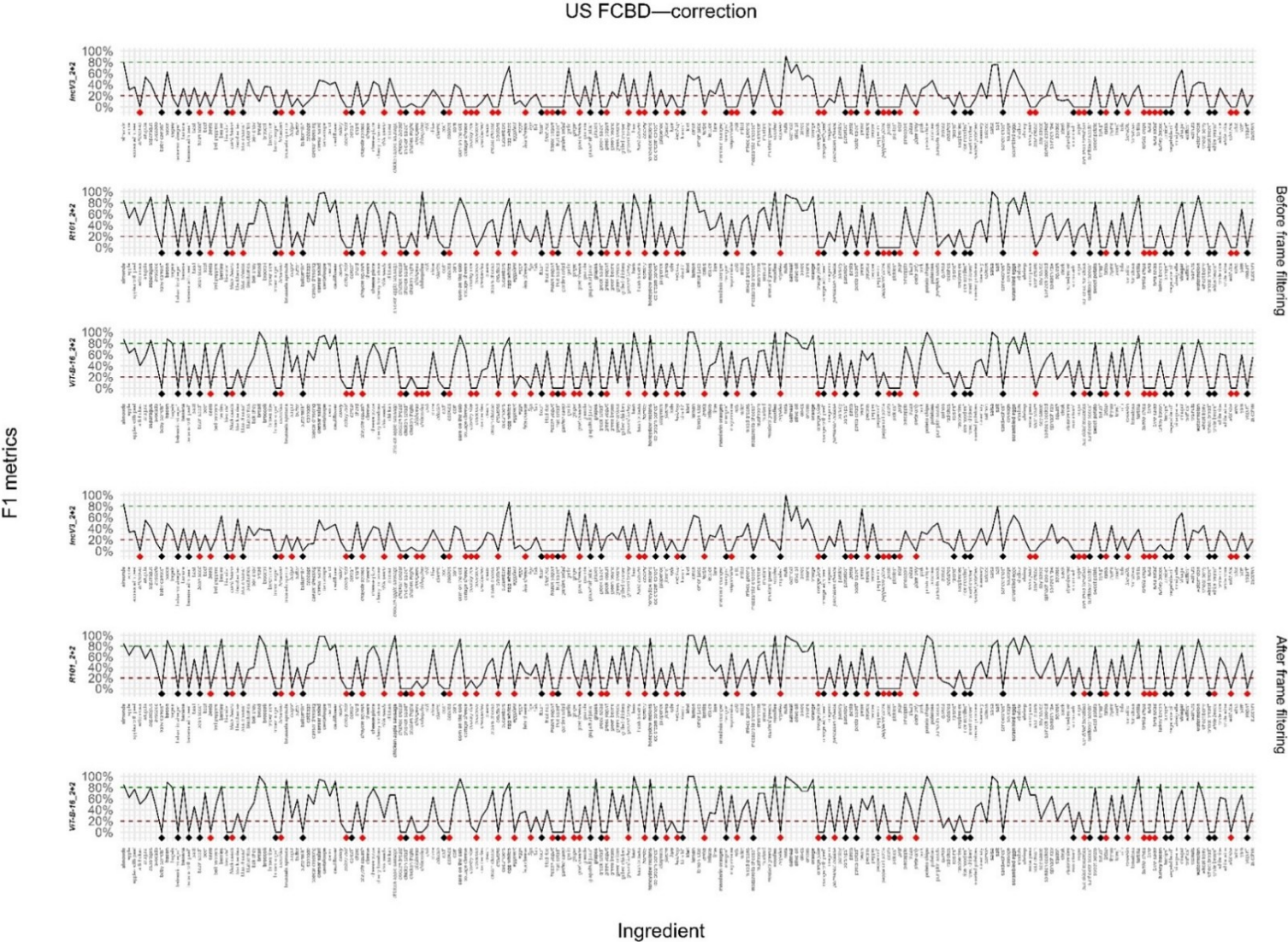


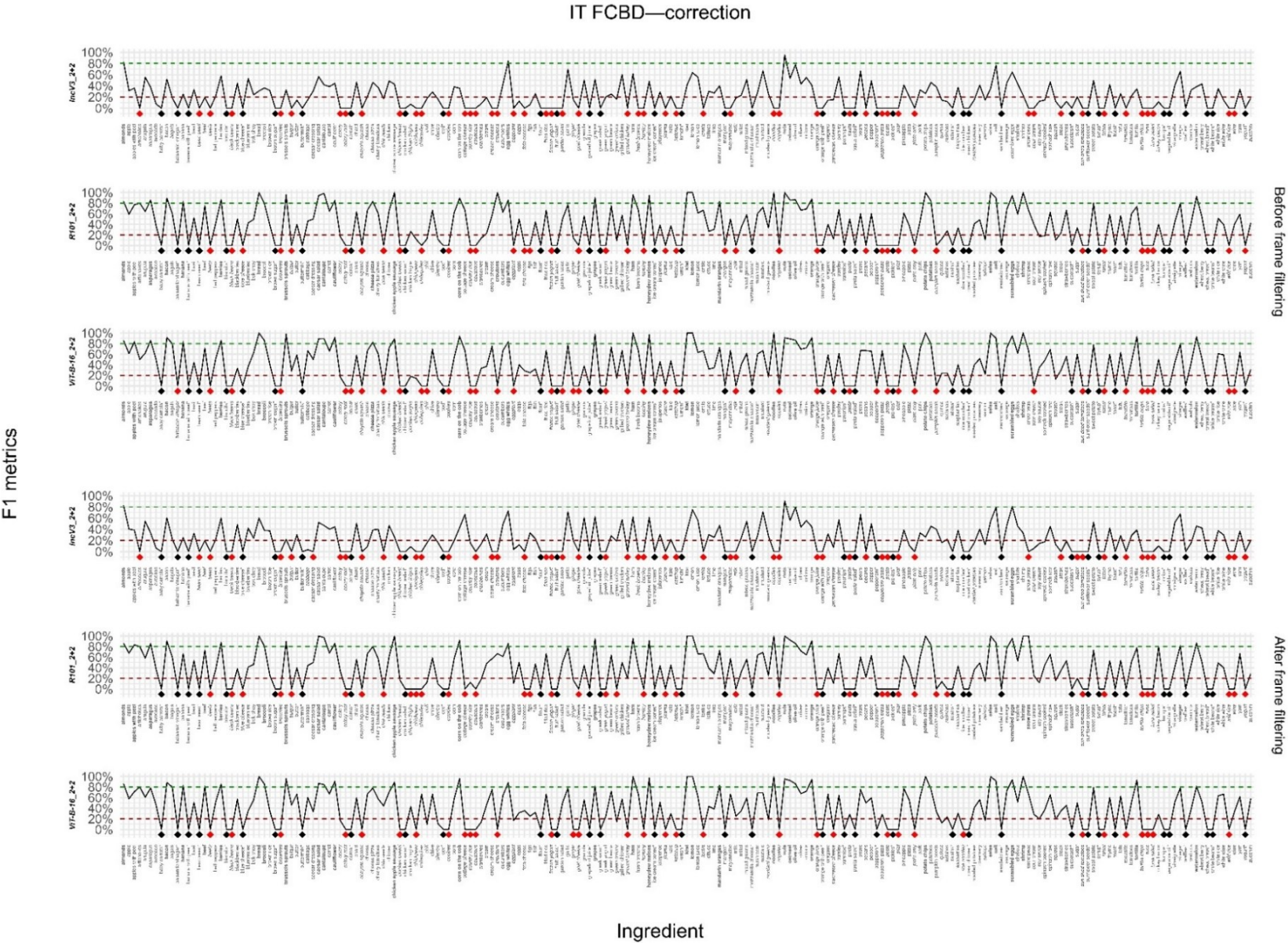
Carbohydrates content (g)



Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

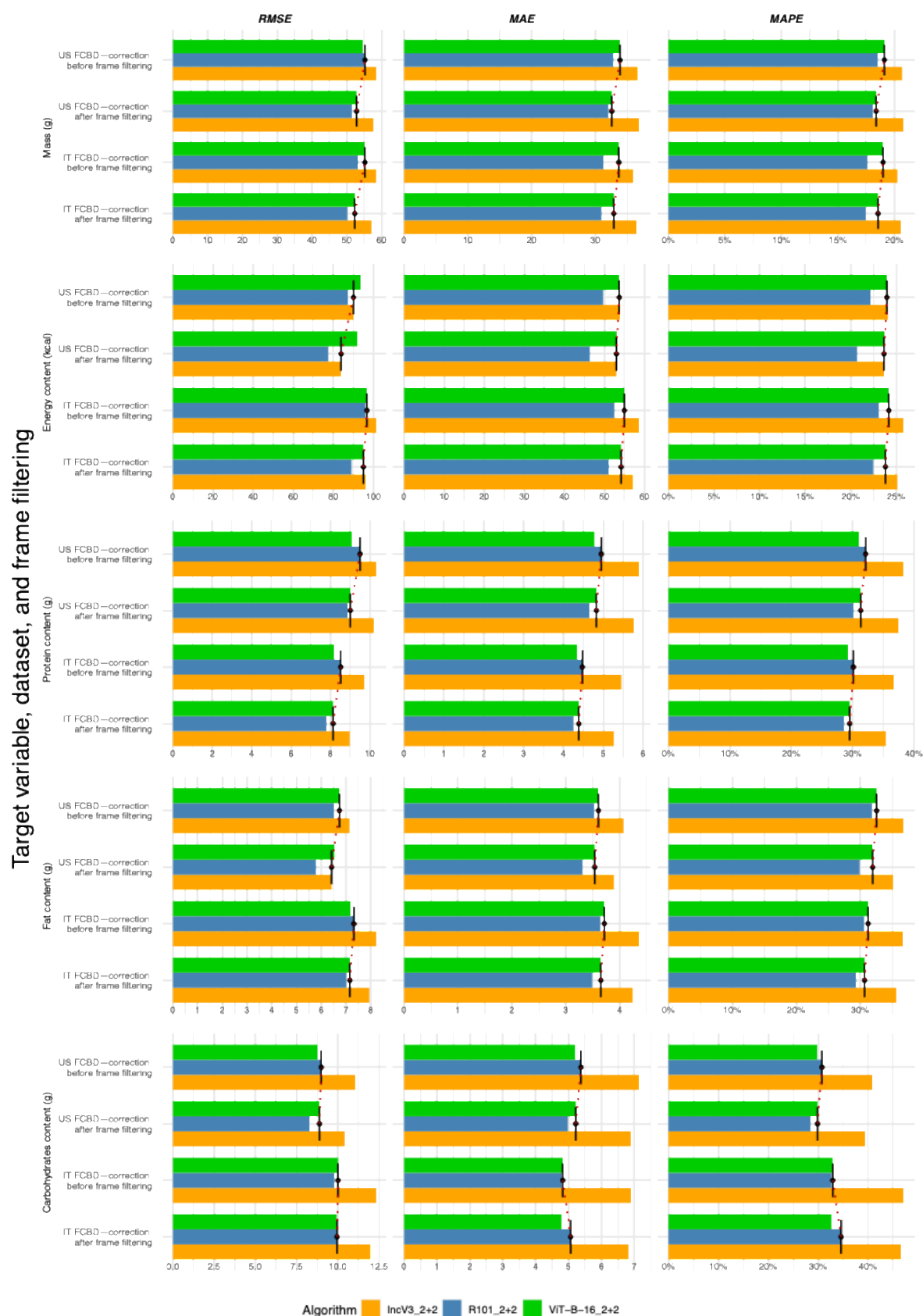
Figures D13-D14. Performance for ingredients prediction as measured by the F1-score, stratified by dataset, algorithm, and frame filtering¹. The red dots indicate NaN_R values (Not a Number, right ingredient prediction), while the black dots indicate NaN_W values (Not a Number, but wrong ingredient prediction), as described in **Tables D4-D5**. The green dashed line indicates an F1 score of 0.80, while the red line indicates an F1 score of 0.20





Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Figure D15. Performance metrics for mass, energy, and macronutrients prediction, stratified by algorithms, datasets, and frame filtering¹



¹To improve readability, each subfigure displays performance metrics using its own scale, reflecting substantial variations in the metric's range. Abbreviations: FCDB, Food Composition Database; IncV3, InceptionV3; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; R101, ResNet-101; RMSE, Root Mean Squared Error; ViT-B-16, Vision Transformer Base-16.

Figure D16. Kernel density estimation plots of the raw absolute difference in prediction errors (MAPE, %) between the current application and Bianco et al. (104) before frame filtering

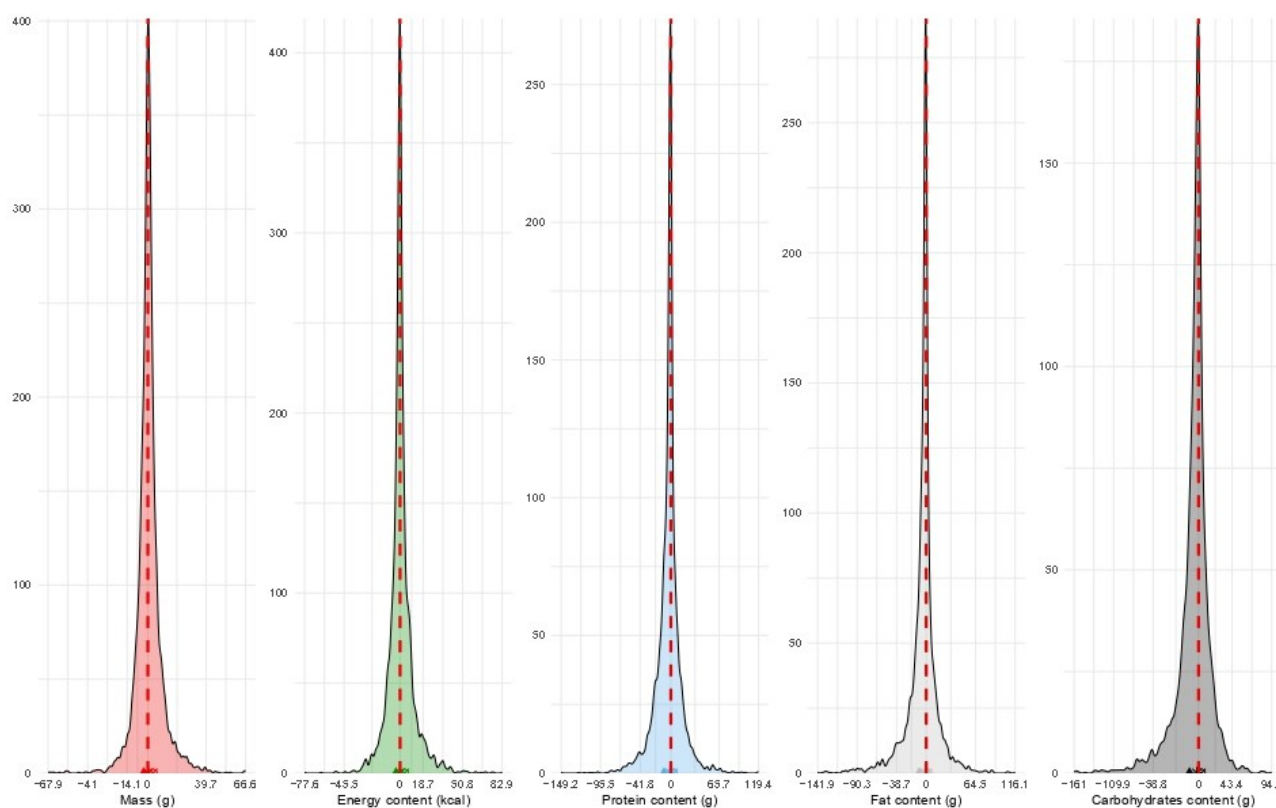
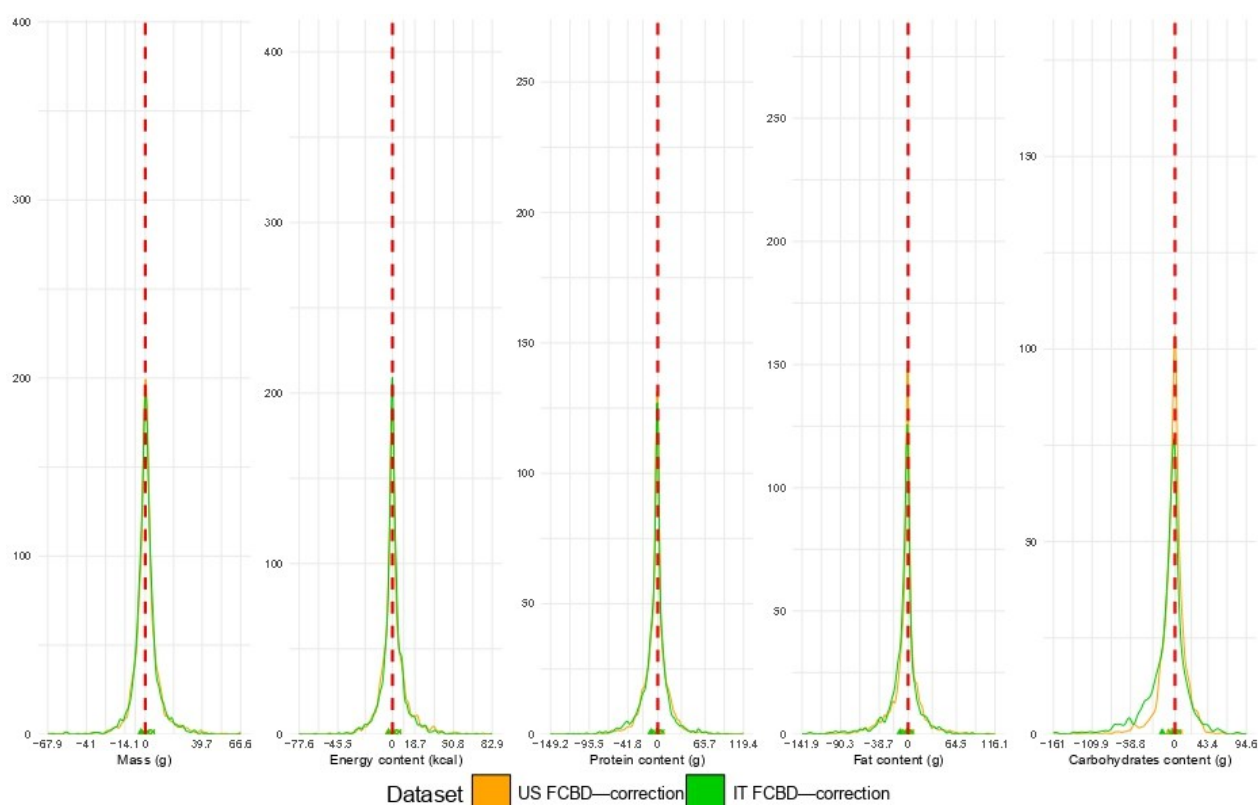
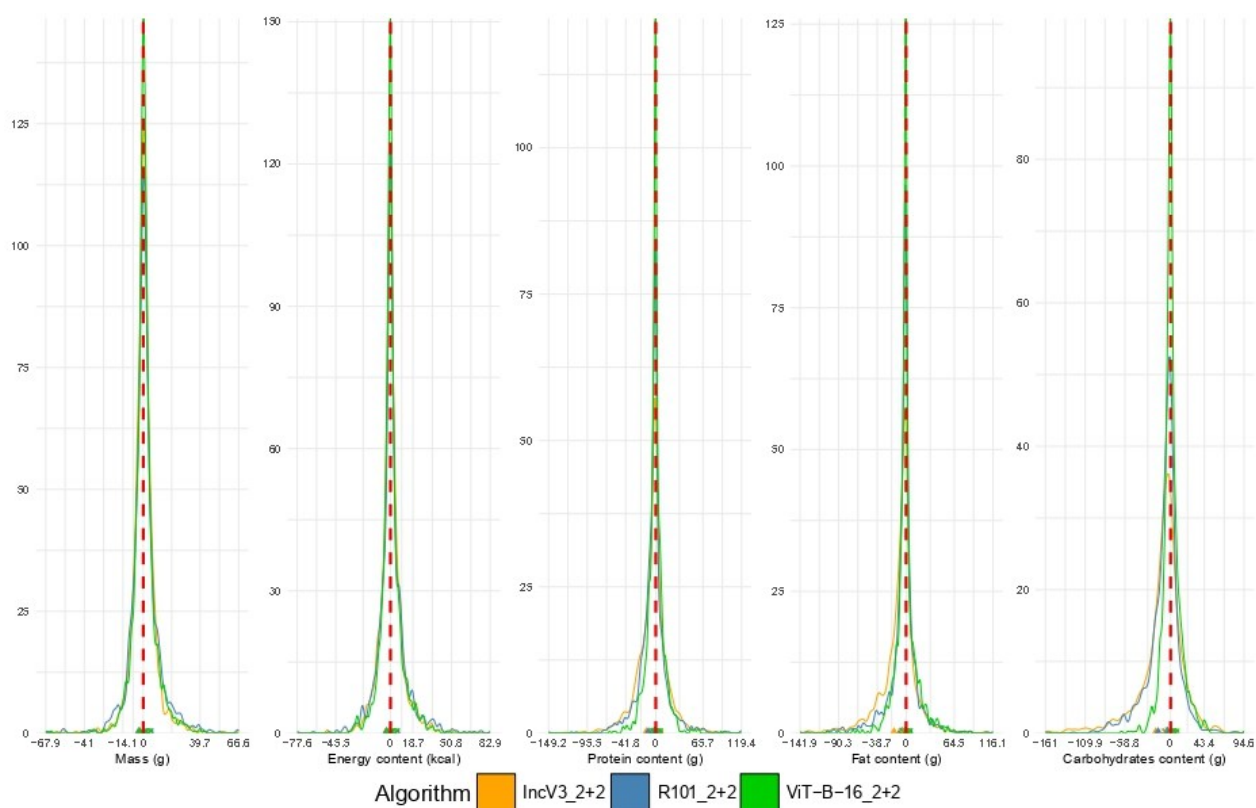


Figure D17. Kernel density estimation plots of the raw absolute difference in prediction errors (MAPE, %) between the current application and Bianco et al. (104), stratified by dataset before frame filtering



Abbreviations: FCDB, Food Composition Database

Figure D18. Kernel density estimation plots of the raw absolute difference in prediction errors (MAPE, %) between the current application and Bianco et al. (104), stratified by algorithm before frame filtering



Abbreviations: IncV3, InceptionV3; R101, ResNet-101; ViT-B-16, Vision Transformer Base-16.

Appendix E: Supplementary Materials Chapter 8

Figures E1–E2. RGB-Depth food-imaging setup, including the camera on its mounting arm, the motorized turntable with the dish, and the laptop interface for real-time capture



Figure E3. Examples of three recipes presented in small, medium, and large portion sizes, with corresponding portion weights¹ and nutrient composition

SPAGHETTI WITH TOMATO SAUCE

SMALL PORTION		MEDIUM PORTION		LARGE PORTION	
					
WEIGHT (g)	245.0	WEIGHT (g)	324.8	WEIGHT (g)	408.0
ENERGY (kcal)	272.1	ENERGY (kcal)	360.7	ENERGY (kcal)	453.1
PROTEIN (g)	9.1	PROTEIN (g)	12.1	PROTEIN (g)	15.2
FAT (g)	6.6	FAT (g)	8.7	FAT (g)	11.0
CARBOHYDRATES (g)	46.1	CARBOHYDRATES (g)	61.2	CARBOHYDRATES (g)	76.8

ROASTED PORK

SMALL PORTION		MEDIUM PORTION		LARGE PORTION	
					
WEIGHT (g)	136.0	WEIGHT (g)	194.0	WEIGHT (g)	228.0
ENERGY (kcal)	219.1	ENERGY (kcal)	312.6	ENERGY (kcal)	367.3
PROTEIN (g)	24.0	PROTEIN (g)	34.2	PROTEIN (g)	40.2
FAT (g)	13.5	FAT (g)	19.3	FAT (g)	22.7
CARBOHYDRATES (g)	0.3	CARBOHYDRATES (g)	0.4	CARBOHYDRATES (g)	0.5

TIRAMISÙ

SMALL PORTION		MEDIUM PORTION		LARGE PORTION	
					
WEIGHT (g)	87.0	WEIGHT (g)	116.8	WEIGHT (g)	146.9
ENERGY (kcal)	236.7	ENERGY (kcal)	317.7	ENERGY (kcal)	399.6
PROTEIN (g)	6.3	PROTEIN (g)	8.5	PROTEIN (g)	10.7
FAT (g)	13.7	FAT (g)	18.4	FAT (g)	23.1
CARBOHYDRATES (g)	23.1	CARBOHYDRATES (g)	31.1	CARBOHYDRATES (g)	39.1

¹Portion weights refer to cooked weights for all dishes except “Tiramisù”, which is assembled raw; its weight is therefore unaffected by any cooking process

Appendix F: Supplementary Materials Chapter 9

Table F1. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the vegetable food group (≥ 14 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.034
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	1.76	1.04–3.02	
Sex				0.992
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.00	0.60–1.64	
Age (x5 years)	316	1.03	0.84–1.27	0.771
Education (class)				0.641
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.76	0.36–1.62	
<i>(17,27]</i>	193	1.02	0.54–1.94	
BMI (class)				0.880
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	1.16	0.65–2.05	
<i>[30,44.4]</i>	31	1.05	0.44–2.39	
CVD risk factors				0.386
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.80	0.48–1.33	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F2. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the fruit food group (≥ 14 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.635
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	1.15	0.65–2.07	
Sex				0.371
<i>Females</i>	195	—	—	
<i>Males</i>	121	0.77	0.43–1.36	
Age (x5 years)	316	1.03	0.82–1.30	0.794
Education (class)				0.022
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.74	0.27–2.00	
<i>(17,27]</i>	193	1.94	0.92–4.43	
BMI (class)				0.136
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.51	0.24–1.02	
<i>[30,44.4]</i>	31	0.60	0.19–1.60	
CVD risk factors				0.403
<i>No</i>	192	—	—	
<i>Yes</i>	124	1.28	0.72–2.26	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F3. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the bread and cereals food group (≥ 14 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.155
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	1.45	0.87–2.45	
Sex				0.002
<i>Females</i>	195	—	—	
<i>Males</i>	121	2.18	1.34–3.57	
Age (x5 years)	316	1.24	1.01–1.53	0.038
Education (class)				0.027
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	1.02	0.47–2.19	
<i>(17,27]</i>	193	2.01	1.06–3.92	
BMI (class)				0.928
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	1.11	0.62–1.96	
<i>[30,44.4]</i>	31	1.11	0.48–2.55	
CVD risk factors				0.594
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.87	0.52–1.44	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F4. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the milk and yogurt food group (≤ 14 times per week)

Characteristic	N	OR	95% CI	p-value
Center				<0.001
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.23	0.09–0.53	
Sex				0.407
<i>Females</i>	195	—	—	
<i>Males</i>	121	0.75	0.38–1.49	
Age (x5 years)	316	0.95	0.72–1.25	0.714
Education (class)				0.259
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	1.21	0.38–3.86	
<i>(17,27]</i>	193	0.62	0.23–1.49	
BMI (class)				0.123
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	2.27	0.96–6.04	
<i>[30,44.4]</i>	31	2.16	0.66–9.78	
CVD risk factors				0.996
<i>No</i>	192	—	—	
<i>Yes</i>	124	1.00	0.49–2.06	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F5. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the dairy food group (< 3 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.642
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	1.13	0.68–1.85	
Sex				0.465
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.20	0.74–1.93	
Age (x5 years)	316	0.84	0.69–1.03	0.090
Education (class)				0.221
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.90	0.43–1.85	
<i>(17,27]</i>	193	0.62	0.33–1.15	
BMI (class)				0.719
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	1.18	0.67–2.05	
<i>[30,44.4]</i>	31	1.33	0.60–3.02	
CVD risk factors				0.319
<i>No</i>	192	—	—	
<i>Yes</i>	124	1.28	0.79–2.09	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F6. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the bakery products food group (< 3 times per week)

Characteristic	N	OR	95% CI	p-value
Center				<0.001
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.32	0.18–0.55	
Sex				0.060
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.63	0.98–2.75	
Age (x5 years)	316	1.33	1.08–1.66	0.008
Education (class)				0.275
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.60	0.28–1.27	
<i>(17,27]</i>	193	0.96	0.50–1.84	
BMI (class)				0.169
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	1.11	0.62–2.01	
<i>[30,44.4]</i>	31	2.35	0.97–6.22	
CVD risk factors				0.383
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.79	0.47–1.33	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F7. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the legumes food group (≥ 3 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.076
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.58	0.32–1.06	
Sex				0.227
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.43	0.80–2.56	
Age (x5 years)	316	1.07	0.84–1.37	0.569
Education (class)				0.126
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.38	0.13–1.00	
<i>(17,27]</i>	193	0.76	0.37–1.61	
BMI (class)				0.105
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.66	0.32–1.31	
<i>[30,44.4]</i>	31	0.31	0.07–0.98	
CVD risk factors				0.769
<i>No</i>	192	—	—	
<i>Yes</i>	124	1.09	0.60–1.98	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F8. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the potatoes food group (≤ 3 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.001
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.14	0.02–0.50	
Sex				0.991
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.01	0.40–2.59	
Age (x5 years)	316	1.23	0.83–1.85	0.305
Education (class)				0.911
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	1.14	0.33–4.02	
<i>(17,27]</i>	193	1.27	0.40–3.71	
BMI (class)				0.394
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.89	0.31–2.81	
<i>[30,44.4]</i>	31	0.42	0.13–1.54	
CVD risk factors				0.517
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.73	0.29–1.90	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F9. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the fish food group (≥ 3 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.280
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.73	0.42–1.29	
Sex				0.454
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.23	0.71–2.12	
Age (x5 years)	316	1.09	0.87–1.37	0.458
Education (class)				0.631
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.89	0.37–2.17	
<i>(17,27]</i>	193	1.24	0.60–2.64	
BMI (class)				0.183
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.55	0.27–1.06	
<i>[30,44.4]</i>	31	0.66	0.24–1.63	
CVD risk factors				0.022
<i>No</i>	192	—	—	
<i>Yes</i>	124	1.90	1.10–3.31	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F10. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the eggs food group (≤ 4 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.412
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.69	0.27–1.65	
Sex				0.192
<i>Females</i>	195	—	—	
<i>Males</i>	121	0.59	0.26–1.31	
Age (x5 years)	316	0.99	0.71–1.40	0.957
Education (class)				0.572
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	1.65	0.44–6.87	
<i>(17,27]</i>	193	0.92	0.30–2.46	
BMI (class)				0.646
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.65	0.27–1.65	
<i>[30,44.4]</i>	31	0.80	0.23–3.77	
CVD risk factors				0.040
<i>No</i>	192	—	—	
<i>Yes</i>	124	2.52	1.04–6.80	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F11. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the white meat food group (≤ 2 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.187
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	1.51	0.82–2.77	
Sex				0.329
<i>Females</i>	195	—	—	
<i>Males</i>	121	1.35	0.74–2.53	
Age (x5 years)	316	1.12	0.87–1.44	0.395
Education (class)				0.310
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.94	0.40–2.18	
<i>(17,27]</i>	193	1.54	0.71–3.22	
BMI (class)				0.526
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	1.09	0.55–2.27	
<i>[30,44.4]</i>	31	0.62	0.26–1.61	
CVD risk factors				0.695
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.89	0.48–1.64	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F12. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the red meat food group (≤ 1 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.163
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.69	0.41–1.16	
Sex				0.100
<i>Females</i>	195	—	—	
<i>Males</i>	121	0.65	0.38–1.09	
Age (x5 years)	316	0.97	0.79–1.20	0.789
Education (class)				0.847
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	1.09	0.50–2.36	
<i>(17,27]</i>	193	0.91	0.47–1.79	
BMI (class)				0.107
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.57	0.30–1.04	
<i>[30,44.4]</i>	31	0.52	0.19–1.26	
CVD risk factors				0.568
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.86	0.51–1.45	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F13. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the processed meat food group (< 1 times per week)

Characteristic	N	OR	95% CI	p-value
Center				<0.001
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.27	0.13–0.54	
Sex				0.188
<i>Females</i>	195	—	—	
<i>Males</i>	121	0.61	0.28–1.26	
Age (x5 years)	316	1.11	0.84–1.48	0.457
Education (class)				0.498
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	0.97	0.34–2.76	
<i>(17,27]</i>	193	0.64	0.27–1.63	
BMI (class)				0.129
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.72	0.30–1.60	
<i>[30,44.4]</i>	31	0.19	0.01–0.99	
CVD risk factors				0.162
<i>No</i>	192	—	—	
<i>Yes</i>	124	0.60	0.28–1.22	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

Table F14. Adjusted odds ratios (95% CI) for adherence to the recommended consumption cut-off for the sweets food group (< 2 times per week)

Characteristic	N	OR	95% CI	p-value
Center				0.002
<i>Milan</i>	112	—	—	
<i>Udine</i>	204	0.37	0.19–0.70	
Sex				0.009
<i>Females</i>	195	—	—	
<i>Males</i>	121	0.40	0.19–0.80	
Age (x5 years)	316	1.14	0.87–1.49	0.348
Education (class)				0.019
<i>[11,15]</i>	59	—	—	
<i>(15,17]</i>	64	4.82	1.56–18.4	
<i>(17,27]</i>	193	3.19	1.14–11.5	
BMI (class)				0.871
<i>[17.4,25)</i>	209	—	—	
<i>[25,30)</i>	76	0.87	0.38–1.86	
<i>[30,44.4]</i>	31	1.20	0.36–3.45	
CVD risk factors				0.331
<i>No</i>	192	—	—	
<i>Yes</i>	124	1.38	0.72–2.65	

Abbreviations: BMI, Body Mass Index; CI, Confidence Interval; CVD, cardiovascular diseases; N, number of subjects; OR, Odds Ratio.

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“And once the storm is over, you won’t remember how you made it through... But one thing is certain. When you come out of the storm, you won’t be the same person who walked in.” (Murakami, H., *Kafka on the Shore*, 2002).

It has been many years since I first read that novel in high school, with the curiosity and naïveté typical of that age, and that line has echoed in my mind ever since. Looking back, I realize that the same naïve curiosity was also present when I decided to embark on what I thought would be a “simple” academic journey. Today, that journey comes to an end. As I write these lines, with a touch of emotion, I cannot help but think of all those who accompanied me along the way. One thing is certain: I was never alone.

I would first like to thank my supervisors, Prof. Maria Parpinel and Prof. Miriam Isola, for giving me the opportunity to carry out this research within the PhD program, for their guidance and valuable advice throughout the different projects...and for the useful tips that helped me discover a bit more about Friuli Venezia Giulia.

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Oh, new adventures. At the beginning of this journey, I already had the feeling that Brianza would not be waiting for me in November 2025. For every path that ends, another begins; that is what I always try to make happen, because standing still means getting a little lost. And no matter how frightening the new may seem, there is always that spark of excitement and adrenaline that drives me to embrace it, something essential both for a researcher and in life.

Here's to new adventures, to every ending that becomes a beginning, to fear giving way to enthusiasm. A bit of madness is the key to seeing new colors, and that is how I want to continue: curious, determined, and brave enough to change direction when needed.

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1. Coluccia S, Marinoni M, **Bianco R**, Parpinel M, Ferraroni M, Edefonti V. Diet and disease risk: a systematic review on machine learning methods. Joint Conference of the Italian and Eastern Mediterranean Regions of the International Biometric Society (IBS-IR-EMR2025), 16-18 September 2025, Salerno, Italy.
2. Coluccia S, **Bianco R**, Marinoni M, Falcon A, Fiori F, Serra G, Ferraroni M, Parpinel M, Edefonti V. Beyond The Nutrition5k Project: Data Curation And Deep Learning Algorithms To Predict The Nutritional Composition Of Dishes From Food Images. XIII Congresso Nazionale SISMEC, 9-12 September 2025, Pavia, Italy.
3. Carioni G, Fiori F, **Bianco R**, Parpinel M, Gnagnarella P. Latest and ongoing updates of the food composition database for epidemiological studies in Italy (BDA): efforts to ensure a comprehensive and reliable tool. 14th International Food Data Conference (IFDC), 1-3 September 2025, Rome, Italy.
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