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Article

Development of a Tool for Evaluating the Influence of Engineering Students' Perception of Generative AI on University Courses Based on Personality, Perceived Roles in Design Teams, and Course Engagement

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Abstract: This research investigates the possible influence of students' perceptions of emerging AI technologies on university courses, focusing on their knowledge and perceived usefulness within engineering design. An evaluation tool implemented in a Microsoft Excel workbook was developed and tested to perform the process of data collection through well-known questionnaires, data analysis, and the generation of results, facilitating attention to class compositions and measuring AI awareness and perceived usefulness. The study considers traditional aspects such as roles within design teams and the psychological factors that may influence these roles, alongside contemporary topics like Large Language Models (LLMs). Questionnaires based on well-established theories were administered during courses on product innovation and representation, assessing both primary and secondary design roles. Primary roles focus on technical skills and knowledge, while secondary roles emphasize problem-solving approaches. The Big Five questionnaire was used to characterize students' psychological profiles based on the main personality traits. Students' perceptions of AI involvement and usefulness in engineering design were evaluated using questionnaires derived from the consolidated literature as well. Data were collected via Google forms from both in-class and off-line students. The first results of the workbook adoption highlight some relationships between personality traits, perceived roles in design teams, and AI knowledge and usefulness. These findings aim to help educators enhance course effectiveness and align courses with current AI advancements. The workbook is available to the readers to collect data and perform analyses in different countries, education disciplines, and as time goes by, in order to add the longitudinal point of view to the research.

Keywords: artificial intelligence—AI; Large Language Models—LLMs; engineering design; engineering education; evaluation tools; Gen Z; product innovation; product representation

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1. Introduction

In today's competitive marketplace, companies are under constant pressure to develop products that not only have to meet functional requirements but also delight users with unique features and enhanced experiences. The demand for innovative, user-centered product design is growing, and so is the need for effective ideation methods. As a result, innovation in product design has become a critical differentiator for success [1–3]. Along with this, the variety of representations available today, from the classic technical drawings or CAD models to the augmented reality, rapid prototyping, etc., requires a deep knowledge to be able to select the best ones depending on the product development stage, the prototype role, etc. [4–6].

In this context, academic educational settings are crucial from several points of view. Understanding the dynamics of engineering design teams is imperative for improving productivity and fostering innovation, as well as teaching students to get the best from artificial intelligence (AI) as a real help in selecting the best product representations, in developing innovative concepts, in discovering unexpected product features to cause the wow effect in consumers, etc. [7–10]. The role of personality traits in shaping students' perception of their roles within design teams, from both a primary role (focusing on technical matters) and a secondary role (referring to problem solving attitudes) is an important area of research [11–13]. Additionally, the integration of AI into university courses on innovation and product representation is reshaping the rapidly evolving educational landscape where the integration of interdisciplinary approaches has become essential to prepare students for the challenges of the modern workforce [14].

Based on these premises, and considering the lack of research in the literature about the analysis of these three aspects in an integrated way, we decided to investigate in this direction. We started from an interest in improving our bachelor's and master's courses and continued by analyzing some aspects related to the students' perception of their roles in design teams already considered in our previous research [15], now adding aspects related to the use of AI tools. This study explores how students perceive their role within design teams and the adoption of generative AI (simply AI, hereafter) to support design, focusing on the impact of personality traits on this perception. The research used consolidated questionnaires and an ad hoc analysis of the collected data. Regarding the consolidated questionnaires, the choice fell on the use of the Big Five personality questionnaire, [16–19]. The Big Five personality questionnaire is widely used in research involving aspects of the professional development of teams and is usually related to the evaluation of team behavior and performance or personnel selection [19,20]. In [21], it was pointed out that personality traits could influence the composition of a successful product design team. The use of the Big Five personality questionnaire in educational environments reflects the research on the correlations between students' personalities and their perceptions about different learning experiences or academic achievements [22,23]. Regarding engineering education, there are a few examples of using the Big Five personality questionnaire to consider students' behavior in contexts related to engineering design tasks. For example, the study conducted in [24] considers the influence of personality traits on collaborative design processes. Other examples of uses of personality traits of engineering students are [25] for aspects related to the entrepreneurial intentions of students and [26] for aspects related to their teamwork competences. The Big Five personality questionnaire was then coupled with a questionnaire on the perceived roles in design teams as proposed by Ullman, specific to the context of mechanical engineering and product development [14,27]. Finally, for aspects related to the perception of AI tools, we chose to adapt the questionnaire proposed in [28] as it allowed us to consider several AI aspects in a structured way. Relative to these aspects, in a previous work [14] we investigated the use of LLMs tools in engineering design and came across several proposed questionnaires [29–32] to understand students' opinions toward AI, of which this one seemed the most comprehensive.

On the basis of the research questions described in the Section 4, the study examines the presence of correlations between these aspects. In particular, it investigates how university courses at different levels, representing different age groups, and students' personalities influence students' perceptions of AI (its engagement and usefulness) and of the primary and secondary roles in design teams.

Thus, the main objective of this research is to investigate the complex interplay among students' personality traits and age, their perceptions of roles within engineering design teams, and their perception of AI. To achieve this goal, this paper introduces a Microsoft Excel workbook developed to support the integration of AI tools in engineering education. The workbook allows for the systematic collection, analysis, and interpretation of data concerning students' perceptions of AI's usefulness in design courses, making it a valuable resource for educators aiming to enhance learning outcomes. The development and validation of this data analysis tool called "COURSE-ROLES-PT-AI relationships in engineering students" is deeply illustrated in the Section 4. Special attention was paid to its usability, as we plan to disseminate it to collect as much information as possible in a cloud repository. In this way, research results will gain objectivity and consistency over time.

The document structure runs as follows. The next section reports the background on the specific topics investigated. Then, the Section 3 presents the university context in which data were collected and the data types. Next, the Section 4 explains the definition of the research questions, the development of the framework, and its validation through the collected data. The Section 5 critically analyzes the research outcomes and the suggestions to improve education activities. The Section 6 closes the paper.

2. Background

To better understand the scope of this research, this section provides an overview of the theoretical background related to roles, personality traits, and AI tools in engineering design teams. Additionally, the paper emphasizes the utility of the workbook as a tool for enhancing data collection and analysis in educational settings. This approach not only supports the current study but also offers a foundation for future research in diverse contexts.

2.1. Design Team Composition

In general, teams are composed of individuals with different skills, abilities, problem-solving approaches, personalities, etc. Understanding all these aspects is crucial for optimizing team performance and outcomes. Considering our specific engineering education context, the classification proposed by Ullman was used to describe roles [13]. This seemed the simplest and most intuitive solution given that it is used in one of the textbooks suggested as a reference for our courses. This classification proposes a distinction between primary and secondary roles in design teams in engineering, and it provides a useful tool for understanding and possibility optimizing team dynamics even in a student context. As will later be detailed in the Section 3, the roles identified as primary are directly related to technical or business skills and industry-specific knowledge. These roles are essential for completing the core activities and achieving the technical objectives of the project. Primary roles have a strong foundation of technical knowledge, which can include engineers, programmers, designers, analysts, etc. They are responsible for critical technical decisions, developing central components of the project, and solving complex technical problems. The main objectives of these roles are to ensure that the product or technical project is developed according to precise specifications and standards, and to guarantee the reliability and technical quality of the work performed. In contrast, secondary roles, while not directly related to technical skills, are essential for supporting the team and facilitating the design process. These roles often focus on organizational, communicative, and problem-solving aspects and also refer to psychological–behavioral aspects. Secondary roles cover skills in management, communication, collaboration, and problem-solving. They help to keep the team coordinated, resolve conflicts, facilitate communication, and manage time and resources. Examples of secondary roles include project coordinator, facilitators, resource manager, communication manager, and process analyst. The objectives of these roles are to ensure that the team works cohesively and that activities are well-coordinated and to facilitate the resolution of non-technical issues that may arise during the project [13]. From our perspective, it is particularly interesting to analyze the combination of primary and secondary roles that individual students, belonging to the different courses, perceive themselves to cover.

2.2. Personality

Another interesting aspect to investigate concerns the perception of personality traits. Human personality can be defined as the set of traits of an individual that account for consistent patterns of behavior across situations and time [16]. Goldberg [17] and McCrae and Costa [18] highlighted personality traits and analyzed them to generate a structured taxonomy known as the Big Five personality traits [16,19]. These traits are as follows.

Extraversion (Personality Trait 1—PT1): extraverts are energetic and optimistic; introverts are reserved rather than hostile, independent rather than followers. Agreeableness (PT2): an agreeable person is basically altruistic, sympathetic to others, and eager to help; unpleasant/antagonistic people are egocentric, skeptical of others' intentions, and competitive. Conscientiousness (PT3): a conscientious person is purposeful, strong-willed, and determined; those with low conscientiousness scores do not necessarily lack moral principles but are less demanding in applying them. Neuroticism (PT4): neurotic people suffer from fear, sadness, embarrassment, anger, etc.; low neuroticism indicates emotional stability. Openness to experience/culture (PT5): open individuals are curious about both inner and outer worlds and their lives are experientially richer; people with low scores tend to be conventional in behavior and conservative in outlook [19]. As highlighted in our previous work [15], the literature offers different ways to evaluate personality. McCrae et al. propose the NEO-PI-3, a 240-item questionnaire designed primarily for adolescents that assesses 30 specific aspects of personality, 6 for each trait [33]. Goldberg et al. define the International Personality Item Pool (IPIP), as a set of over 200 personality items freely available on the Internet. This set is available in 25 languages and researchers continuously update it to make it more complete and more usable in different contexts [34]. In our case, for consistency with our previous research, it was decided to use the Big Five Inventory (BFI), which is a questionnaire made up of 44 items that measures individuals based on the five main personality traits previously reported [35].

2.3. AI Involvement and Usefulness

On the other hand, further support for the initial stages of product development is now offered by AI involvement. In recent years, AI in general or Large Language Models—LLMs—in particular have emerged as promising solutions for supporting idea generation in various domains [8–10]. LLMs can provide designers and engineers with a diverse range of suggestions, from concept development to feature enhancements, thereby fostering a more innovative design process [14]. For example, LLMs-based tools, such as ChatGPT or Gemini, can significantly streamline the brainstorming phase, making it easier for teams to explore a wide array of possibilities without the constraints of traditional ideation methods [36,37]. By using these AI-based tools, designers can quickly generate and evaluate multiple design alternatives, reducing the time and effort required to reach optimal solutions [38]. Furthermore, the ability of LLMS-based tools to understand and process natural language input allows for more intuitive interaction, enabling designers to articulate their needs and preferences in a conversational manner.

2.4. Generation Z Approach to AI

There is a particular predisposition to use and adopt AI-based tools among current university students, the so-called Generation Z. Generation Z (Gen Z), the cohort born between the late 1990s and early 2010s, is characterized by a unique perspective on innovation and technology. Gen Z is known for its digital nativity and comfort with rapidly evolving technologies. They grew up with the Internet, smartphones, and social media, which made them adept at using digital tools and platforms. This generation values authenticity, customization, and seamless user experiences, which influences their expectations and contributions to product design. The use of AI and, in particular, the adoption of LLMs-based tools such as ChatGPT and Gemini may be particularly appreciated by Gen Z, who are used to interacting with AI-based technologies. Their familiarity with digital communication and online collaboration tools means they can effectively use AI tools to enhance their creative processes [39,40]. The AI adoption in the product design process offers a powerful means of enhancing idea generation. Together with the understanding of how personality traits influence creativity and taking into account the unique perspectives of Gen Z, these tools can help design teams to produce more innovative and appealing products. The use of artificial intelligence in the product design process offers a powerful way to improve idea generation. In addition to understanding how personality traits influence creativity and, considering the unique perspectives of Gen Z and these tools, it is interesting to explore how these aspects, individually or in combination, can impact the functioning of design teams by supporting the ideation of more innovative and engaging products.

2.5. Excel Workbook Choice and Specificities

The availability of existing Microsoft Excel workbooks developed in the past for similar purposes is not the main reason why this development tool has been chosen here too. Excel is a powerful tool for managing and analyzing data from questionnaires. While it shows limitations against dedicated software packages like SPSS or R, it offers great flexibility and a more manageable learning curve, making it ideal for both basic and intermediate data analysis projects. It is easily shareable as it is part of the Microsoft Office package which is very popular and does not require heavy programming skills or language for its use, making it possible to also create user-friendly interfaces to guide the operator throughout the data collection and analysis process. Additionally, there are examples in the literature where Excel workbooks have been used to collect and analyze questionnaire data. These examples span a variety of fields, including education, healthcare, social sciences, and business. For example, the studies in [41–45] highlight Excel accessibility, ease of use, and powerful data processing capabilities.

3. Material and Methods

The research described in the paper exploited the data collected in the academic year 2023–2024 at the University of Udine, Italy, during the lessons of the course "Drawing and geometric modelling in engineering" ("Disegno e modellazione geometrica delle macchine") in degree courses in Mechanical Engineering and during the lessons of the course "Product interaction and innovation" ("Interazione ed innovazione di prodotto") in master's degree courses in Mechanical and Management Engineering. Both the cases deal with product representation and engineering design. Clearly, concepts are developed at different levels due to the different age of the students and to the lesson placement inside their course of study. Nevertheless, in both cases, AI and AI tools have been introduced in a two-hour lesson and during some workshops. Regarding the age of the students, those who attended the first course were mainly aged 19 to 21; they were 22 to 25 in the second course. The Microsoft Excel workbook was developed as part of this study, which facilitated the data collection, processing, and analysis.

Given the exploratory nature of our study and the need to establish robust relationships among a diverse set of variables, we considered two potential methodologies. On the one hand, we could start from the goal to achieve—highlighting possible relationships among the variables involved—and develop ad hoc questionnaires to collect data in a format suitable for processing and analysis. Examples of the use of ad hoc questionnaires are given in [46,47]. On the other hand, we could use known questionnaires, already used and validated for years, for data collection, and focus the research effort on how to relate the results. Both approaches showed positives and negatives. Example of the use of well-known questionnaires can be found in [48,49]. By following the first approach, perhaps the results would have been more focused from the beginning, given the use of ad hoc questionnaires, but the risk would have been to suffer the lack of familiarity with the collection tool by the students involved. In other words, this first approach, while potentially yielding highly tailored data, risked introducing biases due to the unfamiliarity of the participants with the new tools, possibly affecting the reliability of the responses. By following the second approach, the questionnaires would have been ready to use and quite well known, but there could have been problems in homogenizing data to be able to process them smoothly. In the end, we decided to follow the second path. The decision to use well-established questionnaires was driven by the need to ensure data validity and reliability, as these tools having been rigorously tested in various contexts. Although data homogenization posed a challenge, the advantage of starting with a solid foundation of validated instruments was deemed more critical for the integrity of our study. Nevertheless, we leave an open door towards the first approach, in the medium to long term. By adopting a hybrid approach in the medium to long term, we aim to combine the strengths of both methods, allowing for more tailored data collection in future iterations while maintaining the rigorous standards provided by validated instruments. This approach not only addresses the immediate research needs but also sets a foundation for more nuanced data analysis in subsequent studies.

The workbook's user-friendly interface and structured format ensure that the data collected is consistent and comprehensive, supporting the study's objectives. Although the dataset was limited in size, it was sufficient to test and validate the workbook's design, ensuring that it could handle the types of data expected in broader applications.

As for some details about the development and structure of the workbook, its current version (5.0) consists of a set of sheets containing data and formulas. There is no VBA code at the moment; it will be added in the near future, when the module to collect and share data via a cloud repository is added to this tool. Now, the MAIN sheet contains the user interface. Its layout replicates the analysis process and information flow. The hyperlinks here allow us to open and print the questionnaires, go to the correct sheets to insert the collected data (INPUT_COURSES, INPUT_ROLES, and INPUT_PT_AI), and go to those showing the results of the analysis, results that are processed in real time. A color code has been used to identify the different sections of the tool and to keep the user focused on the right ones at each point in time. Gray is the color that refers to the courses of the participants; cyan is for the primary and secondary roles in the design teams; yellow refers to the personality traits; and magenta is for the AI issues. The DATA sheet contains the data ready to be processed; the ANALYSIS_PRE sheet calculates the regression values while the ANALYSIS_*p*_values sheet calculates the *p*-values to estimate the reliability of the results. Finally, the ANALYSIS sheet contains the evaluation results, i.e., the significant relationships between the variables involved, and the SETUP sheet allows the user to set the threshold values for the correlation and the calculation of the *p*-values.

Students' perceived primary and secondary roles in design have been collected using Ullman's classification [14]. Primary roles are mainly technological or business-related skill and knowledge; secondary roles refer to the psychological–behavioral aspects of the individuals inside the design team. Students had to select six perceived primary roles (PRs) among the following twelve.

- PR1. Product design engineer (major design responsibility; both creative and analytical; knowledge about design process and technology);
- PR2. Product manager (marketing manager) (ultimate responsibility for the development of the product; link between the product and the customer);
- PR3. Manufacturing engineer;
- PR4. Detailer;
- PR5. Drafter;
- PR6. Technician;
- PR7. Materials specialist;
- PR8. Quality control/Quality assurance specialist;
- PR9. Analyst;
- PR10. Industrial designer;
- PR11. Assembly manager;
- PR12. Vendor's or supplier's representatives.

Students were also asked to select four perceived secondary roles (SRs) out of the following eight.

- SR1. Organizer (mature, confident, trusting, chairperson);
- SR2. Creator (imaginative, impractical);
- SR3. Gatherer or resource-investigator (explores opportunities, develops contacts, enthusiastic);
- SR4. Motivator or shaper (dynamic, finds way around obstacles);
- SR5. Evaluator (good at seeing the big picture, not a leader);

- SR6. Team worker (consensus builder, avoids frictions on the team);
- SR7. Solver (turns ideas into practical actions);
- SR8. Completer-finisher or pusher (conscientious and detail-oriented, delivers results on time);

Students' perceptions of AI have been investigated using a modified version of the questionnaire proposed by Bernabei et al. [28]. This modified version is in Appendix A. The answers to forty-five questions (AI-A1 to AI-E11), expressed in the range [1..5] obeying a classic Likert scale, allowed us to characterize the individual perceptions of AI through the following five dimensions.

- AI1—Attitude to AI;
- AI2—Trust in AI;
- AI3—Social influence towards AI;
- AI4—Fairness and ethics of AI;
- AI5—Usefulness and performance expectancy of AI.

Finally, students' personality traits were collected using the BFI—Big Five Inventory—questionnaire [16,17]. The answers to forty-four questions (PT1 to PT44), again exploiting a [1..5] Likert scale, allowed us to determine the individual personality encoded using the following five dimensions.

- PT1—Extraversion or surgency;
- PT2—Agreeableness;
- PT3—Conscientiousness;
- PT4—Neuroticism;
- PT5—Openness to experience/culture.

For completeness, COURSE has been used as a variable to represent the engagement of the student answering the questionnaire. A value equal to 1 means the earlier course, a value equal to 2 the later one.

Data were collected using Google forms. The purpose of the survey and the content of the questionnaires were adequately explained during the lessons; therefore, the instructor/expert presence was not required for completion. The link for answering the questionnaires was thus sent to all the students of the two courses. As of 1 July 2024, there were 58 students engaged in the earlier course and 19 in the later one. We collected 56 complete responses, available for data processing and analysis, from 41 and 15 students, respectively. Therefore, we had 70.7% and 78.9% of students participating in the survey, respectively. The self-selection method for participation in the survey may have introduced bias; however, these percentages should be reassuring enough about the limited impact of this.

4. Activities

4.1. Definition of the Research Questions

In order to establish a clear direction for the study and to best perform data analysis, some research questions were defined. They have been addressed throughout the activities and answered at the end of them. The authors' experience and background about university education, engineering design, design team composition, personality evaluation and AI and AI-based tools, along with suggestions coming from recent literature works [29,50–53], allowed us to develop the research questions. The development considered the course followed, the personality traits, and the roles in design teams as independent variables and the perception of the AI aspects as a dependent variable. The five research questions were as follows.

- RQ1. Does the course level impact students' attitudes towards AI and their primary and secondary roles in design teams?
- RQ2. Are there relationships between students' primary roles in design teams and their personality traits, and how do these impact their attitudes towards AI?

- RQ3. How do secondary roles in design teams correlate with students' personality traits and their trust in AI and overall attitudes towards AI?
- RQ4. In what ways do personality traits influence students' perceptions of AI, including attitudes, trust, social influence, fairness, and performance expectancy?
- RQ5. How do the combined effects of course level, primary and secondary roles in design teams, and personality traits influence students' views on various aspects of AI?

These research questions will be reconsidered at the end of the validation of the framework section.

4.2. Development of the Framework

The framework has been implemented in a Microsoft Excel workbook. Particular attention was placed on its usability, since the aim is to disseminate it to collect as many pieces of information as possible in a cloud repository. This way, the research results will be able to gain objectivity and consistency as time goes by. This workbook should allow for the collection of data and generation of results, even in different countries and education disciplines.

Figure 1 shows the interface of the framework, named "COURSE-ROLES-PT-AI relationships in engineering students". It lists all the actions needed to feed the database in order to obtain the relationships among the variables involved. The step descriptions are hyperlinks to the PDF files containing the questionnaires to open/print and to the workbook sheets of interest individually.

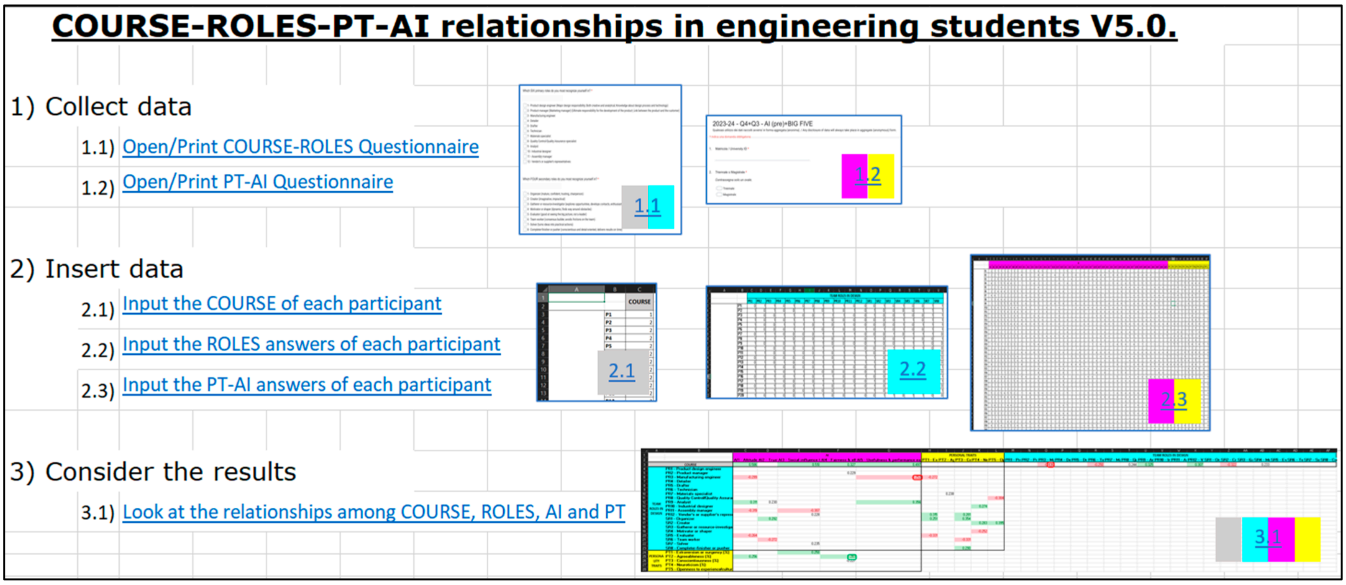


Figure 1. The interface of the Microsoft Excel workbook implementing the framework to highlight the relationships among the course, roles in design teams, personality, and AI perception.

Although the interface should be self-explanatory enough, the required steps to use the workbook are summarized in the following.

1. Collect data. The workbook allows the opening/printing of PDF files of the questionnaire to collect data about the course and primary and secondary roles named COURSE-ROLES questionnaire (1.1) and the questionnaire about personality and AI perception, named PT_AI questionnaire (1.2).
2. Insert data. Collected data must be now inserted in the workbook. The answers of each student to the questionnaires are of concern here. The workbook receives the students' answers to the questionnaires using the data format as it comes from the Google forms datasheets. Regarding the COURSE variable, we used "1" to represent

the earlier (Drawing and geometric modelling in design) and "2" for the older one (Product interaction and innovation). Primary and secondary roles (PR1 to PR12 and SR1 to SR8) appear as binary sequences. Twelve digits are given for the primary role reporting if the corresponding role has been selected (1) or not (0) by the student, and eight digits are given for the secondary role, with the same meaning. Regarding the AI perception, each student corresponds to forty-five values (AI-A1 to AI-E11) in the range [1..5], since the Likert scale was used for the answers. The answers to the questions referring to personality correspond to forty-four values (PT1 to PT44) in the range [1..5] for each student, since the same Likert scale was used.

3. Consider the results. Once all data have been inserted, the ANALYSIS sheet of the workbook will contain the results of the automatic computation. The interface invites the users to take a look at them. To obtain the outcome, the framework computes the mean values of the forty-five AI answers to obtain the five dimensions about AI perceptions, from the attitude to AI to the usefulness and performance expectancy of AI. Also, formulas take care of converting the forty-four PT answers into the five personality traits, from extraversion or surgency to openness to experience/culture, expressed in percentages.

4.3. Validation of the Framework

Figure 2 shows the content of the ANALYSIS sheet of the workbook as it appeared when fed with data collected through the survey. It represents the first statistical data analysis implemented in the current release of the framework. Each cell contains the formula that computes the one-to-one correlation among the variables. The thresholds to highlight values to focus on have been set to −0.25 and 0.25. These values can be set in the SETUP sheet of the workbook. Indeed, these values are quite unusual (they are far from the limits −1 and 1); they have been set this way in order to test the workbook's functioning and to obtain some outcome rather than to obtain meaningful results.

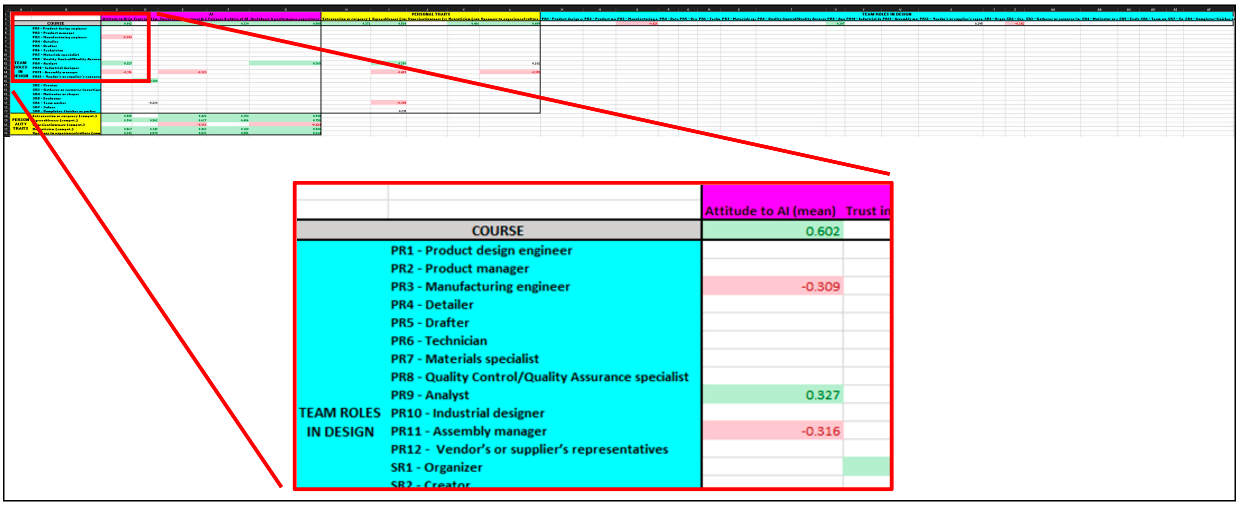


Figure 2. The results of the computation of the workbook.

Regarding the meaningfulness—statistical significance—of the results, all the cells of the sheet containing values passed the *p*-value test. A hidden sheet of the workbook takes care of computing the *p*-values for every cell; after that, formulas take care of hiding those cells not passing this filter. The value chosen for the *p*-value computation is 0.1, different from the classic 0.05. This value can be changed in the SETUP sheet as well. For example, the data available as of 1 July 2024, generate 42 regression values satisfying the *p*-value test. Figure 3 shows the hidden sheet of the workbook performing the *p*-value computations. Once filtered, the linear regression values satisfying the 0.25 threshold are 34, 20 positive and 14 negative. Given the limited data available, this initial validation aimed to test the functionality of the workbook rather than to provide an exhaustive statistical analysis. The results should be interpreted with caution and seen as a demonstration of the tool's capabilities.

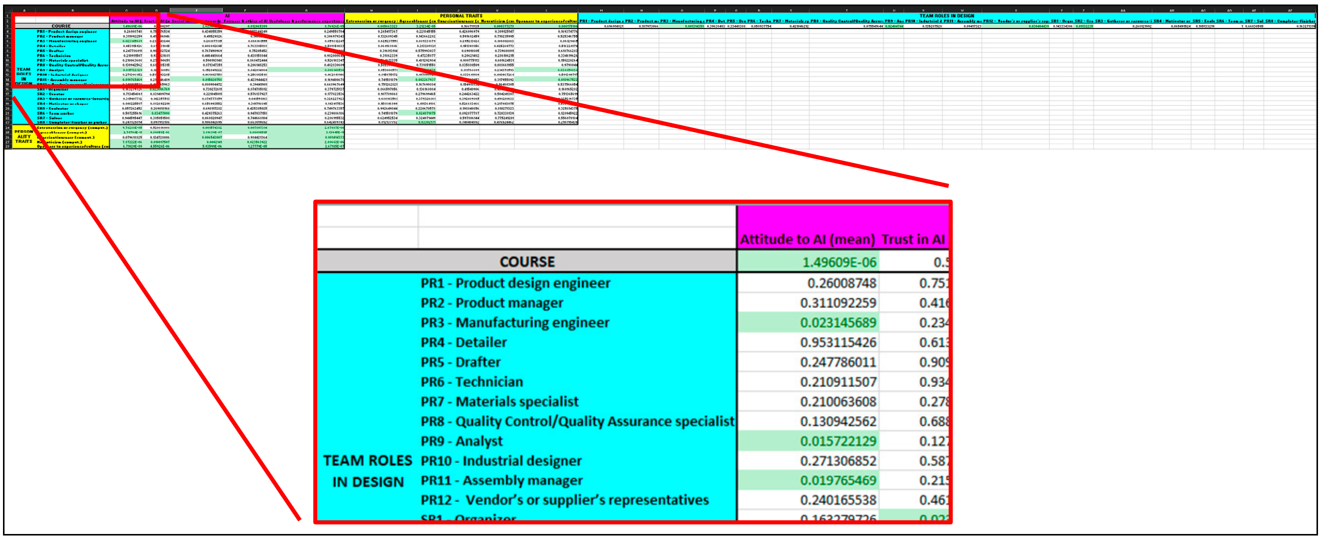
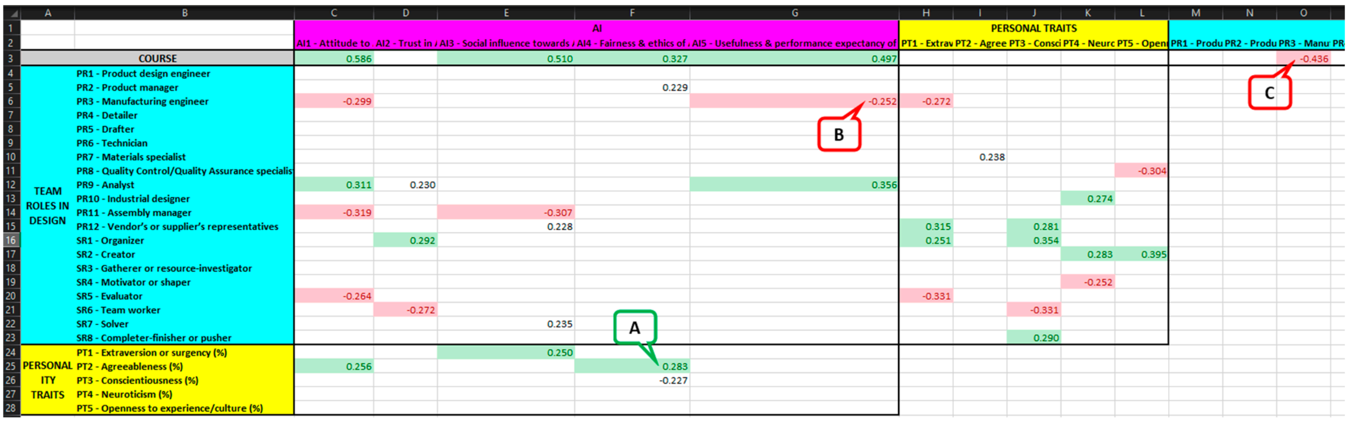


Figure 3. The hidden sheet of the workbook performing the *p*-value computations.

Before we proceed to the interpretation of the outcome, two things are worth mentioning.

First, we must consider that data have been collected using heterogeneous formats. There were continuous variables (personality traits and AI aspects), discrete variables (the course level), and binary variables (the roles in design teams). This suggested caution in data elaboration and analysis. Moreover, we had three different situations when crossing the data, searching for possible relationships: continuous vs. continuous (personality trait vs. AI aspect); continuous vs. discrete or binary (e.g., personality trait vs. role in design teams); and discrete or binary vs. discrete or binary (e.g., course vs. role in design teams). Clearly, the information content of the data is different, as well as the outcome of the three combinations of crossing. This becomes clear in Figures 4–7. Figure 4 shows scatter charts referring to the three types of relationships: continuous vs. continuous (PT2—agreeableness vs. AI4—fairness and ethics of AI) to the left; binary vs. continuous (PR3—manufacturing engineer vs. AI5—usefulness and performance expectancy of AI) in the middle; and discrete vs. binary (COURSE vs. PR3—manufacturing engineer) to the right. All of this has not been addressed for the moment but it will be in the near future.



		AI1 - Attitude to	AI2 - Trust in	AI3 - Social influence towards	AI4 - Fairness & ethics of	AI5 - Usefulness & performance expectancy of	PT1 - Extrav	PT2 - Agree	PT3 - Consci	PT4 - Neurc	PT5 - Open	PR1 - Produ	PR2 - Produ	PR3 - Manu
	COURSE	0.586		0.510	0.327	0.497								-0.436
TEAM ROLES IN DESIGN	PR1 - Product design engineer													
	PR2 - Product manager				0.229									
	PR3 - Manufacturing engineer	-0.299				-0.252	-0.272							
	PR4 - Detailer													
	PR5 - Drafter													
	PR6 - Technician													
	PR7 - Materials specialist							0.238						
	PR8 - Quality Control/Quality Assurance specialis										-0.304			
	PR9 - Analyst	0.311	0.230			0.356								
	PR10 - Industrial designer									0.274				
	PR11 - Assembly manager	-0.319		-0.307										
	PR12 - Vendor's or supplier's representatives			0.228			0.315		0.281					
	SR1 - Organizer		0.292				0.251		0.354					
	SR2 - Creator									0.283	0.395			
	SR3 - Gatherer or resource-investigator													
	SR4 - Motivator or shaper									-0.252				
	SR5 - Evaluator	-0.264					-0.331							
	SR6 - Team worker		-0.272						-0.331					
	SR7 - Solver			0.235										
	SR8 - Completer-finisher or pusher								0.290					
PERSONALITY TRAITS	PT1 - Extraversion or surgency (%)			0.250										
	PT2 - Agreeableness (%)	0.256			0.283									
	PT3 - Conscientiousness (%)				-0.227									
	PT4 - Neuroticism (%)													
	PT5 - Openness to experience/culture (%)													

Figure 4. The references (A, B, and C) for the scatter charts of the three examples of relationships.

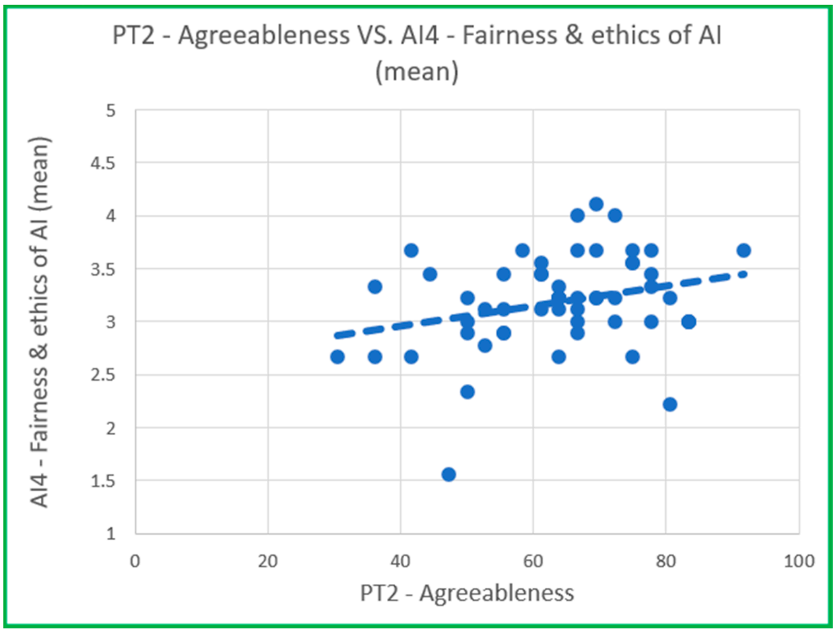


Figure 5. Chart A. Example of the relationship being continuous vs. continuous (PT2—agreeableness vs. AI4—fairness and ethics of AI).

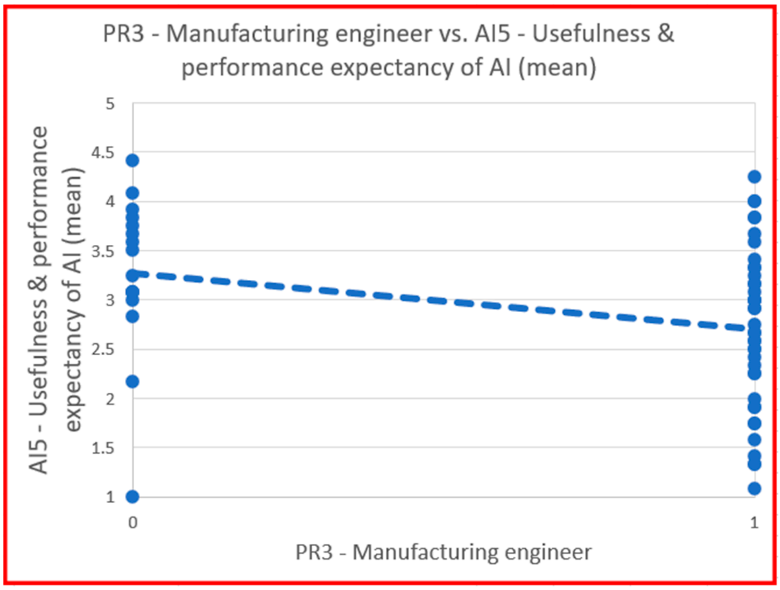


Figure 6. Chart B. Example of the relationship being binary vs. continuous (PR3—manufacturing engineer vs. AI5—usefulness and performance expectancy of AI).

Second, this first release of the workbook does not use multiple linear regression, which would be more suitable to analyze the relationships among all the variables, for two reasons. First, again, the goal for now was solely to set up a working, usable framework; second, the available data were clearly insufficient to allow any deeper evaluation using that statistical approach.

The reader can download the current release of the Microsoft Excel workbook implementing the framework here (https://uniudamce-my.sharepoint.com/:x:/g/personal/stefano_filippi_uniud_it/ESuKJz2b3E9Bv4JoyhFuPKwBJeI8ZHzHGm-h068aLr-7UQ?e=ahxlds (accessed on 4 September 2024)).

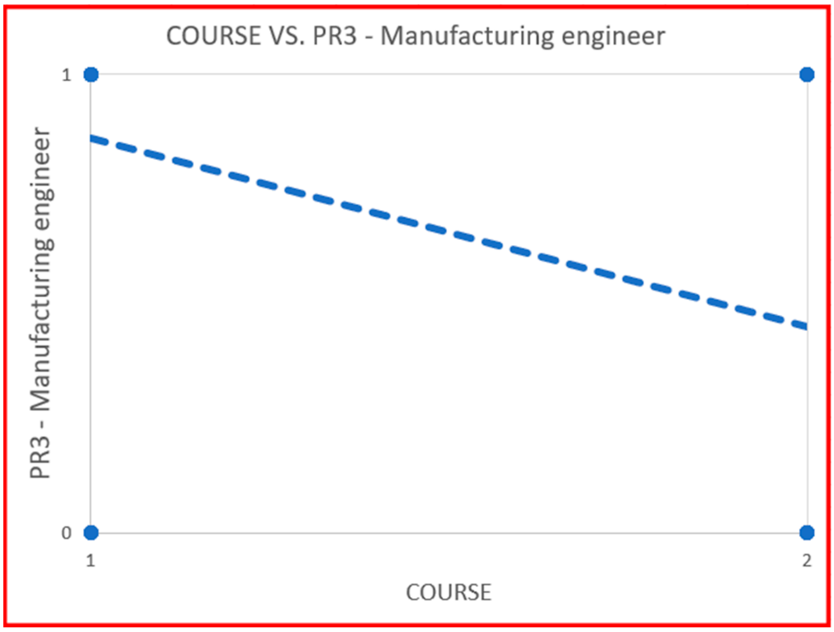


Figure 7. Chart C. Example of the relationship being discrete vs. binary (COURSE vs. PR3—manufacturing engineer).

5. Discussion

The discussion focuses on the implications of using the Excel workbook as a central research tool in this study. The findings from the analysis demonstrate the effectiveness of the workbook in identifying key relationships between AI perception and various student characteristics. The discussion also highlights the potential for the workbook to be adapted for use in other contexts, contributing to the broader field of educational research and AI integration.

The elaboration of the available data, which occurred thanks to the workbook, allowed us to answer to the five research questions. There are five paragraphs in the following. Each of them recalls the specific RQ (in the heading), lists the relationships the answer is based on, develops the articulated answer to the RQ, and lists some suggestions to improve the university courses from the AI consideration point of view.

5.1. Answer to RQ1. Does the Course Level Impact Students' Attitudes towards AI and Their Primary and Secondary Roles in Design Teams?

The answer to this RQ exploited the following relationships.

- COURSE impacts positively on AI1, AI3, AI4, AI5, PR9, PR12;
- COURSE impacts negatively on PR3, PR6, SR2.

Starting from these relationships, it seems that the course level has a significant impact on students' attitudes towards AI and their roles in design teams. Specifically, students in later courses have a more positive attitude towards AI, as seen through improvements in AI1 (attitude to AI), AI3 (social influence towards AI), AI4 (fairness and ethics of AI), and AI5 (usefulness and performance expectancy of AI). Additionally, the course level positively influences certain primary roles such as PR9 (analyst) and PR12 (vendor's or supplier's representatives), suggesting a greater inclination towards analytical and external collaboration roles. However, it negatively impacts other primary roles like PR3 (manufacturing engineer) and PR6 (technician), and the secondary role SR2 (creator), indicating a possible shift away from hands-on and creative tasks as students advance.

The suggestions to improve the courses coming from this answer are as follows.

1. Incorporate AI Modules Early: Given that later courses positively impact attitudes towards AI, consider introducing AI-related modules or topics earlier in the curricu-

lum. This can build a stronger foundation and a positive attitude towards AI from the beginning.
2. Balance Role Focus: Address the negative impacts on certain roles (PR3 and PR6) by ensuring that AI applications in these areas are highlighted. For instance, show how AI can enhance the work of manufacturing engineers and technicians.
3. Creative Integration: Mitigate the negative impact on the secondary role SR2 (creator) by incorporating AI tools that aid in creativity and innovation, demonstrating how AI can be a creative collaborator rather than a hindrance.

5.2. Answer to RQ2. Are There Relationships between Students' Primary Roles in Design Teams and Their Personality Traits, and How Do These Impact Their Attitudes towards AI?

The answer to this RQ exploited the following relationships.

- PR3 relates negatively to PT1;
- PR3 impacts negatively on AI1, AI5;
- PR8 relates negatively to PT5;
- PR9 impacts positively on AI1, AI5;
- PR10 relates positively to PT4;
- PR11 impacts negatively on AI1, AI3;
- PR12 relates positively to PT1, PT3.

There are notable relationships between primary roles in design teams and students' personality traits, which in turn affect their attitudes towards AI. For example, the role of PR3 (manufacturing engineer) is negatively related to PT1 (extraversion) and negatively impacts AI1 (attitude to AI) and AI5 (usefulness and performance expectancy of AI). This suggests that students who are less extroverted and hold this role may have a less favorable view of AI. On the other hand, PR9 (analyst) positively impacts AI1 and AI5, indicating that those in analytical roles tend to view AI more favorably. Additionally, PR12 (vendor's or supplier's representatives) is positively related to PT1 (extraversion) and PT3 (conscientiousness), suggesting that extroverted and conscientious students are more likely to take on this role.

The suggestions to improve the courses coming from this answer are as follows.

1. Personality-Based Role Assignment: Use personality assessments to guide students into roles that align with their traits. For example, more extroverted students (PT1) may thrive and have a better attitude towards AI when placed in roles that require interaction and communication (like PR12).
2. Targeted Support: Provide additional support and resources to students in roles where negative impacts on AI attitudes are noted (e.g., PR3). This could include mentorship, targeted AI workshops, or case studies showcasing successful AI integration in these fields.
3. Highlight Positive Impacts: Emphasize the positive impacts of certain roles (like PR9) on AI attitudes by using these roles as case studies or role models within the course, showing the benefits and successes of AI in these positions.

5.3. Answer to RQ3. How Do Secondary Roles in Design Teams Correlate with Students' Personality Traits and Their Trust in AI and Overall Attitudes towards AI?

The answer to this RQ exploited the following relationships.

- SR1 relates positively to PT1, PT3;
- SR1 impacts positively on AI2;
- SR2 relates positively to PT4, PT5;
- SR4 relates negatively to PT4;
- SR5 relates negatively to PT1;
- SR5 impacts negatively on AI1;
- SR6 relates negatively to PT3;
- SR6 impacts negatively on AI2;
- SR8 relates positively to PT3.

These relationships highlight that secondary roles in design teams show strong correlations with students' personality traits and influence their trust in AI and overall attitudes towards AI. For instance, SR1 (organizer) is positively related to PT1 (extraversion) and PT3 (conscientiousness) and positively impacts AI2 (trust in AI), indicating that organized, extroverted, and conscientious students tend to trust AI more. Conversely, SR5 (evaluator) negatively relates to PT1 and negatively impacts AI1 (attitude to AI), suggesting that less extroverted students in evaluative roles may have a more negative attitude towards AI. Additionally, SR6 (team worker) negatively relates to PT3 (conscientiousness) and negatively impacts AI2 (trust in AI), highlighting a potential lack of trust in AI among conscientious team workers.

The suggestions to improve the courses coming from this answer are as follows.

1. Role-Specific Training: Provide specialized training for secondary roles (e.g., SR1) that show positive impacts on AI trust and attitudes. This could involve workshops or projects that focus on how AI can be leveraged in organizational tasks.
2. Address Negative Correlations: For roles with negative impacts (like SR5 and SR6), develop modules that address common concerns and misconceptions about AI, possibly through guest lectures, industry partnerships, or hands-on AI projects.
3. Promote Positive Examples: Use successful examples of AI integration in roles with positive correlations (like SR1 and SR8) to inspire and educate students about the potential benefits and applications of AI.

5.4. Answer to RQ4. In What Ways Do Personality Traits Influence Students' Perceptions of AI, Including Attitudes, Trust, Social Influence, Fairness, and Performance Expectancy?

The answer to this RQ exploited the following relationships.

- PT1 impacts positively on AI3;
- PT2 impacts positively on AI1, AI3.

Thus, personality traits have a substantial influence on students' perceptions of AI across various dimensions. For example, PT1 (extraversion) positively impacts AI3 (social influence towards AI), indicating that more extroverted students are likely to perceive AI as socially influential. Similarly, PT2 (agreeableness) positively impacts AI1 (attitude to AI) and AI3 (social influence towards AI), suggesting that agreeable students tend to have a more favorable attitude towards AI and recognize its social impact. These findings highlight that students' personality traits play a crucial role in shaping their overall perceptions and acceptance of AI technologies.

The suggestions to improve the courses coming from this answer are as follows.

1. Personality-Informed Teaching: Incorporate knowledge about personality traits into your teaching methods. For example, create group projects that mix different personality types to foster diverse perspectives and enhance the learning experience regarding AI.
2. Customized Learning Paths: Develop learning paths or elective courses tailored to different personality traits, ensuring that each student can engage with AI in a way that aligns with their personal strengths and preferences.
3. Awareness and Development: Include content that helps students to understand how their personality traits influence their perceptions of AI and provide strategies for leveraging their traits to improve their attitudes and trust in AI.

5.5. Answer to RQ5. How Do the Combined Effects of Course Level, Primary and Secondary Roles in Design Teams, and Personality Traits Influence Students' Views on Various Aspects of AI?

The answer to this RQ exploited the following relationships.

- COURSE impacts positively on AI1, AI3, AI4, AI5, PR9, PR12;
- COURSE impacts negatively on PR3, PR6, SR2;
- PR3 impacts negatively on AI1, AI5;
- PR9 impacts positively on AI1, AI5;

- PR11 impacts negatively on AI1, AI3;
- SR1 impacts positively on AI2;
- SR5 impacts negatively on AI1;
- SR6 impacts negatively on AI2;
- PT1 impacts positively on AI3;
- PT2 impacts positively on AI1, AI3.

The combined effects of course level, primary and secondary roles in design teams, and personality traits create a complex interplay that influences students' views on various aspects of AI. The course level generally enhances positive attitudes towards AI (AI1, AI3, AI4, AI5), suggesting that more advanced students are more receptive to AI. However, this is nuanced by specific role-related and personality-related factors. For example, PR3 (manufacturing engineer) negatively impacts AI1 and AI5, indicating a less favorable view of AI among students in this role. Conversely, PR9 (analyst) has a positive impact on AI1 and AI5, reflecting a more favorable attitude among analytical roles. Additionally, SR1 (organizer) positively impacts AI2 (trust in AI), while SR5 (evaluator) and SR6 (team worker) have negative impacts on AI1 and AI2, respectively. Personality traits further influence these views, with PT1 (extraversion) and PT2 (agreeableness) enhancing positive perceptions of AI. This multifaceted interaction underscores the importance of considering the holistic combination of educational level, team roles, and individual personality traits in understanding students' perspectives on AI.

The suggestions to improve the courses coming from this answer are as follows.

1. Holistic Curriculum Design: Design the curriculum to address the combined effects by integrating AI-related content throughout the course levels, ensuring that all roles and personality traits are considered and positively influenced.
2. Interdisciplinary Projects: Encourage interdisciplinary projects that require collaboration across different roles and personality types, showing how AI can be effectively utilized in various contexts and by diverse teams.
3. Feedback and Adaptation: Regularly collect feedback from students about their attitudes towards AI and their experiences in different roles. Use this feedback to continuously adapt and improve the course content and structure.
4. Guest Lectures and Case Studies: Invite industry professionals and alumni who have successfully integrated AI into various roles to share their experiences. Use case studies that highlight the positive impacts of AI across different roles and personality types.
5. Mentorship Programs: Establish mentorship programs that pair students with mentors who have similar personality traits and roles. Mentors can provide personalized guidance on how to navigate AI in their specific context, improving overall attitudes and trust.

Before concluding, it is worth spending some time discussing the completeness of the research. To determine whether the outcomes are sufficient, we need to consider several factors.

- Breadth of Variables. The research covers a broad range of variables, including course levels, primary and secondary roles in design teams, personality traits, and various aspects of AI attitudes. This comprehensive approach is a strength, as it allows for a multifaceted understanding of students' perceptions and attitudes towards AI.
- Significant Findings. The research has identified several significant impacts: course level positively affects attitudes towards AI; specific primary roles have both positive and negative impacts on different aspects of AI attitudes; secondary roles also show varied impacts on trust and attitudes towards AI; personality traits like extraversion and agreeableness positively influence certain AI attitudes. These findings provide valuable insights into how different factors influence students' views on AI, indicating a robust dataset.

- Actionable Insights. The research outcomes have led to actionable suggestions for improving AI education, such as introducing AI concepts early, tailoring AI content based on roles, and addressing specific AI aspects. This demonstrates that the data are sufficient to inform meaningful recommendations.
- Coverage of Research Questions. The research questions were designed to explore the relationships between various variables and AI attitudes. The findings address these questions by highlighting specific impacts, suggesting that the research has effectively covered the intended scope.
- Potential Gaps. While the research provides a good foundation, there may be areas that could benefit from further exploration such as longitudinal analysis—studying changes over time to see how attitudes evolve with continued exposure to AI; deeper role analysis—conducting more detailed studies within each primary and secondary role to understand nuanced perspectives; an expanded sample size—increasing the number of participants to ensure the findings are generalizable across different demographics and educational settings; and additional variables—including other relevant variables such as prior AI experience, technological proficiency, and cultural factors.

In all, the research appears to be well-rounded and comprehensive, providing sufficient outcomes to draw meaningful conclusions and make actionable recommendations. However, there is always room for further investigation to deepen the understanding and address any potential gaps.

6. Conclusions

This research aimed at developing a tool to highlight relationships among Italian students' roles in engineering design teams, generative AI perception, and personality traits. Some existing methods and tools have been exploited to achieve this goal and now there is a framework for data analysis, fully implemented in a Microsoft Excel workbook. We used a dataset to develop the framework and test it. Indeed, this dataset is insufficient to say something definitive about the research results; nevertheless, it started highlighting some alleged evidence and allowed us to say that the framework works and is usable even by non-expert users, ready to be disseminated to obtain more data. The workbook's design ensures its applicability across various educational contexts, making it a significant contribution to ongoing and future research in AI integration in education.

Regarding some research perspectives, the availability of more data will allow the refinement of the statistics by introducing multiple linear regression analysis. The missing module to send data to a cloud repository will be implemented and embedded in the new release of the framework. Moreover, the collection and processing of qualitative data will be taken into consideration; coupling quantitative and qualitative data will allow us to capture nuanced perspectives on AI and make the results more precise and complete. Finally, the self-selection method to participate to the survey will be investigated, aiming at limiting the possible bias as much as possible.

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Appendix A. AI Questionnaire

Table A1 contains the questions for collecting students' perception of AI. Each answer is expressed on a Likert scale [1..5]. The questionnaire is a revised version of that proposed by Bernabei et al. in [28].

Table A1. AI questions administered to the students.

A. Attitude to AI
AI-A1. I have a basic knowledge of programming languages
AI-A2. I am able to code programming
AI-A3. I am updated on news on AI themes
AI-A4. I have already used AI
AI-A5. I have already used AI for a university assignment
AI-A6. I know the strengths of AI
AI-A7. I know the limitations of AI
AI-A8. I consider myself ready to use AI in a university context
AI-A9. I consider myself ready to use AI in a work context
AI-A10. Using AI can make people feel more confident in carrying out university tasks or work activities
AI-A11. Daily interaction with AI will, in the hypothetical future, make people feel comfortable
AI-A12. I know how AI generates answers to my questions
B. Trust in AI
AI-B1. The use of AI may induce fear or dread
AI-B2. AI can induce curiosity
AI-B3. The use of AI may induce addiction or separation anxiety
AI-B4. AI answers are reliable (truthful)
AI-B5. AI answers are exhaustive
AI-B6. AI answers are accurate (detailed)
AI-B7. AI answers are comprehensible
AI-B8. AI answers are topical/up-to-date
AI-B9. AI poses a threat to creativity and originality
C. Social Influence towards AI
AI-C1. I plan to use AI because people around me have mentioned it
AI-C2. I plan to use AI because people around me use it
AI-C3. I plan to use AI because I heard about it on social networks/TV/newspapers
AI-C4. I plan to use AI to stay updated
D. Fairness and Ethics of AI
AI-D1. The use of AI can help students to pass the examination by reducing the actual learning of the content

Table A1. *Cont.*

A. Attitude to AI
AI-D2. The use of AI can result in an overall evaluation consistent with the actual level of learning
AI-D3. The privacy of data is influential in the use of AI
AI-D4. Intellectual property and copyright issues are influential in the use of AI
AI-D5. The use of AI in the university context should be regulated by the university/faculty/department
AI-D6. The use of AI for writing a university assignment is ethically correct
AI-D7. Answers provided by AI will be subject to bias (e.g., gender/context/social factors/geographical origin bias)
AI-D8. An AI answer is distinguishable from a human being's answer
AI-D9. AI can be used to disseminate misleading or false information, encouraging misinformation
E. Usefulness and Performance Expectancy of AI
AI-E1. The use of AI will establish itself in education (compulsory schooling, universities, training courses, etc.)
AI-E2. Using the results provided by AI will simplify the process of reports/essays/written work
AI-E3. Using the results provided by AI will speed up the process of reports/essays/written work
AI-E4. Using the results provided by AI will simplify understanding of the subject matter
AI-E5. Using the results provided by AI will speed up understanding of the subject matter
AI-E6. Using the results provided by AI will simplify learning of the subject matter
AI-E7. Using the results provided by AI will speed up learning of the subject matter
AI-E8. AI may, in the future, generate hybrid teaching approaches, working alongside teachers in the teaching role
AI-E9. AI will facilitate the integration of information into teaching, due to the open way of accessing content
AI-E10. AI will speed up the integration of information into teaching, due to the ability to access content at any time and from any place
AI-E11. AI will motivate students in learning by allowing them to analyze content in a fun and stimulating environment

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