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Review

A survey on recent trends in robotics and artificial intelligence in the furniture industry

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ABSTRACT

In this paper, we present a survey on recent trends in robotics and artificial intelligence in the furniture industry. We first introduce the state-of-the-art applications of traditional and collaborative industrial robots in this field, with a particular focus on finishing, painting, and assembly operations. Then, the main uses of data management and artificial intelligence are described. Finally, we present the case of the International Furniture and Panel Technology Campus of Friuli Venezia Giulia region (Italy), and the results of a questionnaire submitted to ten companies of the furniture sector.

Contents

1. Introduction

In recent years, robotics and artificial intelligence have profoundly transformed various sectors, including that of manufacturing [1]. This is particularly evident in the era of Industry 4.0, which is marked by the integration of digital technologies into traditional manufacturing processes.

The furniture industry stands as a prime example of transformation and innovation [2], and this holds true for robotics and artificial

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Table 1
Previous review papers on the implementation of Industry 4.0 technologies in the furniture industry over the last five years.

Reference	Focus of the paper
[8]	Awareness, readiness, and barriers to the adoption of Industry 4.0 in the Malaysian furniture industry
[1]	Technologies enablers for the implementation of Industry 4.0 to traditional manufacturing sectors, like footwear, textiles and clothing, furniture and toys
[2]	Application of Industry 4.0 to the wood sector, from forest to finished products
[3]	Application of deep learning to wood defect detection
[4]	Application of machine vision technology in furniture manufacturing process
[9]	Industry 4.0 awareness, perceptions, and actions of employees in furniture and board businesses

intelligence (AI) technologies as well. For instance, deep learning has been extensively applied to detect defects in wood [3], and vision systems have been utilized for gathering information, conducting quality control, automatically detecting and sorting parts, and performing intelligent monitoring [4]. Another example pertains to how data collected can be leveraged to minimize waste generation [5], and to optimize production by adapting various processes to changes in system dynamics [6]. Recent advancements in human–robot collaboration have also enabled new cooperative scenarios that merge the capabilities of human operators and machines, thereby enhancing both flexibility and productivity [7]. Despite these benefits, challenges such as a lack of skilled workers and high implementation costs remain significant barriers to the widespread adoption of these technologies [8,9].

Table 1 summarizes previous review papers about the implementation of Industry 4.0 technologies in the furniture industry over the last five years. However, none of the existing reviews focuses on the application of robotics and AI in such a domain.

This paper presents a comprehensive survey of the latest trends in robotics and AI specifically within the furniture industry. By examining recent developments, applications, and challenges, the survey provides insights into the integration of these technologies, their impact on production efficiency, product quality, and overall innovation within the furniture manufacturing sector, exploring the following research questions:

- What are the general needs of the furniture industry that can be addressed through Industry 4.0?
- What are the state-of-the-art technologies currently adopted in the furniture industry?
- What operations are performed using robotic and AI technologies in the furniture industry?
- How can robotics and AI improve the productivity and working conditions in the furniture industry?
- What are the prospective advancements and challenges in robotics and AI for the furniture industry?

Furthermore, we explore the case study of the *International Furniture and Panel Technology Campus* based in the Friuli Venezia Giulia region (Italy) (from now on, the *FVG Cluster* for brevity). Through a comprehensive questionnaire administered to ten prominent companies operating in this institution, we analyze the current and perceived impact of robotics and AI on the furniture industry, focusing on the challenges and impacts of these technologies.

In summary, the main contributions of the paper include: (i) a survey on the state of the art on robotic technologies in the furniture industry, including both traditional and collaborative robotic systems; (ii) an extended review of the applications of AI and data science in the furniture industry, which focuses on both data management and machine learning solutions; (iii) the outcomes, and their critical analysis, of a questionnaire submitted to ten prominent companies of the *FVG Cluster*.

The paper is organized as follows: in Section 2 the state of the art of robotics and AI in the furniture industry is presented. Then, the case of the *FVG Cluster* is analyzed in Section 3. A short discussion of the emerging picture, which takes into account also future trends, is provided in Section 4. Conclusions are drawn in Section 5.

2. Survey of the state of the art

We first give an account of the methodology followed to systematically retrieve the body of literature on the topics of our interest. Then, a description of the existing contributions about traditional and collaborative robotics follows. An analysis of the contributions in the areas of data management and AI concludes the section.

2.1. Methodology

The research on the state of the art of robotic and AI applications in the furniture industry was performed by consulting the Scopus database, limiting on the works published no later than December 2023. The time horizon and the keywords used for the papers collection are different for the three considered main topics, i.e., robotics, data management, and AI.

For what concerns robotics, an analysis of scientific articles published in Scopus from January 2018 was performed, and the search criteria involved the use of the following combination of words within article titles, abstracts, and keywords: (“robot” OR “robotics” OR “collaborative robotics” OR “cobot” OR “human–robot collaboration” OR “human–robot interaction”) AND (“furniture” OR “wood”). A total of 975 unique papers were identified. We chose this time window since before 2018 there was less interest in this topic (814 papers found), and most of the published contributions were not aligned with the objective of our research. Out of the total number of publications retrieved, we subsequently narrowed down our selection to only those pertaining to robotics applications in the furniture industry, excluding for example the applications in the construction of wooden structures. As a result of this filtering process, 26 articles were selected.

Concerning data management, we first retrieved a set of publications via Scopus. The following (case insensitive) query was used in searching within English article titles and abstracts: (“furniture” OR “wood processing”) AND (“manufacturing” OR “industry” OR “process”) AND (“DBMS” OR “*SQL*” OR “DSS” OR “DMS” OR “information system” OR “decision support system” OR “information system” OR “IoT platform”). The research produced 96 contributions, leading to the selection of 16 articles that aligned with our research objective: case studies focused on the wood furniture manufacturing context.

As for AI, we retrieved the publications via Scopus as well. The following combination of words was used in searching within English article titles, abstracts, and keywords: (“artificial Intelligence” OR “machine learning” OR “learning machine” OR “deep learning” OR “AI” OR “neural network” OR “neural networks” OR “CNN” OR “RNN” OR “LLM” OR “NLP” OR “digital twin” OR “random forest” OR “genetic algorithm” OR “linear regression” OR “decision tree” OR “Bayesian model”) AND (“wood” OR “wooden” OR “chipboard” OR “manufacturing”) AND “furniture”. We found 177 contributions, that resulted in a selection of 59 articles according to the objective of our research: artificial intelligence and machine learning applied to the (wood) furniture industry. Such a selection of articles has been used as a seed in Litmaps,[1] to identify other possible relevant contents, leading to a final pool of 67 papers.

[1] https://www.litmaps.com/

(a) (b) (c) (d)

Fig. 1. Examples of pick-and-place of large and heavy components for loading a wood processing center [10] (a), and for moving wooden panels from the storage to the conveyor (b), (c), (d).

2.2. Robotics and automation

The introduction of robotic systems in industry made it possible to replace human operators in repetitive and non-ergonomic operations, such as moving heavy parts (Fig. 1), or in tasks dangerous to health, as, for instance, welding or spray painting (Fig. 2) [11]. Thanks to the use of robotic systems, human operators can focus on physically less demanding activities and with greater added value [12]. Furthermore, robots can reduce production time and costs [13]. Traditional industrial robots are usually confined in a protected and delimited environment to avoid possible dangers for the human operators. In this context, it is not always straightforward to reconfigure their operations in case a flexible production is needed [14].

Nowadays, recent advances in robotics and automation as well as in safety systems allow industrial robots and human operators to collaborate in a shared workspace, without the need for protective barriers [15,16]. Collaborative robotics serves as a convergence point for the expertise of human operators and robots [17]. Collaborative robotics applications offer opportunities for precision, repeatability, force, and productivity (which are advantages of automation), while incorporating problem-solving skill, creative abilities, and know-how (human capabilities) [18]. Moreover, collaborative robots are usually more flexible in terms of programming, require less effort in the workstation design, are generally lightweight, and more transportable. Therefore, the framework of collaborative robotics can indeed enhance the flexibility of manufacturing processes, and bring the human operator in a central role in the industrial production [14].

Both traditional and collaborative industrial robotic systems find applications in the furniture industry, where they can enhance the performances of many production processes. In recent years, attention has been focused on the automation of assembly, finishing, painting, and pick-and-place tasks, as well as on the improvement of ergonomics and operator safety. Several studies have been carried out on these topics and various solutions have been developed, both for traditional and collaborative robotics, as it is described in Sections 2.2.1 and 2.2.2.

2.2.1. Traditional robotics

The application of traditional robotics in the furniture industry has made it possible to replace human operators in repetitive, non-ergonomic, force-demanding, and dangerous tasks. It enables operators to focus on cognitive activities that better leverage their skills, such as quality control, product development, and process optimization. Applications of traditional robots to the furniture industry are focused on the automation of pick and place, finishing, painting, and assembly tasks. These operations can be performed autonomously by the robots, without any human intervention.

Pick and place. In the furniture industry, robotic manipulators are often used to pick and place large and heavy materials, e.g., raw panels and semi-finished products, as well as for loading and unloading manufacturing machines, e.g., panel saws, edgebanders, drilling machines, sanders, and insertion machines. Fig. 1(a) shows a robotic arm used for loading a wood processing center, whereas in Figs. 1(b), 1(c), and 1(d) examples of manipulators moving wooden panels from the storage to the conveyor are reported. Automating the movement of components has the main advantage of reducing costs, time, and human effort, increasing the productivity, and preventing operators from performing heavy tasks.

Finishing. In addition to load handling, surface finishing is another application where robotic systems are often used [19]. This operation demands precise control over applied pressure to achieve the desired surface roughness and uniformity, as well as high precision and maneuverability. For this application, the main challenge is to replicate human sensitivity and adaptability, such as compensating for positioning and production tolerances and working on complex, hard-to-reach surfaces [20].

The requirements mentioned above for the finishing of wooden components have led to the exploration of robots equipped with appropriate sensors, such as force and torque sensors [19,21]. As an example, the authors in [22] present a system that enables instructing a robot on how to polish chair legs using a haptic device for teleoperation control, based on a master–slave logic. The positions and orientations adopted by the end-effector during the teaching phase are continuously recorded, allowing the robot to replay the trajectory.

The data acquired from sensors can also be used to evaluate the finishing quality. As an example, the authors in [23] use normal force data from a UR5e robot equipped with a force and torque sensor and an orbital sander. The robot maintains the desired normal force with a force regulator and adjusts the feed rate based on force signals to minimize execution time. Similarly, in [24] a force control with position compensation is applied to a Fanuc M-20IA robot equipped with a polishing tool for the surface polishing of wood panels. The position of the polishing tool is continuously corrected processing data from the force sensor in real time. This feedback reduces the initial contact force overshoot and improves the controller stability. Together with the force sensors, a customized robotic system for sanding wooden boxes that applies structured light to assess the quality of sanding and ensure a uniform finishing is presented in [25]. The structured light is also exploited for acquiring the box position and dimensions, which offers high accuracy and robustness against changing lighting conditions. From the data collected by the cameras, the CAD model of the box is reconstructed and sent to a planner that computes optimal trajectories for sanding the various surfaces of the furniture component.

Spray painting. Spray painting is another operation that is often performed by robots in the furniture industry, especially to remove human operators from hazardous environments, due to the risk of inhaling toxic spray particles [26]. Moreover, precision and maneuverability are essential to obtain a high-quality and reliable painting result [27]. Automating spray painting enables a reduction in costs, time, and human effort, and a more uniform coating with paint waste reduction [28]. Spray automation can, indeed, reduce the gaseous pollution and enhance the sustainability of the entire painting process. An example of robotic spray painting is shown in Fig. 2, where the automated painting of a chair (Fig. 2(a)), a nightstand (Fig. 2(b)), and a window (Fig. 2(c)) are shown. In spray painting, it is important to guarantee a constant tangential velocity of the paint gun to obtain an even color distribution [29]. This requirement can be addressed through a proper planning of the painting path and trajectory [30–32]. A recent challenge in automating painting furniture is the identification of both the location and type of object to be painted, especially in scenarios involving diverse products, as in the furniture industry [33].

Recently, the development of vision systems allows to automatically identify both the location and the type of object to be painted, like, for instance, different parts of a chair placed on a conveyor belt [28], enabling the customization of operations for specific components to be painted. By pre-planning and saving the robot painting trajectories for each distinct component, the painting system can be adapted when it recognizes the component to be painted and its position, easily deriving the appropriate trajectory to execute. An example can be found in [34], where the authors present a system for estimating the pose of a chair to be painted using an RGB-D camera. First, several images are acquired from different positions, and then an artificial neural network (ANN) is used to estimate the pose of the chair with respect to the robot. Vision systems can also be used for on-line trajectory planning, as in [35]. In that work, the authors develop a system for the automating painting of panels for cabinet doors that acquires the point cloud of the panels thanks to a linear laser sensor and automatically plans the painting trajectory by processing the point cloud.

Assembly. Once the individual components of a furniture have been manufactured, finished, and painted, the final step is to assemble them together to obtain the final product. In the furniture industry, the assembly process is often a tedious operation. First of all, it is not trivial to understand, starting from the single parts, how and in which order to assemble them. Furthermore, connecting the various parts requires manipulation skills and strength to correctly hold and align the components to be joined together.

Developing a robot that autonomously assemblies a furniture is a complex multidisciplinary problem that requires the following operations:

1. perceive the type and the position of the parts to be assembled;
2. understand the assembly sequence;
3. plan appropriate trajectories and physically execute the assembly task.

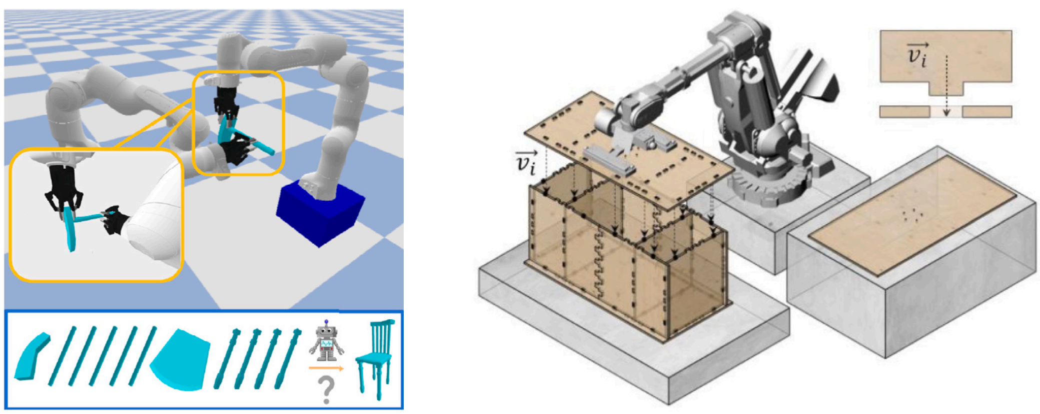
The detection of parts is mainly performed through computer vision (CV) systems, employing one or multiple cameras. To simplify this task, the authors in [37,38] propose the application of a specific marker to each assembly component to assemble tables and Integrally Attached Timber Plate Structures (IATPS), respectively. In this way, when a camera detects a marker, the location and type of the part can be easily derived. Nevertheless, the primary drawback of this approach is that each marker associated with a specific component has to be unique. Therefore, this strategy is not efficient when dealing with numerous components. Another possibility is to use CV algorithms based on feature recognition, as proposed in [39,40]. CV systems process the images recorded by cameras for recognizing desired features like corners, edges, lines, circles, or arbitrary shapes. To correctly identify their position with respect to the robot, a proper camera calibration is needed. Implementing this method is more challenging than using markers, but it is more suitable for large numbers of parts.

The second element of an autonomous assembly system is the intelligence of the system. One approach to solve this problem is to manually provide the assembly sequence to the system, as in [37,41], and [40], where the assembly of tables and chairs is shown. Manually specifying assembly sequences works well for standardized production, such as chairs, tables, and cabinets. However, for customized production, autonomous assembly sequence derivation is preferred. The authors in [39,42] propose to use reinforcement learning and imitation learning algorithms for the assembly of different types of chairs, tables, and bookshelves. The proposed algorithms need a limited set of training cases to provide good results in automatic defining the correct assembly sequence. An example of this process is shown in Fig. 3(a), where two Franka Emika arms are used for the simulated assembly of a chair. Differently, in [38,43], the assembly sequence is defined starting from the 3D model of the furniture. In [43], the authors aim at finding a sequence that can successfully disassemble a polygonal furniture (for instance, cabinets and bookshelves) with a UR5 robot, avoiding collisions among different parts and ensuring that each piece not removed from the assembly remains in contact with at least another one. If a suitable sequence can be found, it is then followed in reverse to define the strategy to assemble the components. Furthermore, the authors in [38] develop a system for assembling IATPS structures with an ABB IRB 6400R robot. In IATPS structures the joints needed for coupling components are comprised into parts shape. Consequently, the assembly sequence is closely related to the geometry of the joints.

The last requirement of an autonomous assembly system is the trajectory planning and the physical execution of the assembly. Knowing the assembly sequence, appropriate trajectories have to be planned so

(a) (b) (c)

Fig. 2. Automated painting of a chair (a), a nightstand (b), and a window (c) [36].



(a) (b)

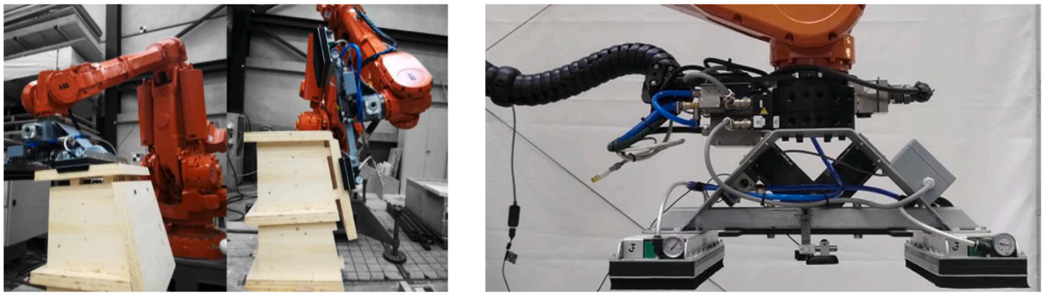
Fig. 3. Simulation of a chair assembly process (a) [42], example of path planning for piece insertion (b) [38].

as to avoid collisions with the parts already assembled and correctly manipulate the remaining ones. The authors in [37,40] propose to plan trajectories relying on a task template (such as connecting, screwing, and grasping), which offers the advantage of modularity, allowing for reprogrammability and reusability of the system for different types of furniture, like chairs, tables, cabinets, and nightstands. The authors in [38,43] plan trajectories starting from the 3D model of the assembly, through the same procedure by which they derived the assembly sequence (Fig. 3(b)). Differently, a hierarchical reinforcement learning algorithm is adopted in [41] to plan trajectories for a Sawyer robot, which can be adapted to different furniture types, such as chairs, tables, and shelves. Furthermore, the authors in [44] develop a system for task allocation and motion scheduling for dual-arm robots to avoid collisions and interference between the arms. Their experimental configuration involves two KUKA LBR iiwa robots situated on a table with extensively overlapping workspaces, utilized for gluing and inserting bolts into a panel constituting part of a shelf.

Concerning the physical execution of the task, robotic arms with six or seven degrees of freedom (DOFs) are mainly used, since they provide better dexterity and manipulation capabilities with respect to other types of robot (e.g., Cartesian or SCARA). In this context, the most used manipulators are the Franka Emika manipulator with seven DOFs [39,40,42], the UR5, UR5e, and UR10e robots by Universal Robots with six DOFs [43], the KUKA robots with six DOFs like the KUKA LBR iiwa robot [44], the ABB robots with six DOFs like the ABB IRB 6400R robot [38], the Sawyer robot and the Baxter robot by Rethink Robotics with seven DOFs [39,41]. Custom manipulators are also employed, as in [37], where a custom robotic arm with six DOFs is used. Good dexterity and manipulation capabilities are important features in the furniture assembly, where pieces and structures can be challenging to be manipulated and a high level of dexterity is required for completing the assembly task. Moreover, multiple robots can also be adopted in order to increase manipulation capabilities [40,42].

In the furniture industry, and more in detail in the assembly of furniture products, vacuum grippers equipped with suction cups are often used as end-effector in robotic systems to grasp planar and large components, like wooden panels and chipboard [38,43]. An example of vacuum grippers is reported in Fig. 4. Instead, fingered grippers are suitable for small and arbitrary-shaped parts like chair legs [37,41]. Additionally, drill modules can be introduced in the system to perform screwing tasks [40]. Fig. 5(a) illustrates an example of an entire assembly framework, composed of three Franka Emika robots for handling the components during the assembly process, two drill modules, a RGB-D camera for perceiving pieces position, some connector holders, and worktables. Fig. 5(b) shows the details of the equipment used for the robot end-effector and drill modules.

Table 2 reports an overview of the applications of traditional robotics in the furniture industry. Regarding painting applications, the attention is mainly focused on automatic pose estimation, geometry acquisition, and painting trajectory planning, whereas for finishing operations the robotic arms are equipped with sensors, e.g., force sensors,



(a) (b)

Fig. 4. Automated assembly of the structure (a), and particular of the vacuum gripper (b) [38].

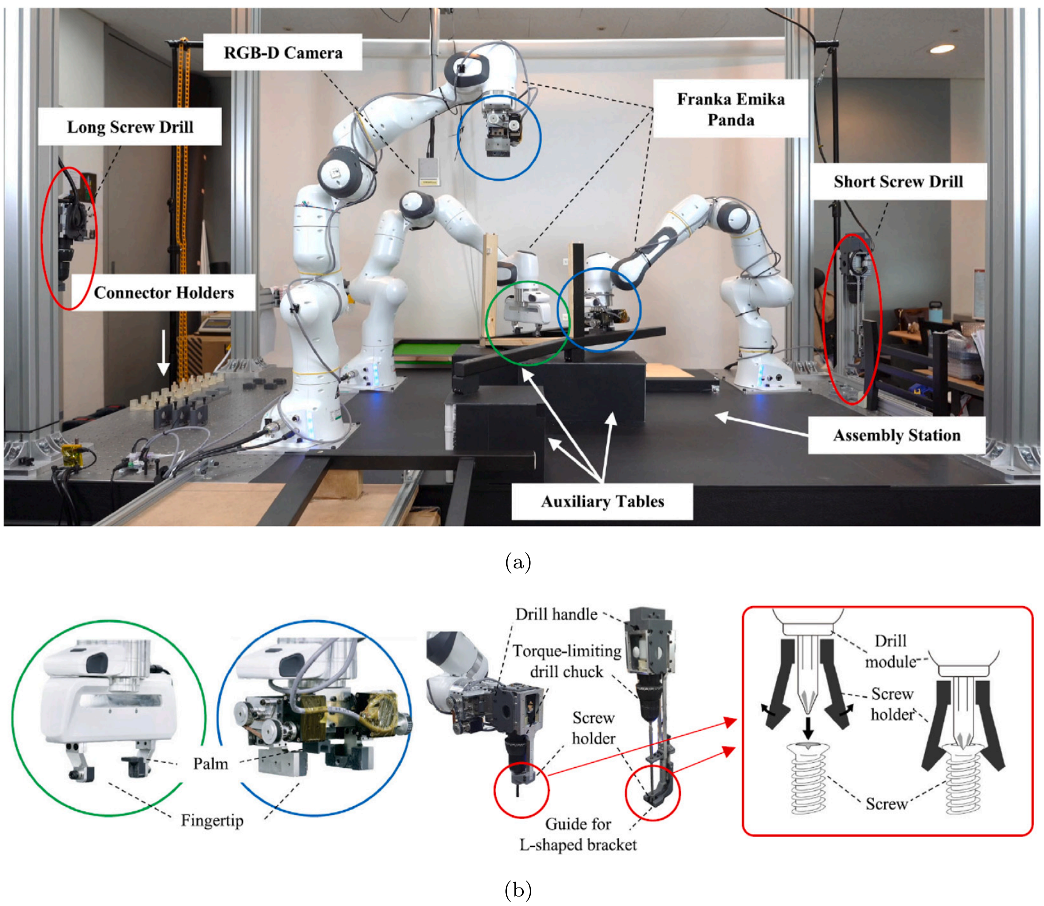


Fig. 5. Assembly framework (a), robot end-effectors and drill modules (b) [40].

in order to obtain a good surface finishing quality. The assembly of the furniture is mainly performed with robotic arms with six or seven DOFs to ensure good manipulation capabilities. Moreover, solutions for piece position detection, assembly sequence planning, and trajectory planning have also been developed.

2.2.2. Collaborative robotics and ergonomics

In the context of Industry 4.0, where product customization and process adaptability are pivotal, human–robot teams are emerging as a solution to these demands, leveraging the complementary capabilities of humans and robots [45]. Safety in such collaborations is paramount, with various safety measures aligned with the ISO/TS 15066 [46] being implemented to address this concern [47]. In the furniture industry, human–robot collaboration is mainly applied to assembly workstations [14], where the risk of musculoskeletal problems for operators performing manual tasks has to be minimized [48].

Collaborative assembly. In order to perform a human–robot collaborative assembly of a furniture product, human and robot share a workspace with the aim of completing a common task. To avoid potential unwanted collisions with the human operator, the robot has to perceive the location and actions of the human operator monitoring its workspace by using cameras [16,49] or tracking the position of operators by means of wearable sensors [50]. Moreover, as for traditional robotics, in such frameworks the position and the type of the pieces to be grasped have to be recognized so as to correctly execute the desired task [51,52].

In collaborative robotics, endowing robots with decision-making abilities is crucial. This capability enhances flexibility, enabling robots to adjust to changes in tasks, such as assembling different chair types. For reliable decision-making, robots require awareness of events in their surroundings, allowed by tracking systems. Additionally, robots

Table 2
Overview on traditional robotics applications in the furniture industry.

Reference	Application	Methodology	Robot
[34]	Painting chairs	• Computer vision for detecting objects • Object pose estimation	–
[35]	Painting panels for doors	• Geometry acquisition through laser sensors • Painting path planning	–
[28]	Painting furniture parts	• Computer vision for detecting parts • Painting trajectory planning	–
[22]	Finishing chair legs	• Teaching through teleoperation • Applied force control	FANUC M-20iA/35M
[25]	Finishing wooden boxes	• Computer vision for detecting objects • Trajectory planning • Force control	Custom robot with 4 DOFs
[23]	Finishing panels	• Applied force control • Feed rate control • End-effector vibration measures	UR5e
[24]	Finishing furniture parts	• Applied force control • Position compensation	FANUC M-20iA/35M
[37]	Assembly tables	• Computer vision and markers for detecting pieces • Skill-based programming	Custom robot with 6 DOFs
[43]	Assembly cabinets, bookshelves, and similar	• Simulation • Assembly sequence planning • Assembly path planning	UR5
[44]	Assembly furniture in general	• Task allocation • Task scheduling • Learning by demonstration	KUKA LBR iiwa
[38]	Assembly IATPS structures	• Computer vision and markers for detecting pieces • Assembly path planning	ABB IRB 6400R
[42]	Assembly chairs	• Simulation • Assembly sequence planning • Assembly path planning	Franka Emika
[39]	Assembly furniture in general	• Simulation • Data acquisition from sensors • Assembly path planning	Franka Emika, Sawyer, Baxter
[41]	Assembly chairs	• Simulation • Assembly trajectory planning	Sawyer
[40]	Assembly chairs	• Computer vision for detecting parts • Task template and compiler • Assembly path planning	Franka Emika

have to ensure operator assistance without compromising safety. The proper action to perform can be chosen either autonomously or following a request from the operator. Methods for instructing the robot and requesting it to perform a specific action include manual guidance, teleoperation, as well as gesture and vocal commands.

In [49], a system that uses a hybrid conditional planning based on answer set programming is introduced for assembling a table in collaboration with a Baxter robot. The proposed framework allows determining the actions to perform to reach a goal state from a given initial state, in the presence of incomplete knowledge about the environment and human actions, behavior, and intentions. In the developed system, the robot can communicate with the operator, by making requests or offering help. The communication task is accomplished using Google Translate text-to-speech API, whereas Google Speech API is used to recognize the responses of the human. An example of this application is reported in Fig. 6, where a human operator assembling a table in collaboration with a Baxter robot is shown. The authors in [50] present a human–robot collaboration framework that allows a decomposition of procedures into their constituent elements and the logical relationships between them, deciding what to do based on human actions. Differently, in [53], a system based on an artificial neural network is introduced to cooperate with a robot by guiding it through gestures. A camera tracks the skeleton of the hand and a supervisory controller associates a specific gesture to its correspondent action, such as pick up or assembly furniture parts.

Another method for teaching the robot is manual guidance. In this strategy, the robot holds the load, whereas the operator leverages his cognitive abilities to guide the robot during assembly, as presented in [51]. In that work, a KUKA robot, equipped with a humanoid hand as end-effector, is controlled using impedance control to ensure a safe collaboration between human and its robotic counterpart, allowing the operator to adjust the position of the robot hand as needed (Fig. 7). Similarly, the authors in [52] instruct the robot through a framework consisting of two collaborative robotic cells, a “teaching cell” and an “execution cell” (Fig. 8(a)). The first cell is tailored to human–robot collaboration, employing learning-by-demonstration techniques to instruct the robot in executing articulated movements (Fig. 8(b)). The second cell derives the sequence of operations from information acquired from the first cell and executes the tasks. Their system comprises three UR10e robots equipped with an end-effector designed for performing screwing operations and assembling timber structures. A different example is provided in [54], where a humanoid robot is guided by the operator through a haptic device to perform the assembly task of chairs (Fig. 9). In this way, operations that require strength and precision can be easily executed.

Fig. 6. Human–robot collaboration for the assembly of a table with a Baxter robot [49].

Ergonomics. In the furniture industry, the movements of the operators are often repetitive and uncomfortable. Therefore, ergonomics can help in reducing the risk of injuries and musculoskeletal disorders for operators in performing manual tasks, while also improving workstation efficiency and productivity. The literature provides examples of the application of safety and ergonomics concepts to collaborative robotics in the furniture industry [12,55]. For instance, an approach where the physical behavior of a KUKA robot, equipped with a Pisa/IIT Softhand as end-effector, is adapted in real time to the human fatigue for sawing and polishing wooden components is presented in [56]. The human fatigue is estimated using sensors which measure the human muscle activity (electromyography). In that system, the robot employs a hybrid force and impedance controller, and initially follows and imitates the human. The robot learns the task gradually executing it collaboratively with the operator. When a predefined fatigue level is reached, the robot uses the learned skills to perform the task by itself.

Different examples of ergonomics application can be found in [57–59]. In those works, the authors analyze the working conditions of operators in an assembly workstation for the production of medium-density fiberboard (MDF) frames for shelves and tabletops, and improve them with the introduction of collaborative robots. Criteria for assessing the risks and problems of assembly stations are proposed as well. The main criterion is the analysis of musculoskeletal risks associated with the manual assembly process (Fig. 10). First, these risks are evaluated through indexes like the Rapid Upper Limb Assessment (RULA) and the Strain Index (SI), obtained equipping operators with wearable sensors. The RULA and SI indexes assess the postures assumed by operators during the tasks and associate a level of musculoskeletal problems risks with each movement. Questionnaires among workers on their perceptions of comfort and working conditions are also conducted.

Similarly to [57–59], the authors in [60] propose a method to design human–robot collaborative systems that combine ergonomics with productivity requirements. This approach takes as input the ergonomic and production constraints and tests different combinations of robot, end-effector, sensors, and task allocation between human and robot. The ergonomic risks are evaluated according to standard assessment indexes, such as RULA and Occupational Repetitive Actions Index (OCRA), whereas the productivity is assessed in terms of cycle time and quality performance. The method has been tested in a collaborative robotic workstation for assembling drawers with the support of a UR10e robot, demonstrating that it can greatly reduce ergonomic risks for the operator while meeting production constraints.

In [48], a robotic system that adapts in real time to support an operator in a quality control workstation is developed. The proposed framework, based on an UR10e robot, integrates a vision system that maps the workspace and recognizes the operator position and posture, the product and the task to be carried out. Relying on a database built in a previous training phase and based on the RULA index, the robot controls the end-effector pose to minimize the operator ergonomic risk (Fig. 11). Moreover, the operator hand skeleton is tracked to guide the robot motion through gestures.

In Table 3, an overview on collaborative robotics applications is provided. The table shows that collaborative robotics primarily assists human operators in assembly tasks. These robots, equipped with vision systems and decision-making capabilities, can be manually guided and improve ergonomic conditions for human operators.

2.3. Data science and artificial intelligence

In the following, we explore the applications of data science and AI to the furniture industry, highlighting how it is transforming traditional practices and contributing to advancements in efficiency, sustainability, and customization. Data science is a relatively new field that emerged in the past few decades, fueled by a significant increase in data availability and advances in computational power. It is an interdisciplinary area that makes use of a variety of scientific approaches, methods, processes, and algorithms to extract knowledge and insights from structured/highly organized data, e.g., relational tables, semi-structured data, e.g., XML documents and machinery logs, and unstructured data, that is, data lacking a predefined organization, like, for instance, free texts [61]. In the last years, data science has proven to be crucial across various industry sectors, contributing to the emergence of Industry 4.0 [62]. In the furniture manufacturing, the applications of data science can deeply transform decision-making processes, streamline supply chain operations, and enhance manufacturing practices [63].

Although data science often uses sophisticated machine learning (ML) algorithms to analyze data, the foundation of its success lies in accurate data modeling, that is, accurate data cleaning, integration, and representation (e.g., [64]) are essential to solve downstream analytical tasks effectively. In view of that, Section 2.3.1 explores data management systems in the furniture industry, highlighting their critical role in the development of an enterprise-wide information system. Then, Section 2.3.2 focuses on AI applications that feed on the previously modeled data. The overall aim is to illustrate the transformative potential of AI when backed by accurately modeled data, demonstrating its capacity to drive innovation and efficiency in industry.

2.3.1. Data management

Technologies for data management, including databases (relational, NoSQL, and NewSQL databases [65]), data warehousing [66], decision support systems, decision management systems, and information systems [67], are becoming more and more crucial in enhancing operational efficiency, decision-making processes, and strategic planning in the furniture industry. In the following, we present the most important contributions in the area grouped by the adopted technology, starting from the most fundamental one (databases).

Databases. The foundation of any data analysis task lies in effective data storage and management. On the one hand, traditional relational databases offer robust transactional integrity and structured query capabilities, making them ideal for tasks such as managing orders and inventory. On the other hand, NoSQL databases offer scalability and flexibility necessary for handling unstructured data such as customer preferences and interactions. NewSQL databases attempt to merge the

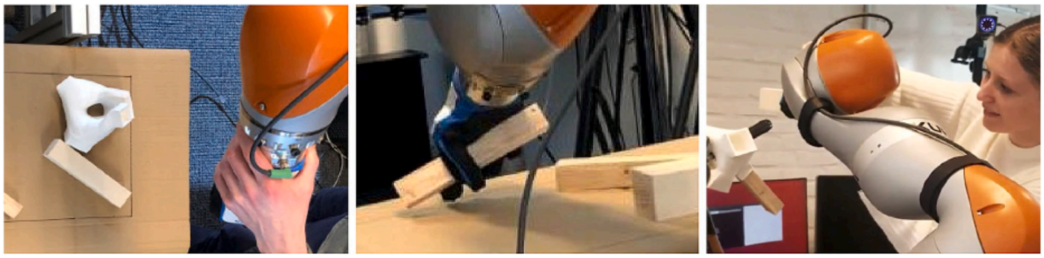
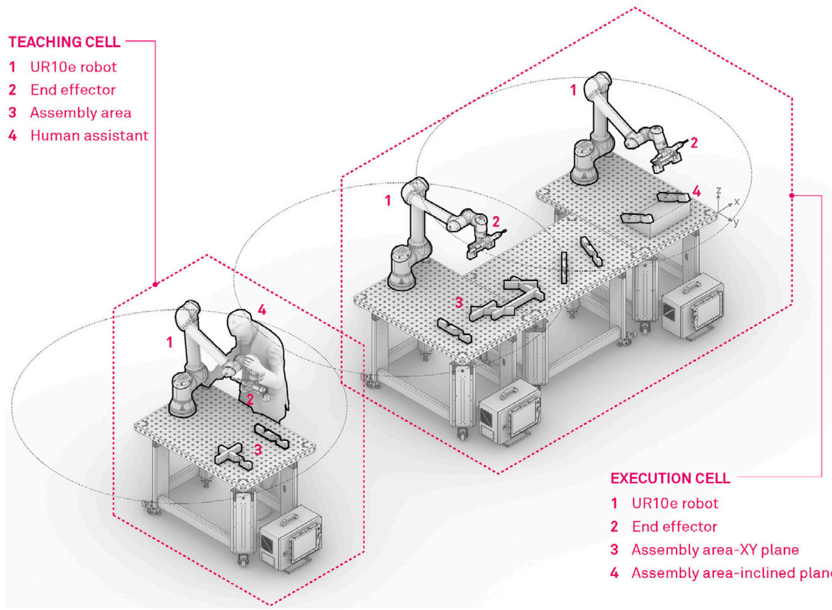
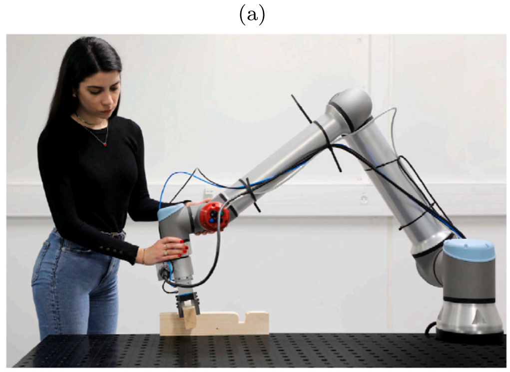


Fig. 7. The robot learns the assembly process through manual guidance [51].



(a)



(b)

Fig. 8. Teaching cell and execution cell (a), and operator during the robot teaching phase (b) [52].

strengths of both, providing high performance for real-time analytics and operational intelligence. The European furniture industry faces significant challenges, notably a lack of flexibility and efficiency, which hinders its response to rapidly changing market demands, especially in specialized batch production. This issue is particularly relevant for small and medium-sized enterprises (SMEs), which often suffer from poor information flows across their operations. To address this problem, the author in [68] proposes an integrated furniture manufacturing system that employs advanced computer-integrated manufacturing (CIM) concepts, previously underutilized in this sector due to the unique properties of wood and furniture design requirements. At the core of the system lays a distributed, multi-user, object-oriented database, which acts as the central platform for integrating various CIM tools. Similarly, the benefits of database technologies for SMEs in the wood sector are discussed in [69]. By implementing a Relational Database Management System (RDBMS), enterprises can access detailed company information at various levels, supporting strategic planning and standardization of practices, and the development of e-marketing and e-commerce applications.

Data warehousing. An effective data warehousing strategy is crucial for aggregating and analyzing data from various sources, such as, for instance, independent databases, to enhance decision-making processes. By providing a unified view of data, data warehouses allow companies to make informed strategic decisions. In this context, the authors in [70] discuss a methodology for combining SQL and NoSQL databases

Table 3
Overview on collaborative robotics applications in the furniture industry.

Reference	Application	Methodology	Robot
[49]	Assembly tables	• Computer vision for parts and human recognition • Markers for simplify pieces detection • Answer set programming for making decisions • Communication with the operator	Baxter
[50]	Assembly tables	• Computer vision for parts and human recognition • Decision-making capabilities	Baxter
[51]	Assembly urban furniture	• Computer vision for parts and human recognition • Assembly trajectory planning • Impedance control for manually guiding the robot	KUKA
[52]	Assembly timber structures	• Computer vision for parts and human recognition • Learning from demonstration	UR10e
[53]	Assembly drawers	• Computer vision for parts and human recognition • Robot guidance through gesture commands	Kinova Gen3
[54]	Assembly chairs	• Learning from demonstration	Humanoid robot
[56]	Human fatigue reduction	• Human fatigue monitoring • Hybrid force and impedance control to allow manual guidance • Learning from demonstration	KUKA lightweight robot
[57]	Improving assembly ergonomics	• Ergonomic conditions analysis • Evaluation of possible application of collaborative robotics	UR10e
[58]	Improving assembly ergonomics	• Ergonomic conditions analysis • Process redesign to allow human–robot collaboration	UR10e
[59]	Improving assembly ergonomics	• Ergonomic conditions analysis • Tasks scheduling and allocation between human and robot	UR10e
[60]	Improving assembly ergonomics	• Ergonomic conditions analysis • Tasks allocation between human and robot • Layout optimization	UR10e
[48]	Improving quality control ergonomics	• Ergonomic conditions analysis • Computer vision for parts and human recognition • Robot guidance through gesture commands • Quality control	UR10e

Fig. 9. An operator guides the robot to perform the assembly of a chair [54].

to streamline the operations of two online furniture e-commerce platforms. The integration merges product data from both systems into a new, unified one, addressing the challenges of working with heterogeneous database systems in a web environment. The specific solution employs web services for data retrieval from each database and a synchronization system to manage data storage in the new system.

Decision support and management systems. The application of decision support systems (DSSs) and decision management systems (DMSs) in the furniture industry is increasingly important in order to optimize production processes and to enhance strategic planning. These systems are often centered around a properly designed enterprise-wide data warehouse. Exploring various applications of these systems, a DSS is proposed in [71], which considers wood quality feasibility parameters across five criteria: physical properties, mechanical properties, wood grade, age, and substance content. The alternatives that have been evaluated include teak, trembesi, mahogany, and acacia wood. By exploiting these parameters, the software system conducts a thorough analysis, the outcome of which is a decision on the best wood to be

Fig. 10. Manual assembly and skeleton tracking for evaluating the ergonomic conditions of workers [59].

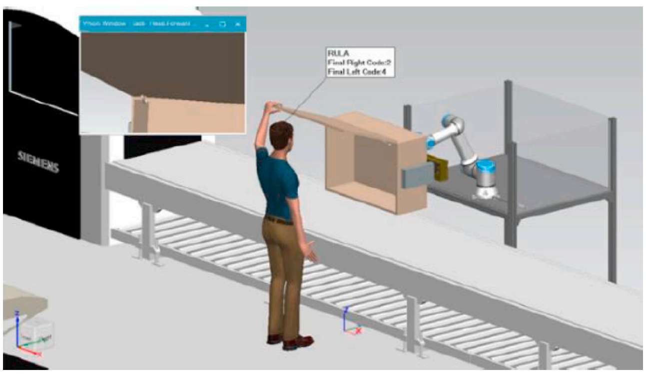


Fig. 11. Ergonomic risk evaluation for a tested configuration [48].

used as material for handicraft furniture. Once the needed kinds of wood have been identified, a proper inventory management of them is paramount. In this context, the authors in [72] present the case of a company that produces wood office furniture. The authors discuss how errors in decision making in particle board supplies can affect the production cycle and, in turn, have an impact on increasing waste and cost, and decreasing profit. Then, they show how to reduce such errors by using DSSs to assist the decision-making process in the particle board inventory process in the warehouse of raw materials, helping logistics managers in determining the right scenario in order to achieve optimal results.

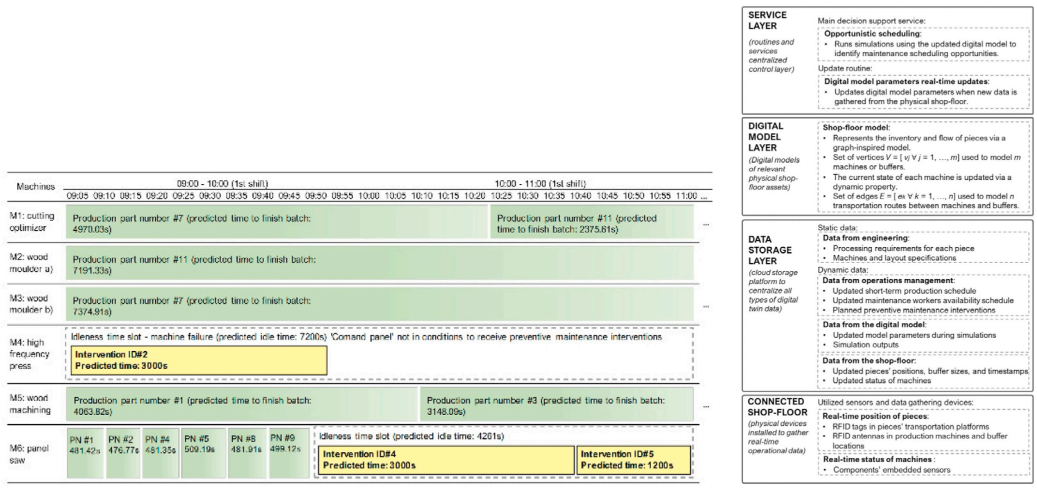
Seeking for the optimal relationship between the inventory and the output of the production process, the work in [73] describes the development and application, within a furniture company, of a DSS to enhance production profits through the mapping of timber types and product counts. The DSS uses the Analytical Hierarchy Process (AHP) method to systematically compare and prioritize various criteria and alternatives, e.g., quality and kind of the wood to utilize, and number of products to make, aiming at optimizing inputs for maximal output and profit. The system comes with an interface that manages data entry, criteria calculation, and report generation, significantly enhancing operational efficiency and data-driven decision making. When optimizing a production process, it is important to consider not just the economic factors, but also sustainability and ethical matters. In this perspective, the work in [74] presents a prototype of a DSS, called EvaSus, specifically designed for the Indonesian furniture industry. From a technical standpoint, the work is characterized by the integration of a sustainability model for production that assesses current performance in terms of the Triple Bottom Line (economic, environmental, and social). From a practical point of view, EvaSus provides managers with a user interface that allows them to input and analyze various performance parameters. This facilitates the periodic evaluation of performance and helps decision makers to identify factors contributing to the increase or decrease in performance. Additionally, the system provides a sustainability index for production, offering a comprehensive overview of the company's sustainability.

When fully optimizing production processes, proper attention should be given also to the maintenance of machinery. Under this respect, the authors in [75] design and implement a decision support system that uses a Digital Twin (DT) architecture to schedule predictive maintenance activities in a manufacturing context. The DSS receives a predetermined production schedule as input and it works to minimize productivity losses caused by pre-planned maintenance interventions. The DT is used to provide maintenance managers with an updated schedule that optimizes machine downtime (Fig. 12(a)). The DT consists of a physical workshop connected to the digital world, a data storage platform to record all generated data, a digital model of the workshop relevant assets, and a service layer that provides analytical support (Fig. 12(b)). The system is applied to a case study of a furniture manufacturing company based in the state of Santa Catarina, Brazil.

Finally, it is important to underline that for any DSS to be functional to the objectives of a company, it must be accepted and supported by its users. To this end, the application of the ISO 9126 standard to improve the evaluation of DSS in the manufacturing industry, with a particular focus on the furniture sector is explored in [76]. The research addresses critical user concerns about DSS, such as the speed of information reporting, the order reception, and the accuracy of raw material usage calculations, which are vital to enhance production decision-making processes. The study employs a comprehensive methodology, including interviews, observations, and questionnaires, to gather data on user satisfaction with DSS. Key findings reveal positive evaluations of DSS across several ISO 9126 features, such as suitability, accuracy, interoperability, security, maturity, fault tolerance, recoverability, and reliability compliance. This means that DSS, when evaluated and refined on the basis of ISO 9126 standards, can significantly address user concerns and improve conventional business processes within the furniture manufacturing industry.

Information systems. An information system (IS) is an integrated set of elements to collect, store, process, and communicate information. It is a general infrastructure that encompasses one or more of the previously-discussed components. The adoption of information systems within the wood processing sector, including furniture manufacturing, is investigated in [77] with a focus on the Croatian case. Specifically, the study aims at assessing the level of information technology integration in business operations and its contribution to the enhancement of business performance in this industry. Through a survey methodology, the research predominantly collected responses from SMEs. The findings indicate an average deployment of IS modalities among the surveyed companies. Despite not detecting a statistically significant relationship between the financial benefits of IS implementation and company performance, the research notes subjective improvements in non-financial indicators, such as, for instance, significant benefits of IS in improving inventory and sales efficiency. Overall, the study suggests that the application of IS, especially when tailored to specific company needs, can address user concerns and enhance business processes within the manufacturing industry.

Often, the adopted information systems deal with the whole production process. This is the case of [78], which discusses the development of a web-based IS designed to help furniture companies to monitor



(a) Example of idle time slots and intervention scheduling.

(b) Architecture.

Fig. 12. An example of the use of a Digital Twin in the context of the timber industry [75].©2024, with permission from Elsevier.
Source: Reprinted from [75].

and oversee their production processes, from raw material selection to the final quality control. This is essential for maintaining high-quality furniture production that meets both domestic and international standards, while adhering to the intended production schedules. Another notable example is portrayed in [79], which introduces a versatile platform designed as an accessible, easy-to-use support tool for SMEs to conduct what-if analyses aimed at enhancing their products design, and that of the related production processes. The platform has a modular, multi-layer architecture, including a Decision-Making Layer, a Data Exchange Layer, and a User Management Layer, each one consisting of specific modules. Tools to facilitate production simulations, finite element analysis, and material utilization optimization are incorporated as well. The modular design of the platform allows one to integrate additional functionalities, such as quality control and supply chain management, potentially broadening its utility and effectiveness. The validity of the system is empirically demonstrated by a case study involving a company in the furniture industry, which highlighted the platform ability to optimize the design and production of a new bookcase, leading to increased operational efficiency, cost reductions, and enhanced profitability.

Other, more dedicated information systems are used to support client customization. Among them, we would like to mention the work in [80], which focuses on the development of data collection and management systems for mass customization in the furniture industry. Furniture manufacturing needs to adapt digital processes to effectively collect and process customer demands and to respond rapidly to market needs. The resulting IS must be able to support design, production, inventory control, quality control, and customer relationship management. The role of MES (Manufacturing Execution Systems) as a useful source of data is also highlighted. In [81], the integration of Enterprise Resources Planning (ERP) with a Computer Numerical Control (CNC) machining center at a kitchen furniture manufacturing company is presented. The integration aims at improving production process flexibility and efficiency, and product customization. More precisely, the integration of the ERP system and the CNC machinery enables the automatic generation of the necessary components and their machining programs on the basis of the orders of customers. The work in [81] also takes into consideration the modules to be manufactured and the corresponding options for model, color, material, handle, and so on.

Identifying and fulfilling customer demands is crucial to enhance the efficiency of the production process. A closely related issue is the cutting stock problem (CSP) in the wood industry, which is addressed by the IS described in [82]. This system generates efficient cutting plans that minimize waste and utilize leftovers. It is tailored to SMEs, which typically lack access to such technology. However, producing a certain amount of waste is unavoidable. Aware of this, the authors in [83] develop an Internet-based Geographic Information System (GIS) to connect waste/wood scrap producers from the furniture industry with potential buyers, enabling optimal recycling, and making the collection and transportation of said scraps more sustainable and efficient. Waste producers input information about the quantity and price of their waste, while those involved in the collection/purchase of processing scraps can enter information about their location. The system then displays optimal solutions based on the minimization of delivery costs and other criteria.

2.3.2. Artificial intelligence

Artificial intelligence (AI) and machine learning (ML) technologies are becoming ubiquitous and pervasive in any aspect of our life. Furniture industry is not an exception, with applications already beginning to be deployed in real facilities (Fig. 13), ranging from classical topics, like defect detection, wood classifications, and optimization of the production process, to more recent ones, enabled by new learning paradigms, like design support and machine monitoring to aid predictive maintenance. In the following, a review of the scientific literature on the application of AI and ML methods and techniques in these areas is reported.

Production process optimization. One of the first AI applications for the optimization of the production process of furniture companies is the work in [84]. Furthermore, by exploiting Genetic Algorithms (GAs), the authors in [85] develop a hybrid algorithm that optimizes the sequence of lumber drying operations and inventory allocation to minimize costs while ensuring production deadlines are met and reducing the costly outsourcing.

Several studies focus on optimizing job sequencing and scheduling. In [86], lead-time reduction and makespan minimization for cut and sew operations in upholstered furniture manufacturing are investigated. That research work employs a GA with a heuristic for multiple setups per group, leading to significant improvements in schedule makespan. Similarly, the works in [87,88] propose a hybrid approach combining GAs and a Feedforward Neural Network (FNN) or Multilayer Perceptron (MLP) [89,90], to effectively generate near-optimal schedules while accounting for the unique characteristics of custom furniture production. Further advancements in scheduling optimization are reported in [91], which explores integrated production–distribution scheduling

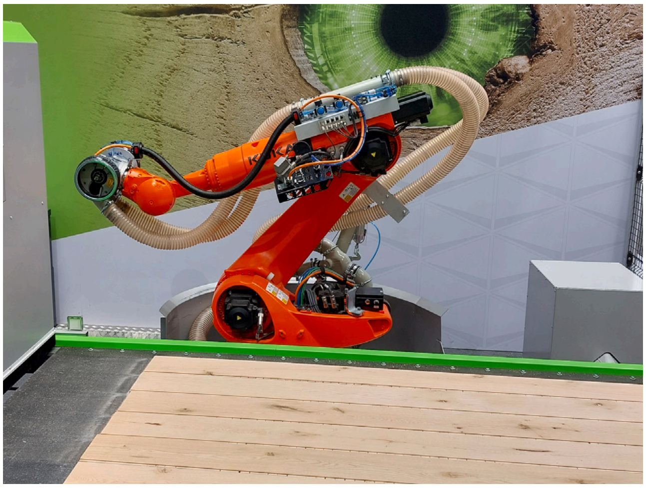


Fig. 13. Example of robotic system coupled with a vision device and AI capabilities for defects identification on wood planks.

in a parallel machine environment, aiming at minimizing tardiness and delivery costs. In that work, the authors propose a mixed-integer linear programming model and develop improved GAs, showcasing optimal solutions for a real-world case study. A lean hybrid furniture production control system based on MLPs and simulation modeling to optimize production planning and resource utilization under variable demand conditions is presented in [92]. The research in [93] extends the resource-constrained project scheduling problem by incorporating an operator assignment, based on human factors, wage, and power consumption, to minimize total cost and carbon footprints. The study proposes two GA-based memetic algorithms [94], demonstrating their superior performance compared to well-established algorithms as NSGA-II [95] and NSGA-III [96], in terms of both solution quality and computational efficiency.

Optimizing material utilization is crucial as well. The authors in [97] investigate the application of a Genetic Annealing Algorithm [98] for the cutting stock problem in fiberboard furniture manufacturing, focusing on efficient resource utilization and material savings by optimizing cutting patterns and minimizing waste. The work in [99] further tackles the solid wood board cutting stock problem, aiming at maximizing the utilization rate of original boards. In particular, an Ant Colony-Immune GA [100,101] is designed to combine the strengths of both algorithms to achieve higher precision and global search ability: the solutions computed by the ant colony algorithm are used as the initial population of the immune GA, which is then used to find the optimal solution.

An accurate processing time estimation is essential for efficient production planning and cost control. The works in [102,103] explore the use of variable structure Takagi–Sugeno–Kang (TSK) fuzzy rules [104], learned through genetic programming, to estimate the processing time. The resulting system, when tested on five different machines of a furniture industry, shows high accuracy and gives valuable insights into the dependencies between processing time and input variables, facilitating better production planning and decision making.

To reduce processing time, the work in [105] focuses on the optimization of the feed rate at CNC (Computer Numerical Control) routing operations for wooden furniture parts, developing a multistage optimization procedure that exploits binary search and GAs.

As for sales and cost forecasting, the authors in [106] propose an MLP-based model using Bayesian regularization, whereas the performance of ARIMAX [107], MLP, and ARIMAX-ANN hybridization for sales forecasting, showcasing the effectiveness of these methods in predicting future demand are compared in [108]. Furthermore, the authors in [109], focusing on milling, develop a mathematical method, incorporating an MLP, to maximize productivity and reduce costs, taking into account parameters like cutting velocity, feed rate, and total volume of removed material to predict surface roughness, process duration, and process cost. In [110], the importance of performing an accurate cost estimation in the early stages of a custom furniture manufacturing project is emphasized. That work points out how this estimation involves factors like materials, labor, sales, overhead, and more, and proposes an ML-based approach, that makes use of historical data from previously-manufactured products to estimate the costs of new ones. The outcomes, based on real data coming from custom furniture production, shows that ML (specifically, random forests [111]) can simplify and speed up the process of cost estimation, providing accurate and reliable estimates, albeit requiring an adequate set of historical data to allow the model to identify essential data characteristics. Close in spirit is the work in [112], that focuses on forecasting market demand trends in the context of a French furniture company. To this end, the authors develop an MLP based on historical data, appropriately configured to reduce the problems derived from seasonality, i.e., the presence of variations occurring at specific regular intervals in a time series, and the relative scarcity of available data.

Last but not least, looking to the future of furniture manufacturing, the work in [113] proposes a human-centric digital twin framework for Industry 5.0 [114]. This framework goes beyond the traditional digital twin by integrating workers and their digital replicas, enabling the monitoring, simulation, and optimization of human-machine interactions.

Defect detection. Early researches in defect detection, such as [115, 116], showcase the potential of automatic systems in identifying defects in hardwood lumber. The pivotal observation is that, depending on the manufacturer, the product, and the required quality of the latter, the nature of what constitutes a removable defect can and does vary. These studies focus their attention on such an inherent variability, proposing systems that may adapt themselves to different requirements and species. The authors in [117] investigate the use of Support Vector Machines (SVM) [118] and feature extractions from wavelet transformation for defect detection in various materials, including furniture. The analysis of color-based texture also emerged as a promising technique for defect detection. Relying on an approach that combines GAs and neural networks, a scanning system is outlined in [119] to analyze and classify the texture and color of wooden tiles and identify defects, like knots, heart wood, cracks, holes, and grades.

With the evolution of deep learning, researchers started to leverage more the power of Convolutional Neural Networks (CNNs) [120]. The authors in [121] use a faster, region-based CNN [122] to identify defects on wood veneer (a thin layer of 0.5–3 mm, usually hardwood sheet, intended for coating various surfaces of furniture, doors, or interior element), also incorporating pre-training and data augmentation techniques (flip, rotation transformation, and resize transformation). The specific goal was that of improving the speed of the defect identification task as the automatic visual inspection system had to run on an actual conveyor belt and was programmed on a wood veneer sorting conveyor line. The authors in [123] develop a new approach to defect detection using an Extreme Learning Machine (ELM) [124] and a pre-processing of wood images based on the nonsubsampled shearlet transform [125] (see Fig. 14). The ultimate goal is to reduce the inaccurate localization of defects and the lack of information about their contours, while limiting the computational cost required for image processing. A GA is also exploited to optimize the initial parameters of the ELM and to stabilize the classification performance of the model, enabling fast (187 ms/image) and accurate (96,72%) defect detection.

The application of ML to defect detection extends beyond wood surfaces to encompass other aspects of furniture production. The work in [126] deals with the segmentation of drilled holes in furniture panels using a modified U-Net deep learning architecture [127]. This approach successfully distinguishes holes from the surrounding texture and other features, as shown in Fig. 15.

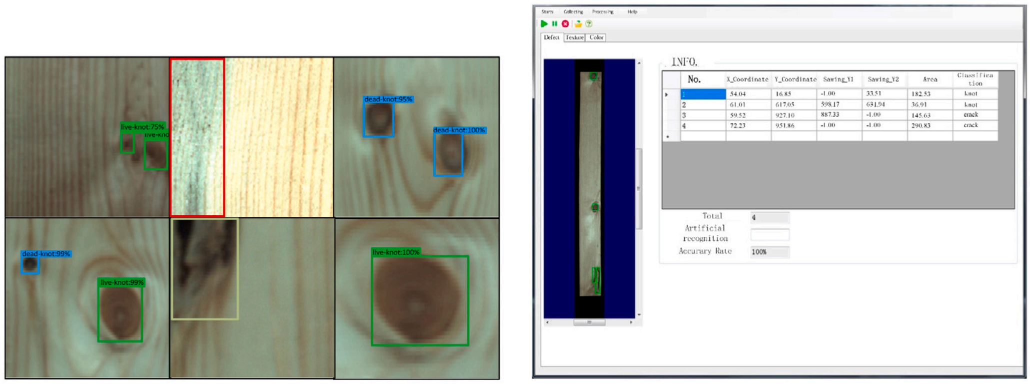


Fig. 14. An example of the use of machine vision to detect and classify wood defects [123].

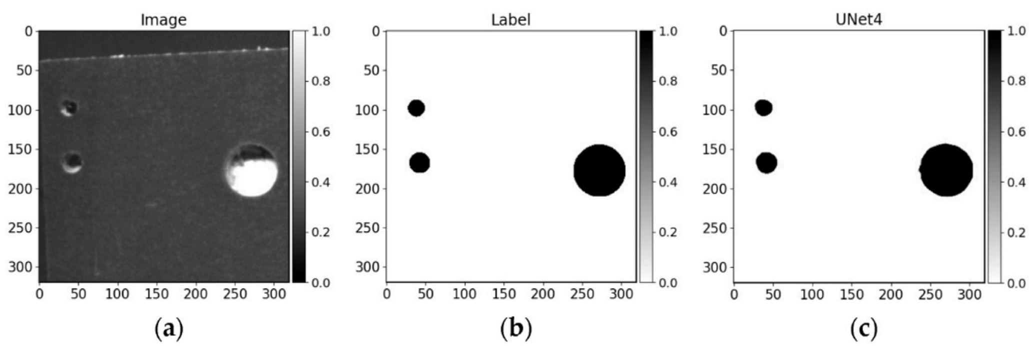


Fig. 15. An example of segmentation from [126] that makes use of a modified U-Net model.

Other contributions, including [128,129], and [130], explore various CNN architectures and data augmentation techniques to improve the accuracy and robustness of wood defect detection. The work in [129] exploits convolutional and generative neural networks: the former (a modified Mask region-based CNN [131]) is used for the identification, localization, and segmentation of defects (nodes, worms and cracks); the latter (Cycle GAN [132]), together with data augmentation techniques, is used to generate new versions of images, with applied defects observed in others. The idea is to transfer defects to new images of panels/boards with a different type of wood (Fig. 16), so that a larger set of (synthetic) instances becomes available, providing greater variability than the cases observed in nature. The expected outcome of such an operation is an increase in performance and robustness of the process of defect recognition at runtime. Compared to the work in [123] (see Fig. 14), such a solution identifies not only the position, but also the exact contour (segmentation) of the defects, as shown in Fig. 17. The authors in [130] focus on edge-glued wooden defect detection. These defects, including residues (visible glue marks), bluntness (the tape is trim or has scrap on the edge), and incorrect lengths (tape shorter/longer than the length of the panel) and heights (tape lower/higher than the surface of the panel), are difficult to identify, especially for human operators or conventional cameras. To overcome these limitations, a system pairing computer vision and deep learning, called WDD-DL, is also proposed. WDD-DLv makes use of various techniques, classical, pre-processing, and a CNN (Inception-ResNet-V2 [133]), that allow it to simultaneously analyze an image through a camera and one through a laser (see Fig. 18(a) for the entire pipeline), enabling immediate detection and correction of defects during the manufacturing process thanks to its real-time usage capabilities (Fig. 18(b)). The system shows promising results (accuracy, sensitivity, and F1 equal to 0.97, 0.90, and 0.92, respectively), with its main limitations being the (relatively) limited number of wood types considered (21) and the availability of few defect images about long and short edge bands.

Finally, the work in [134] proposes a ResNet-50 model [135], improved with a convolutional block attention module and a cross-stage partial network [136,137], to identify defects on wood surfaces, achieving high accuracy in detecting knots, cracks, and color-related defects.

Last but not least, in [138], a method is proposed to combine CNNs (fine tuned from a pre-trained Inception-ResNet-V2 model) and image processing techniques to detect defects in wooden structures as well as to quantify their characteristics, such as crack length, width, and angle, proving the potential of ML to provide comprehensive information for decision making (Fig. 19).

Design support. As for the use of AI to enhance and optimize various aspects of the design process, ML has been exploited in anthropometric data analysis to improve furniture ergonomics. Contributions like [139,140] prove that neural networks and multiple linear regression can be used to predict critical anthropometric dimensions for furniture design in several settings. More precisely, the authors in [139] develop a method to support the design of ergonomic chairs for students in school settings. In common practice, five, not easy to measure, anthropometric dimensions are taken into consideration. In contrast, the authors show that by using four easily measurable anthropometric dimensions, it is possible to estimate those five needed for the ergonomic design. In addition, they show that neural networks generally perform better than linear regression models. Similarly, the authors in [140] develop a methodology to design ergonomic furniture, focusing on the case of university students, again relying on the concept of anthropometric measurements and exploiting a multi-layer perceptron.

The work in [141] explores the application of deep generative models in a social manufacturing context. This approach leverages Variational Autoencoders [142] to empower users with AI-driven tools for furniture design. In order to enhance user involvement in the design process, a cyber–physical system that leverages mixed reality and deep learning (SliceGen, a novel generative neural architecture) to empower

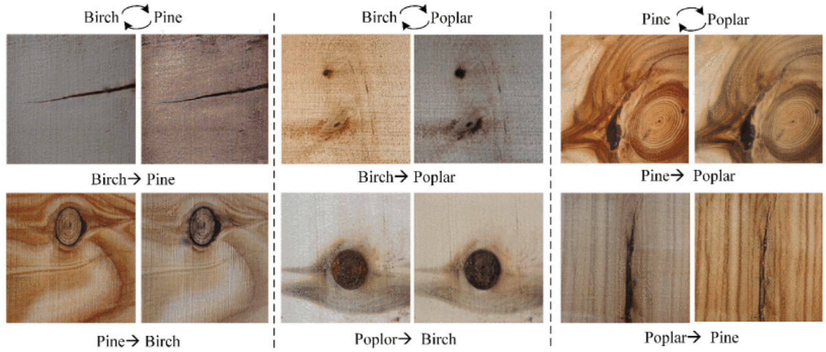


Fig. 16. The transfer of defects among woods of different types via *Cycle GAN*-like model [129].

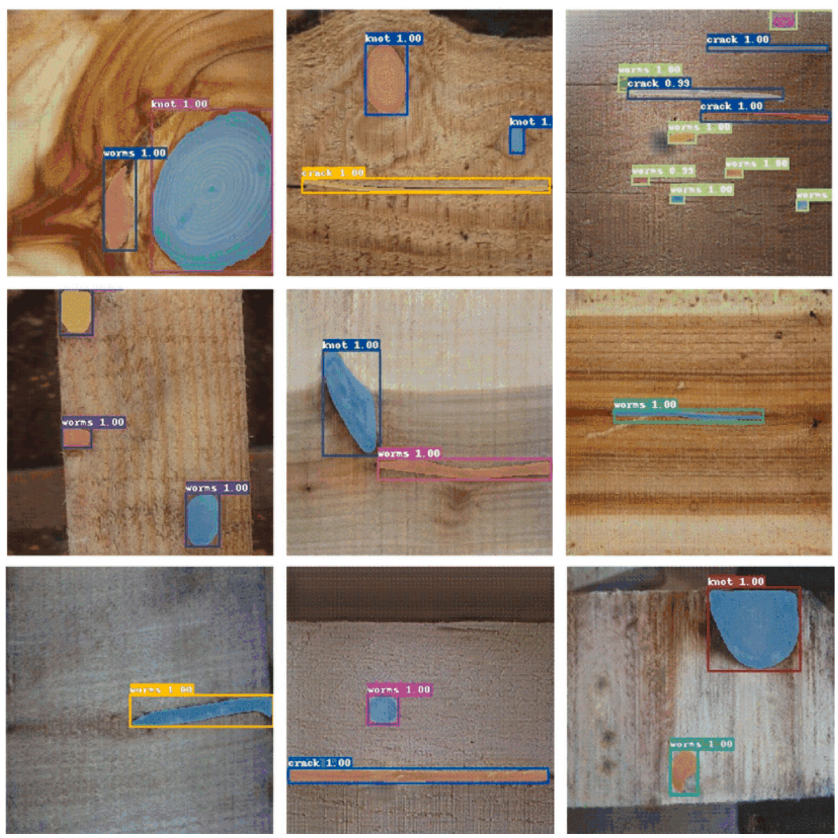


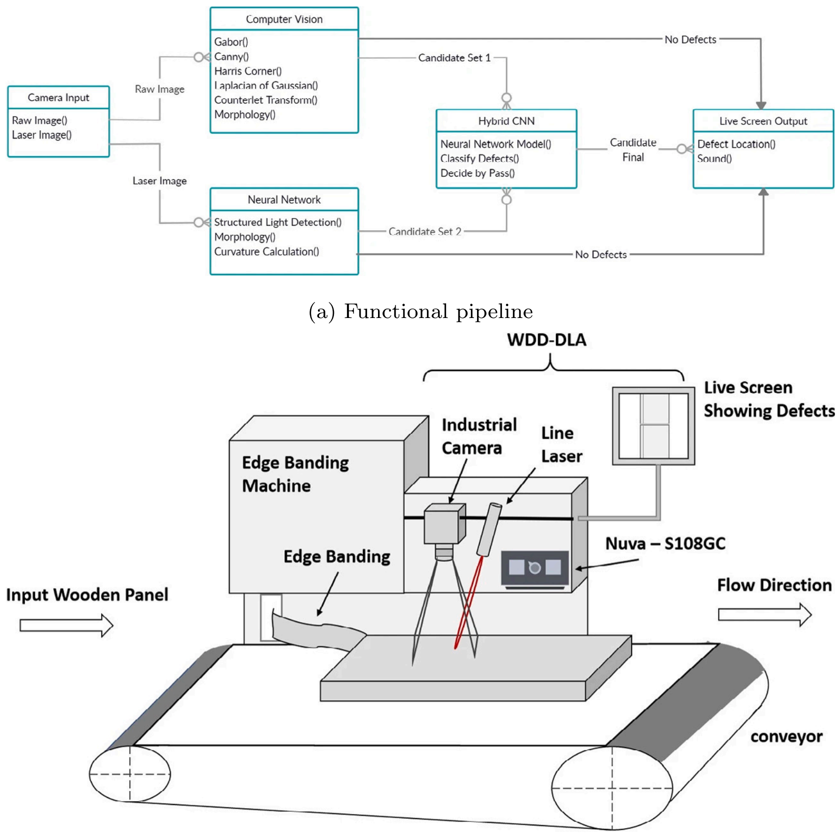
Fig. 17. An example of the use of computer vision for identification, localization, and segmentation of defects (knots, worms and cracks) in wood [129].

users to directly engage with the design process is introduced in [143]. This system enables users to generate and manipulate 3D models of furniture in real-time within a mixed reality environment, offering a novel and immersive approach to furniture design. All in all, social manufacturing platforms have the potential of democratizing the design process, fostering greater creativity and personalization in furniture production.

The authors in [144] apply *sentiment analysis* (a field of natural language processing concerned with building systems to identify and extract opinions from text [145]) to customer-written reviews of wooden furniture sold on a Chinese furniture e-commerce platform (MeiLeLe Furniture). The goal is that of extracting meaningful information about customers' attitudes, emotional tendencies, and preferences with respect to different aspects of wooden furniture. First, the authors collect, clean, and manually label data about reviews; then, they use a Bayesian algorithm to build a text classifier to categorize the emotional tendency of the reviews. The study finds that customers pay more attention than usual to quality, price, and appearance when purchasing wood furniture.

As an addition to this rich landscape, the work in [146] emphasizes the critical role of big data analytics in the fuzzy front end of the innovation process. Such a study presents an intelligent product design framework that integrates big data analytics with fuzzy association rule mining and a genetic algorithm. The framework is designed to bridge the gap between customer attributes and design parameters, enhancing market performance, design performance, and sustainability in product design, enabling continuous evolution, thanks to its flexibility, a self-improvement mechanism, and the availability of a large data volume.

Machine monitoring. Machine learning proved itself to be a valuable tool also for predictive maintenance, in particular concerning tool wear monitoring, enabling timely interventions to prevent production disruptions and quality issues. The authors in [147] utilize features, like



(a) Functional pipeline

(b) Implementation in the production chain

Fig. 18. WDD-DL system for automated quality control in the edgebanding process [130].

statistical information, and Fourier and wavelet representations, extracted from multiple sensor signals, such as feed force, cutting torque, noise, vibration and acoustic emission, to classify drills as "useful" or "useless." This approach, employing SVMs and tree-based ensemble methods, successfully identifies worn-out drills in the context of laminated chipboard drilling process. The work in [148] improves such an approach by distinguishing among three-class, namely, "useless", "needs assessment", and "useful", and making use of Long Short-Term Memory (LSTM) networks [149]. Shifting to vision-based methods, the work in [150] employs Siamese neural networks [151,152] to classify (again, referring to the above three classes) drill wear based on images of drilled holes, using a data collection approach simpler than that of sensor-based methods. The proposed solution demonstrate high accuracy, especially in not misclassifying sharp and worn-out drills.

As for other woodworking tools, the works in [153,154] focus on monitoring tool wear during milling operations. The former makes use of features extracted from the spindle power signals and an approach combining Particle Swarm Optimization [155] with an MLP, while the latter employs discrete wavelet transformation and a genetic algorithm, again combined with an MLP. Both approaches show high accuracy in detecting tool wear under varying milling parameters. Still in the context of milling operations, the authors in [156] introduce a novel approach tailored to chipboard. They evaluate several pretrained CNN (VGG16, VGG19, and RESNET34 [135,157]) clipped on learning spectrogram representations of time-series data to classify tool conditions into "Green", "Yellow", and "Red" states on the basis of wear levels.

Quality monitoring. Traditional quality control methods often fall short in their ability to proactively prevent defects in various stages of furniture production. The authors in [158] present a data mining approach to manage defective products in a furniture production company. By employing MLP and decision tree [159] models, they identify the sources/causes of defects, achieving a 90.12% correct prediction rate with the classification and regression tree algorithm. Similarly, the authors in [160] work at an online quality process monitoring system assisted by MLPs. Their research, tested in the context of a high quality lacquerer company in the furniture industry, demonstrate the effectiveness of the approach in predicting quality issues and maintaining a robust and adaptable control system.

The work in [161] presents an MLP to determine optimal CNC processing parameters to achieve the best wood surface quality. The system proposed in that study models the surface roughness values, determining the effects and optimal values of tool diameter, spindle speed, and feed rate parameters for different wood species. Likewise, the works in [162,163] investigate the optimization of drilling operating factors, namely, drill tip angle, tooth bite, and drill type of the delamination factor at the inlet and outlet, thrust force, and drilling torque, for wood particleboard and MDF panels. Those research works combine MLP (for particleboard) modeling with Response Surface Methodology (for MDF panels) to predict such factors. The authors in [164] employ a radial basis function artificial neural network [165] and a TSK fuzzy model with subtractive clustering to assess surface roughness in the MDF milling process. Their research demonstrated that integrating information on cutting kinematics and vibration data from an industrial piezoelectric sensor improves the accuracy of surface roughness prediction, also allowing for real-time monitoring and control of surface quality during the milling process. Furthermore, the paper in [166] explores the use of models such as decision trees, random forests, and Gaussian processes [167] to predict the bending strength of impregnated wood materials, observing that all algorithms are suitable for the task at hand.

In [168], the authors develop a method for monitoring drilling conditions based on image analysis. The method uses pictures of the holes made in melamine-coated particleboard, a common material in

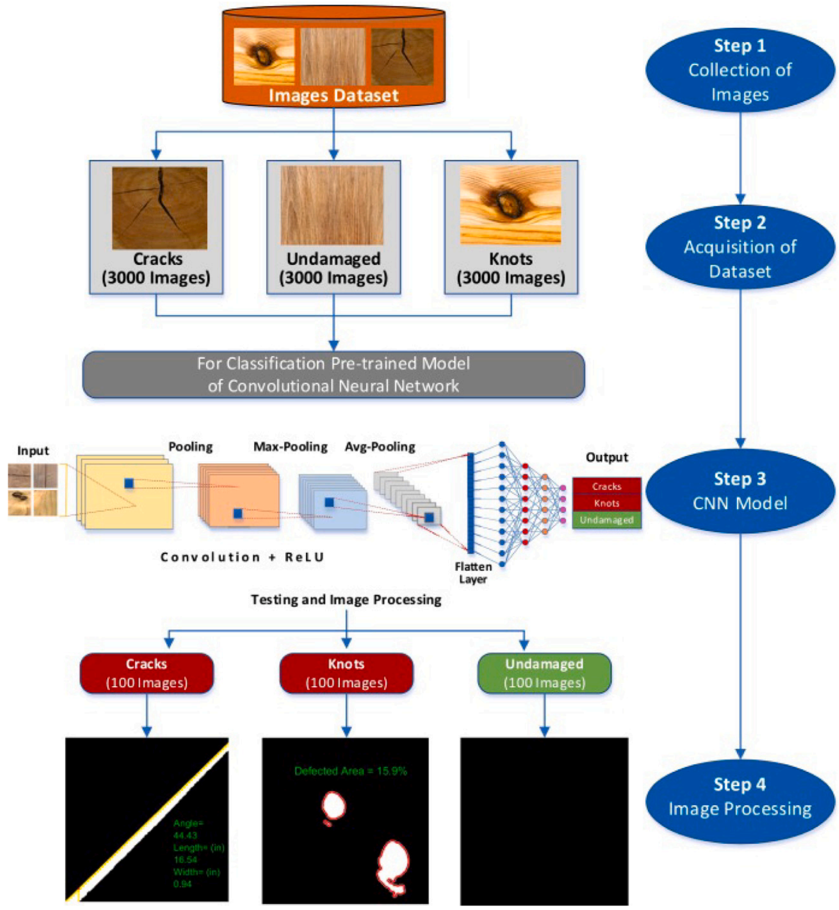


Fig. 19. The workflow of the approach outlined in [138] to characterize defects. © 2024 with permission from Elsevier.
Source: Reprinted from [138].

the furniture industry. Multiple classifiers, including K-Nearest Neighbors [169], Random Forest, SVM, Radial Basis Function, and MLP, are trained on a number of image-derived features, such as contour and hole perimeter deterioration, allowing one to assess that Random Forest performed the best, approaching 100% accuracy. In practical terms, by using the proposed method in an industrial setting with cameras installed to constantly monitor the condition of the edge during/after a drilling operation, both detection of low-quality panels due to inaccurate holes and identification of the wear condition of the drill to perform its maintenance are enabled. Focusing on the painting process of flat parts, the work in [170] presents a model to predict the amount of paint to be applied to a single piece, exploiting both data from paint machine sensors and data on the weight of parts before and after painting for training. On the basis of the outcomes of several experiments, the authors show that a model based on Random Forest achieves the best prediction accuracy. The system may help in reducing the time taken to set up the machine for each new order as well as the waste associated with defective parts produced during such an adjustment process. The authors highlight how the lack of interoperability among different machines is a challenge, raising difficulties related to proper data acquisition, data aggregation and labeling, and model re-training when changes occur in the machine or in the painting process.

Wood classification. Early explorations into automated wood classification started with [171], which proposes a multi-resolution neural network approach to analyze wood texture at different spatial scales (as texture appearance changes when the scale changes), effectively extracting features at multiple granularity levels for accurate classification. On the basis of the observation that wood classification is time consuming and highly dependent on the operator experience and fatigue, the work in [172] proposes an embedded, low-cost system based on an MLP exploiting the emitted spectrum of wood samples filtered through optical filters, demonstrating promising results for the classification of wood types. Additionally, for the same task, the work in [173] investigates the use of features extracted from fluorescence spectra coupled with inductive classification systems (SVM and quadratic Bayes normal classifier [174]), highlighting the potential for real-time usage of the proposed solution, especially given its low computational cost. The approach distinguished among 21 types of wood, with an accuracy higher than 90%. [175] employs Gray Level Co-occurrence Matrices (GLCM) [176] to extract texture features from coconut wood images, utilizing MLP and SVM classifiers. The goal is to determine high quality pieces, so to increase the usage of coconut wood in Indonesia. The authors in [177] further demonstrate the versatility of GLCM by combining it with an MLP and features extracted using statistical methods representing color and texture, with the ultimate goal of distinguishing among 4 type of tropical hardwood species.

Moving to deep learning, a novel architecture is presented in [178], namely split-shuffle-residual based CNN, which is designed for real-time classification of rubber wood boards. This architecture achieves satisfactory performance in terms of the trade-off between speed and accuracy, and yields to fast (26.55 ms/image) and accurate (94.86%) classification performance. The work in [179] introduces an optimized CNN model incorporating spatial pyramid pooling [180] and attention mechanisms into a ResNet101, for feature extraction from sawn timber images. SVM and XGBoost [181] classifier are then used to distinguish among the different species. Furthermore, in [182], the application of unsupervised learning is explored by developing a system for color classification and texture recognition of solid wood panels (from a

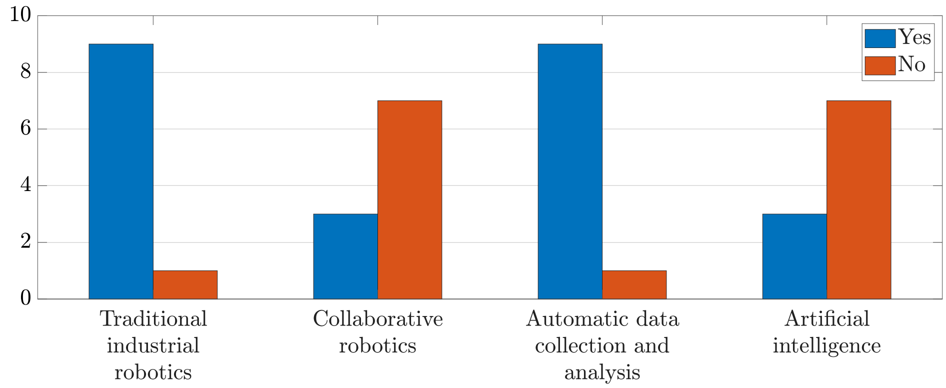


Fig. 20. The level of adoption of the considered technologies.

single species) using K-means clustering [174] on features extracted from color channels.

Recently, a comparison of various machine learning models, for classifying wood types with high similarity, but different economic value (jeungjing, puspa, and suren wood) is presented in [183]. Furthermore, the work in [184] delves into feature fusion techniques by combining Local Binary Pattern, GLCM, and Tamura features, which are based on psycho-physical studies of the characterizing elements that are perceived in textures by humans, extracted from micro CT images, to classify 24 rosewood species using ELM. Finally, the authors in [185] evaluate multiple CNN architectures (DenseNet [186], ResNet50, and MobileNet [187]) for wood species identification considering different magnification levels, so to understand the impact of such a change on the task at hand.

3. The case of the friuli venezia giulia (FVG) cluster

To assess the state of robotics and AI technologies in the furniture industry in the Italian FVG region, a specific questionnaire was developed and administered to 10 businesses participating in the *International Furniture and Panel Technology Campus* (*FVG Cluster*) [188]. Located in Brugnera, at the heart of North-east Italy's industrial hub, this *Campus* was established through a collaboration between the public sector and a significant number of Friulian and Venetian companies, all key players in the region's furniture and panel sectors. The primary goal was to create a comprehensive training center focused on integrating digital technologies into production processes.

The *FVG Cluster* is one of the most relevant consortia in the region, given its substantial number of active enterprises, workforce, export value, and contribution to the regional GDP. In 2022, the FVG region exported wood and furniture worth 2.5 billion euros [188]. The 10 surveyed companies produce various furniture components, including MDF and chipboard panels, doors, chairs, tables, beds, cabinets, bookshelves, and bathroom furniture.

The questionnaire (details are given in Appendix) covered several aspects, including the sectors where the companies operate as well as the used technologies and their applications. The questions also explored the proximity of robotic operations to human operators, strategies for energy efficiency and sustainability, and the purposes for which technologies like AI and data analysis are used. Additionally, companies were asked to rate the importance and future enhancement of these technologies and to identify potential obstacles to their implementation.

As for the adoption level of the considered technologies, from Fig. 20 it can be observed that both the traditional industrial robotics and data collection and analysis tools, that is, those technologies that are the well established in the market, are widely adopted, with the exception of one company. As for emerging technologies, the adoption of collaborative robotics and artificial intelligence is currently relatively low (30%). Furthermore, there seems to be no direct correlation with the size of the company, except for the fact that the largest one adopts all technologies.

As for the use of robotics, it emerges that robotic systems are mainly applied to handling within production lines, specifically in loading/unloading machines. Additionally, albeit less frequently, robots are used for assembly, storage, and packaging. For the few companies using collaborative robotics, applications include quality control through scanners, packaging, and assisting operators in assembly, sorting, and storage operations.

The applications of automatic data collection, modeling, and analysis, and of artificial intelligence are broader. Almost all companies (90%) apply data collection and analysis tools to monitor the production process, in to particular to measure efficiency and to get an overview of the processes. In some cases (20%), more specific pieces of information are collected in order to suitably plan maintenance activities. In addition, there are applications in automated quality control, monitoring waste, and energy efficiency.

Various initiatives have been undertaken to implement strategies for energy efficiency and increasing sustainability (this is the case with 80% of companies). Interventions include the use of photovoltaic panels, co-generation plants, biomass plants, reuse of waste and recycled wood (also used as fuel), inverters for electric motor operation, low-consumption lighting, e.g., LED lamps, liquefied natural gas for heating and cooling, waste reduction for compressed air and suction, and overall plant modernization for consumption reduction.

The majority of companies recognize the significant role of the technologies described in this document, as shown in Fig. 21. They include both current technologies, such as traditional robotics and data collection, and more innovative ones, like those for predictive maintenance, automated quality control, and AI. However, some companies (in between 30 and 50%) consider collaborative robotics and AI to be less impactful. This is understandable, as many recent technologies in these areas are still largely at research level, and there are only partial knowledge and/or some difficulties in understanding how to effectively use them in the considered industrial context. Nonetheless, taking AI as an example, it is true that it can be already used within a production context in a transparent manner, e.g., in automatic data processing and production optimization, just as it happens in everyday life, e.g., translation software, search engines, and conversational agents.

Looking towards the future and analyzing how companies plan to enhance the presence of the various technologies in their production context, the picture emerging from Fig. 22 differs from the perceived importance. There is a general trend towards further enhancing existing technologies, such as traditional robotics, data collection and analysis, as well as energy efficiency and sustainability strategies.

Moreover, from Fig. 23 it is clear that there are some significant obstacles in the adoption and implementation of the new technologies.

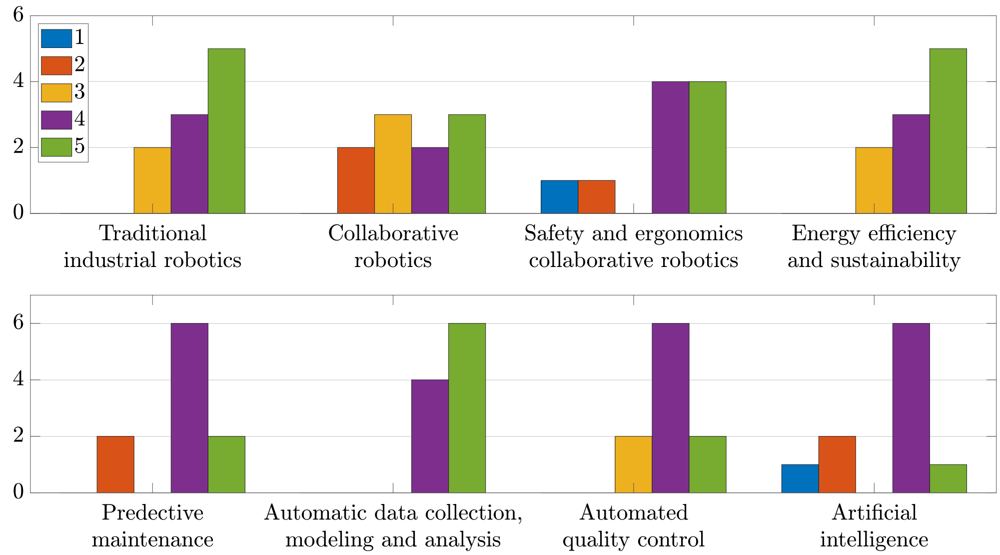


Fig. 21. Perceived importance for the development of the various technologies taken into consideration within the companies (1 - less important, 5 - very important).

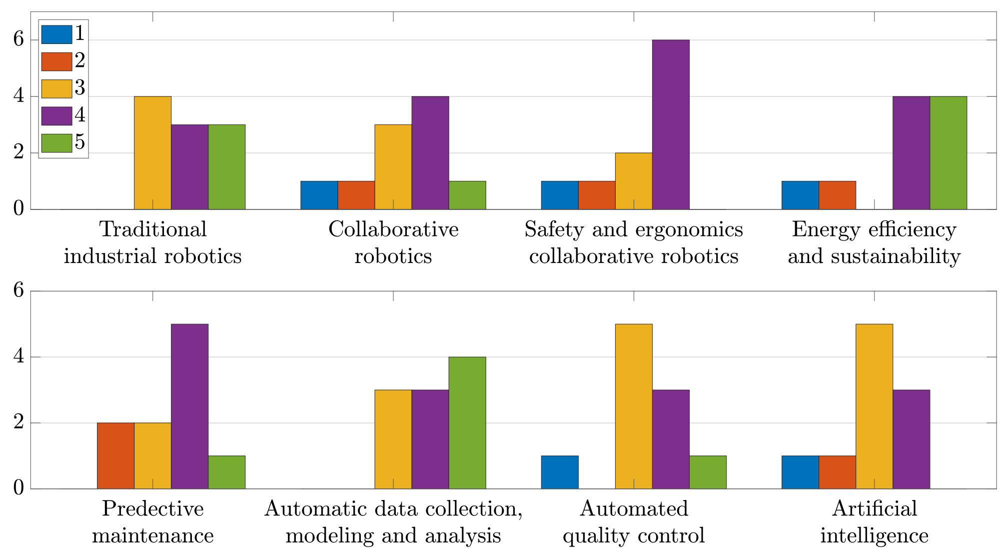


Fig. 22. Expected level of enhancement in the future adoption of various technologies (1 - minor enhancement, 5 - major enhancement).

As for robotics, economic aspects are secondary; the main issues concern the difficulty in finding specialized personnel, even in the case of traditional robotics, the safety aspects, and the challenging integration with the current production systems, especially for collaborative robotics and ergonomics. In the area of data science and AI (remember that automated quality control and predictive maintenance are, in fact, two applications of AI), the situation is more complex to discern, as no predominant issue emerges. Certainly, compared to robotics, the potentially high cost, the cost–benefit ratio, which is not entirely clear, and the perceived usefulness of individual technologies, which is not immediately apparent, are identified as critical. Interestingly, despite these technologies typically need a more direct access to the machines than in the past (e.g., adding and/or monitoring sensors), there is no perceived difficulty in their integration with the current production systems. There seem to be more obstacles on the information technology side, indicating a possible lack of understanding of the tools in question. Once more, this is fully justified, as we are talking of computer-based tools, which are starting now to be applied outside the context of scientific research. Last but not least, finding specialized personnel remains a cross-cutting issue.

4. Discussion and future trends

On the basis of the systematic analysis of the state of the art that we have presented, we can conclude that in the last years we are seeing a growing interest in applying robotics and AI in the furniture industry.

Robotic systems are employed not only for moving materials, but also in more specific operations, like, for instance, painting, finishing, and assembly processes. Robots can be integrated with cameras for automatic parts detection and with automatic trajectory planning algorithms for spray painting, whereas adding force sensors can improve the surface finishing quality. Robotic devices can also perform assembly tasks, both alone and in collaboration with human operators. In the furniture industry, the attention is focused on recognition of parts, automatic assembly sequence and trajectory planning, and endowing the robot with decision-making capabilities. Furthermore, the adoption of collaborative robotics may enhance the conditions of workers, reducing the fatigue and the risk of muscoloskeletal problems.

AI system have been extensively investigated, especially for what concerns production process optimization and the usage of computer vision to solve several tasks. The feedback gathered through the *FVG Cluster*'s companies indicates that the former is widely adopted. Yet, the

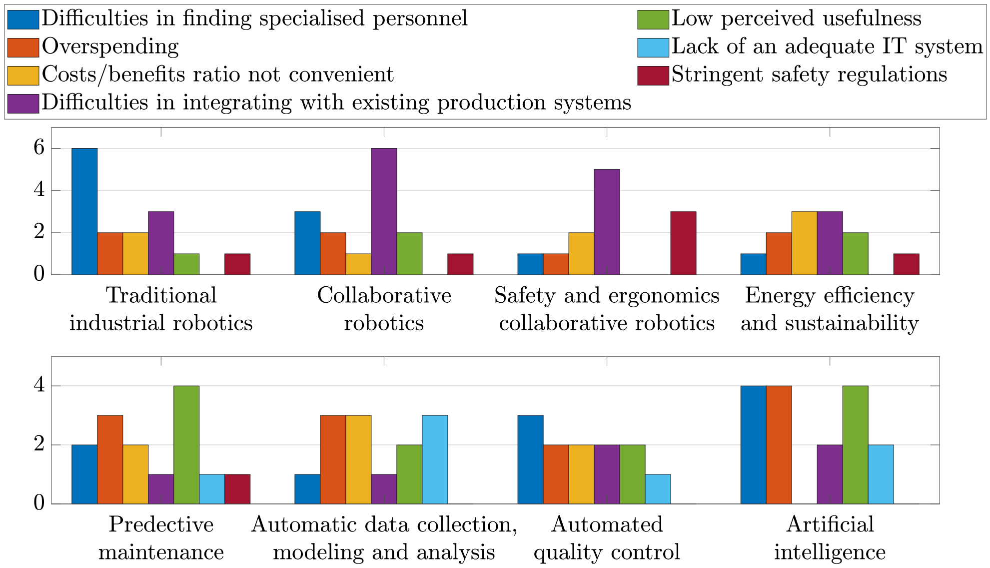


Fig. 23. Obstacles perceived by the various companies about the implementation of the considered technologies.

latter is often hard to apply in practice given the specific needs of the companies and due to the fact that they have to manage increasingly large catalogues, which results in demanding a high level of generalization from these systems (this is one of the Achilles' heels of many modern AI models). In the forthcoming years, it is expected that Generative AI approaches may play a major role in this industry, especially to ease the design process, even when a high level of personalization is required by customers. Multimodal foundational and instruct-tuned large models [189,190] may make the interaction with customers particularly natural. Still, it can be observed that there is a very limited usage of unlabeled data. Moreover, a few approaches consider strategies like contrastive learning or self-supervised learning [191,192]. The same holds for non-vision modalities, like sensor-derived data: they have been seldom utilized in furniture industry. Given that computer vision has some non-trivial shortcomings, e.g., some defects are very hard to detect on the basis of the color of the panel or the type of processing that is performed, exploiting sensor data, especially with self-supervised learning [193], is a possible alternative to develop more robust and generalizable solutions, as well as to increase the range of applications of AI in furniture industry, including, for instance, interpretable anomaly and failure detection [194,195]. Emerging concerns in the development and deployment of AI systems also include safety and adherence to ethical guidelines. Our review revealed that in the furniture industry, most existing AI-based solutions are geared toward practical tasks, currently posing minimal risks to humans in terms of these dimensions. However, as IoT and highly digitalized manufacturing plants are already well-established, incorporating digital security by design to mitigate the impact of cyberattacks becomes increasingly critical, particularly as we transition toward intelligent factories [196]. Additionally, the development of AI applications for tasks such as, for instance, monitoring compliance with safety standards [197], automating production process optimization, and decision-making [113] introduces new challenges. These include ensuring accountability, transparency, and privacy, especially when such applications involve the broader use of AI technologies beyond computer vision to strictly monitoring machinery or components [198]. These issues demand further consideration and study in the evolving domain of AI in furniture industry.

5. Conclusions

This paper surveyed the scientific literature on recent trends in robotics and AI technologies applied in the context of Industry 4.0, with a focus on the furniture industry. By examining recent developments, applications, and challenges, this survey provides insights into the integration and implementation of currently-available solutions and technologies, their impact on production efficiency, product quality, and overall innovation within the furniture manufacturing sector.

The first part of the document presented an analysis of robotics and automation. We first analyzed the application of traditional robotics in the furniture industry, with particular focus on the automation of pick and place, finishing, painting, and assembly tasks. Furthermore, the application of collaborative robotics in the furniture industry is considered, discussing the topics of collaborative assembly and ergonomics in this challenging sector.

Then, the topics of data science were examined, with a special attention to data management (databases, data warehousing, decision support and management systems, and information systems), as well as the applications of artificial intelligence and machine learning to the furniture industry (with focus on production process optimization, defect detection, design support, machine monitoring, quality monitoring, and wood classification techniques).

In the last part of the paper, the outcomes of a questionnaire investigating the perception of robotics and AI technologies in ten companies of the International Furniture and Panel Technology Campus of the Friuli Venezia Giulia region (Italy) have been provided. The results of the questionnaire and the critical analysis of the outcomes showed that the technologies that are the more consolidated in the market (traditional industrial robotics, data collection and analysis tools) are widely adopted, whereas collaborative robotics and AI are currently only partially exploited. Obstacles in the adoption and implementation of new technologies are, mainly, difficulties in finding specialized personnel and in the integration with existing production systems, a potential high cost, and a low perceived usefulness.

CRediT authorship contribution statement

Andrea Brunello: Writing – original draft, Methodology, Investigation, Data curation, Formal analysis, Resources. **Giuliano Fabris:** Writing – original draft, Methodology, Investigation, Data curation, Formal analysis, Resources. **Alessandro Gasparetto:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Angelo Montanari:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Nicola Saccomanno:** Writing – original draft, Resources, Methodology, Investigation, Formal analysis, Data curation, Writing – review & editing, Conceptualization. **Lorenzo**

Scalera: Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT Plus (GPT-4) and Vertex AI (Gemini 1.5 Pro) to synthesize and improve writing quality. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Questionnaire submitted to the FVG Cluster companies

In this section, we report the questions that have submitted to the companies of the FVG Cluster, which responses have been discussed in Section 3.

1. In which sector does your company operate?
2. Within your company, which technologies among *traditional industrial robotics*, *collaborative robotics*, *automatic data collection and analysis*, and *artificial intelligence* are utilized?
3. What are the applications of robotics within your company?
4. What are the applications of automatic data collection, modeling, and analysis, as well as artificial intelligence within your company?
5. In your company, are robotics operations carried out in close proximity to human operators (collaborative robotics)? If yes, which ones?
6. In your company, are energy efficiency and sustainability strategies implemented? If yes, which ones?
7. For what purposes, among *energy efficiency and sustainability*, *predictive maintenance*, *automated quality control*, or *others*, are tools for automatic data collection, modeling, and analysis, as well as artificial intelligence used in your company?
8. Please specify for what other purposes the above-mentioned technologies are used in your company.
9. Please consider *traditional industrial robotics*, *collaborative robotics*, *safety and ergonomics in collaborative robotics*, *energy efficiency and sustainability*, *predictive maintenance*, *automatic data collection*, *modeling and analysis*, *automated quality control*, and *artificial intelligence*:
   (a) How important do you think (on a scale of 1 to 5) is the introduction of the aforementioned aspects within your company?
   (b) How much do you expect (on a scale of 1 to 5) to enhance the presence of the aforementioned aspects within your company in the near future?
   (c) Among *difficulties in finding specialized personnel*, *excessive economic expenditure*, *unfavorable cost/benefit ratio*, *integration challenges with the current production systems*, *perceived lack of utility*, *absence of a suitable information system*, and *stringent safety regulations*, which could be the obstacles to the implementation of each of the aforementioned aspects within your company?

Data availability

Data will be made available on request.

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