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Marco Simonetto

Design and management of Assembly Systems 4.0

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of
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Department of Mechanical and Industrial
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Trondheim, December 2022

Marco Simonetto

Summary

In recent years, companies have faced great customer demand change involving, for example, a change in colour (aesthetic design), shape (measurement) or technical characteristics of some components (functionality) (Piller, 2005) of the products that companies assemble in their assembly systems (ASs) (Battaïa et al., 2018). Hence, if companies decide to accept those requests from their customers, they must be ready to produce more complex and diverse products (Otto and Li, 2020). The greater the complexity and diversity of the products that companies need to assemble, the greater the chance that ASs will fail to achieve their goals. Here the goal would be to have high efficiency, maximising throughput with minimum resources, to have high flexibility, rapid changes in the production volume and type of products to be assembled, to minimise the work in progress (WIP), assemble high-quality products, minimise the inventory level, utilise the workforce effectively and to minimise the disruptions in production (Bukchin and Masin, 2004; Hu et al., 2011; Vallandingham et al., 2017) and, thus, satisfying the demand. Therefore, companies are required to find ways that can enable them to handle this complex and diverse demand while achieving and maintaining their AS goals. One way might be the implementation of Industry 4.0 (I4.0) technologies (e.g., Internet of Things (IoT) technologies, data analysis, cloud computing, collaborative robots (cobots), augmented reality (AR), virtual reality (VR) and mobile robots, etc.) in the ASs, creating the so-called Assembly System 4.0 (AS4.0) (Bortolini et al., 2017; Dolgui et al., 2022). Although I4.0 technologies promise increased flexibility, better quality and improved productivity of ASs (Zhong et al., 2017), if they are not implemented correctly, they may cause risk for the ASs performance. This especially happens when the companies do not know how to design and manage AS4.0. In fact, although companies should know how to design and manage a traditional AS where no I4.0 technologies are implemented (Battini et al., 2011), there are no clear roadmap on how to design and manage AS4.0 (Dolgui et al., 2022). Therefore, the main goal of the present research study is to support and create new knowledge for the academy and managers and practitioners who would like to design and manage AS4.0.

We start the current research by conducting a systematic literature review (SLR). The SLR work give the opportunity of not only understanding the state of the art of AS4.0, but also the opportunity of identifying the nine future research opportunities concern the introduction of

methods ("a method is a systematic approach to achieve a specific result or goal and offers a description in a cohesive and (scientific) consistent way of the approach that leads to the desired result/ goal." (Verbrugge, 2019)) and models ("a model is the presentation in schematic form, often in a simplified way, of an existing or future state or situation" (Verbrugge, 2019)) for the design and management of AS4.0. Examples of methods are descriptive, rational, and experimental (e.g., observations, framework, and decision support systems), while example of models are graphs, flow charts, 3D models, diagrams, and equations. The nine future research opportunities are models of dynamic reconfigurable AS4.0; models to support the selection of a suitable level of automation; models for dynamic assignment of technologies on AS4.0 configurations; methods for ergo-efficient workplace design; models of new feeding policies; models for real-time multiobjective balancing of assembly line subsystem (ALS) and the scheduling of assembly line feeding subsystem (ALFS); smart and real-time methods for sequencing of ALS and routing of ALFS; methods for efficient control of AS4.0; and models and methods for maintenance of technologies (Dolgui et al., 2022). Based on three of those future research opportunities (i.e., models of dynamic reconfigurable AS4.0, methods for ergo-efficient workplace design and methods for efficient control of AS4.0), we derive the below three research questions:

- RQ1: How can AS4.0 configurations be affected by Industry 4.0 technologies?
- RQ2: How can ergo-efficient AS4.0 workplaces be designed?
- RQ3: How can material management be controlled in AS4.0?

To answer these research questions, the below methods are applied:

- RQ1: exploratory research and experimental research
- RQ2: experimental research
- RQ3: simulation modelling

The main outcomes are derived by answering the three research questions by using those methods:

- RQ1:
  Factors for the modelling of dynamic reconfigurable configurations of an Assembly Line Subsystem and the impact of Industry 4.0 technologies on these factors
  - Identification and definition of the factors relevant for modelling dynamic reconfigurable configurations of an ALS and identification of how Industry 4.0 technologies impact those factors.
  - Investigation of the impact of augmented reality on the identified factors.
- RQ2:
  A framework to design the workplace of an Assembly Line Subsystem by using Virtual Reality and a motion capture system
  - Identification of the steps to design an ergo-efficient workplace of an ALS by using VR and a motion capture (mocap) system.
  - Identification of how the age of human workers can be included in the design of a workplace of an ALS.
- RQ3:
  A Decision Support System to select the best material management solution among traditional Kanban, electronic Kanban, and Digital Twin
  - Development of a digital twin (DT)-based model for the control of the material management in an ALFS.
  - Identification of the best solution among traditional Kanban, electronic Kanban and DT to control the material management in an ALFS.

Finally, by the outcome of the SLR and research questions, we reach our main goals that are: "support and create new knowledge for academy and managers and practitioners who would like to design and manage AS4.0". In fact, by the SLR work, we aim to present the state of the art and possible future research opportunities related to the design and management of AS4.0. Also, we aim to support companies implementing I4.0 technologies in their ASs, showing them the decisions that they have to make, level by level (strategic, tactical and operational), for each technology if they want to achieve and maintain the goals of the ASs. In answering RQ1, we aim to provide companies information during the design phase of their

ASs, explaining to them the impact that each I4.0 technology has on those factors relevant to the decision of which AS configuration to choose. With the answer to RQ2, we aim to encourage companies to use VR when designing the workplaces in their ASs. In fact, they can use our five-step methodological framework, which considers the age of the operators in designing ergo-efficient AS workplaces, here by using VR together with a motion capture system. Finally, based on the answer to RQ3, we aim to support companies in deciding which solution to choose to control the material management activity in their ASs. In fact, we provide a decision support system (DSS) by which companies can choose the most convenient material management solution, here based on investment and operational costs, among traditional Kanban, e-Kanban and DT-based solutions, by considering the demand and layout parameters of their ASs.

Abbreviations

AM - Additive manufacturing

ALFS - Assembly line feeding subsystem

ALS - Assembly line subsystem

AS - Assembly system

AS4.0 - Assembly System 4.0

Cobot - Collaborative robot

DSS - Decision support system

E - Kanban - Electronic Kanban

FW - Fixed-worker

I4.0 - Industry 4.0

IoT - Internet of Things

KPIs – Key performance indicators

Mocap - Motion capture

NTNU - Norwegian University of Science and Technology

PAR - Projected augmented reality

SD - Standard deviation

SL – Straight line

SLR - Systematic literature review

US - U-shaped

VR - Virtual reality

WIP - Work in progress

WW - Walking worker

List of Appended Papers and Declaration of Authorship

Paper	Title	Declaration of authorship
1	Dolgui, A., Sgarbossa, F. and Simonetto, M., 2022. Design and management of assembly systems 4.0: systematic literature review and research agenda. International Journal of Production Research, 60(1), pp.184-210.	Simonetto conceptualized the paper and conducted the systematic literature review. Simonetto wrote the paper with feedback from Dolgui, and Sgarbossa.
2	Simonetto, M. and Sgarbossa, F., 2020, August. Introduction to Material Feeding 4.0: Strategic, Tactical, and Operational Impact. In IFIP International Conference on Advances in Production Management Systems (pp. 158-166). Springer, Cham.	Simonetto conceptualized the paper and conducted the literature review. Simonetto wrote the paper with feedback from Sgarbossa.
3	Simonetto, M. and Sgarbossa, F., 2021, September. Straight and U-Shaped Assembly Lines in Industry 4.0 Era: Factors Influencing Their Implementation. In IFIP International Conference on Advances in Production Management Systems (pp. 414-422). Springer, Cham.	Simonetto conceptualized the paper and conducted the exploratory research. Simonetto wrote the paper with feedback from Sgarbossa.
4	Simonetto, M., Peron, M., Fragapane, G. and Sgarbossa, F., 2020, October. Digital assembly assistance system in Industry 4.0 era: a case study with projected augmented reality. In International Workshop of Advanced Manufacturing and Automation (pp. 644-651). Springer, Singapore.	Simonetto conceptualized the paper. Simonetto and Peron collected the data and Fragapane analyzed the data with input from Simonetto and Peron. Simonetto, Peron, and Fragapane wrote the paper with feedback from Sgarbossa.
5	Simonetto, M., Arena, S. and Peron, M., 2022. A methodological framework to integrate motion capture system and Virtual Reality for assembly system 4.0 workplace design. Safety Science, 146, p.105561.	Simonetto conceptualized the paper and created the methodological framework together with Peron. Simonetto and Peron collected the data and Peron analyzed the data with input from Simonetto. Simonetto and Peron wrote the paper with feedback from Sgarbossa.
6	Simonetto, M., Saporiti, N., (under review). Traditional Kanban, e-Kanban or Digital Twin: a Decision Support System for material management solution. Industrial Management & Data Systems.	Simonetto conceptualized the paper together with Saporiti. Simonetto and Saporiti created the simulations models and analyzed the data. Simonetto and Saporiti wrote the paper.

Contents

Part I: Main report

1. Introduction

This section discusses the context and motivation for the current research investigation. Therefore, first, as the background, the main topics of the research study—assembly system (AS) and Industry 4.0—are introduced to familiarise readers with the terms that will be used throughout the rest of the study. Second, the main motivation to conduct this research study is explained. Next, the scope of the current study clarifies and positions the research study within the literature to then present the objectives of the study and derived research questions. Finally, to guide readers who may be interested solely in a specific part of the work, a summarised version of the content of each section and the structure of the present research study are presented.

1.1. Background

Assembly is an essential part of the manufacturing process that is performed in what are called ASs. Generally, an AS is composed of two subsystems: the assembly line subsystem (ALS) and the assembly line feeding subsystem (ALFS) (Battini et al., 2009). In each subsystem, different activities are performed to make sure that the goals of the AS are achieved and maintained (e.g., to have high efficiency, that is, by maximising throughput with minimum resources, having high flexibility, having rapid changes in the production volume and type of products to be assembled, minimising the work in progress (WIP), assembling high-quality products, minimising the inventory level, utilising the workforce effectively and minimising disruption to production (Bukchin and Masin, 2004; Hu et al., 2011; Vallandingham et al., 2017). Hence, the activities of an ALS are assembly and control, while the activities of an ALFS are transportation, preparation and material management (Battini et al., 2009; Sali and Sahin, 2016; Schmid and Limère, 2019). Depending on whether these activities are done manually, automatically or both, an AS can be manual, automatic or hybrid (Levitin et al., 2006; Gil-Vilda et al., 2017; Weckenborg et al., 2019; Zhang et al., 2019).

The costs of an AS is typically between 25% and 50% of the total cost of manufacturing, with the percentage of operators involved in their execution ranging from 20% to 60% (Ritchie et al., 1999; Bi et al., 2007; Buckhorst et al., 2022). If the companies aim to remain competitive in the market, they should try to keep the costs of their ASs as low as possible. In fact, regardless of the goals companies want to achieve regarding their AS, achieving high profits while keeping costs low is considered one of the most important overall goals for most companies. To achieve this, companies would require to learn how to design and manage their ASs (Battini et al., 2011).

The design of an AS, as the word may suggest, concerns all the decisions to be made, at a strategic and a tactical level, with the aim of designing and making ASs operational to reach the desired goals (Battini et al., 2011). Therefore, when companies have to design their ASs, they first need to know the products that they are going to assemble and resources necessary to assemble them. The characteristics of the products and equipment will influence the decision about the configuration and level of the automation of the ASs. The configuration of an AS is related to how the workplaces where the resources will perform the assembly tasks will be arranged in the space allocated for the creation of the AS. The most widely adopted configuration is the straight-line (SL) configuration, followed by the U-shaped (US) line configuration (Bagher et al., 2011; Rabbani et al., 2012; Mukund and Ponnambalam, 2016). The SL configuration is represented by a sequence of workplaces in a line. By simply rearranging the workplaces in the SL into a U-shape, it is possible to obtain the US line configuration. Other examples of configurations that can all be reconfigured or treated as a line in terms of how they operate are two-sided lines, systems with rotary tables, the SL with fixed workers (FW), the US line with walking workers (WW) and so on (Battini et al., 2011; Calzavara et al., 2021); here, the level of automation refers to whether the AS is manual, automatic or hybrid. Next, the workplaces of the ASs need to be designed, along with the assembly tasks assigned to the workplaces, hence balancing the work that will be performed in each of them. Finally, it is necessary to choose the feeding policies necessary to transport the components and then schedule the transportation devices to transport these components to the ASs.

Once the design is complete, the ASs need to be managed to meet the established goals and be cost-efficient to operate, especially in terms of their adaptability to changing product and volume requirements triggered by a turbulent market environment (Kuzgunkaya and ElMaraghy, 2006; Matt, 2013). In fact, the management of an AS is related to all those activities responsible, at a tactical and operational level, for planning the short period of the AS and controlling the AS so that it can operate while keeping throughout its life the performance to reach the goals for which it was designed (Gordon et al., 2002; Gao et al., 2012). The main decisions during the management of an AS are the planning of the sequence of products that need to be assembled day by day, the planning of the routes that transportation devices must take to transport the components to assemble those products, the planning of the quantity of components and the type of information that need to be managed in the ASs, along with how to control the entire AS so that everything works. If something is not working properly, the management of an AS must intervene so that any problems can be resolved as soon as possible. Therefore, the management of an AS has the important role of making the entire AS more flexible and reactive by ensuring that the decisions made during the design of the AS, such as workforce balancing, feeding policies and transportation scheduling, are properly processed, which can be done by changing the sequence of products to be produced or the routes of the transportation devices and by training and monitoring the resources of the ASs so that they can handle the demand for a higher quantity and variety (MacDuffie et al., 1996; Colledani et al., 2016).

Therefore, based on the above definitions, during the design and management of an AS, managers and practitioners must make different decisions (Wänström and Medbo, 2009; Battini et al., 2011; Fragapane et al., 2021; Dolgui et al., 2022), such as deciding on the configuration of the system, the level of automation, workplace design, assembly line balancing, sequencing, the feeding policy selection, scheduling, routing and material/information management and control of the AS.

However, although companies make the best decisions for their ASs, nowadays, it is more complicated than ever for ASs to achieve their goals. In fact, because of the rapid growth in customer demands for products with greater variety and shorter life cycles, AS activities are becoming extremely complicated, resulting in time losses, human errors and other negative effects on system performance (Battaïa et al., 2018; Bläsing et al., 2020). Therefore, to cope with these negative effects, companies have started to implement Industry 4.0 (I4.0) technologies in their ASs, creating the so-called Assembly System 4.0 (AS4.0) (Bortolini et al., 2017, Dolgui et al., 2022). According to the literature, Industry 4.0 technologies include Internet of Things (IoT) technologies, cyber-physical systems (CPSs), data analysis, cloud computing, collaborative robots (cobots), augmented reality (AR), virtual reality (VR), mobile robots, cybersecurity, blockchain and additive manufacturing (AM) (Stock and Seliger, 2016; Dalenogare et al., 2018; Ghobakhloo, 2018). These technologies can be implemented in the

ASs with the objective of reducing the set-up and processing times, as well as reducing the labour and production costs (Brettel et al., 2014; Jeschke et al., 2017). In fact, thanks to I4.0 technologies, ASs could become up to 35% faster and 30% more efficient (Nokia, 2022). Moreover, other similar facts have been reported by MIT, PWC and Deloitte. In fact, an MIT study has shown that I4.0 technologies help cut employee downtime by 85% and increase the average productivity rates by 11% (Globalluxsoft, 2017). A PWC study on the impact of I4.0 technologies on business instead forecasts a 18% increase in average productivity within 5 years of the mass implementation of these technologies in the ASs because of the ability to predict and minimise equipment downtime, thus optimising the operational efficiency (Globalluxsoft, 2017). Finally, Deloitte has reported that, by using I4.0 technologies, ASs can reduce the time needed to plan and execute the asset maintenance by up to 50%, resulting in 20% longer equipment uptime and up to 10% lower asset and total expenses, which can save millions in the long run (Coleman et al., 2017). Furthermore, more benefits can be derived from the increase in production line availability by 5% to 15% and the opportunities for energy-saving through optimisation. Indeed, for example, in a case study of a multinational in the plastics sector, I4.0 technologies were found to reduce the power consumption in one of its plants by around 40%, which saved over USD200,000 a year in energy (Sirimanne, 2022). If we look at those countries that have so far invested the most in I4.0 technologies, that is, the US and China, and in general at the worldwide investment in I4.0 technologies, the estimated value was at USD 71.7 billion in 2019 and is expected to reach USD 156.6 billion by 2024 (Globalluxsoft, 2017). Considering the creation of job opportunities, Lorenz et al. (2015) explained that, in Germany, by 2025, the use of I4.0 technologies will add 350,000 jobs, particularly in information technology and data science. Finally, in its 2020 Industry 4.0 study, the consulting company McKinsey & Co discovered that companies employing I4.0 technologies were better able to withstand the effects of the COVID-19 pandemic on business. In fact, 94% of the more than 400 companies polled stated that I4.0 technologies helped them continue operating during the pandemic. Furthermore, 56% of respondents said that I4.0 technologies were crucial to how they dealt with the pandemic (Agrawal et al., 2020; Uzialko, 2022).

Although I4.0 is implemented in the ASs, it is not certain that the benefits that these technologies seem to promise are then automatically achieved. In fact, for technologies to work correctly and, hence, ensure performance, they must be properly implemented and integrated into the ASs (Bortolini et al., 2019; Cohen et al., 2019a; Cohen et al., 2019b). Therefore, proper models and methods should be followed when implementing technology in an AS. However, current research has focused more on understanding how I4.0 technologies work or on the creation of new applications with the technologies rather than studying how the technologies impact the decision areas related to the design and management of an AS. Consequently, the absence of models and methods can mean that, once implemented, the technologies do not perform as expected, generating a negative impact on the performance of the ASs.

Therefore, the current research study will investigate how the application of I4.0 technologies impacts the decision areas related to the design and management of ASs. In particular, it will start to examine some of the abovementioned decision areas, providing solutions (e.g., a framework and a decision support system (DSS)) that can support managers and practitioners who want to understand, for example, which I4.0 technologies to implement in their ASs, how to use the I4.0 technologies or when to implement I4.0 technologies during the design of their ASs and for managing their ASs.

1.2. Research motivation

The present research study is motivated by the fact that, although companies are implementing the I4.0 technologies in their ASs, creating what is referred to as AS4.0, many of them then still design and manage their ASs as if they had not in fact implemented any of these technologies (Bortolini et al., 2017; Cohen et al., 2017; Cohen et al., 2019b). Therefore, although I4.0 technologies are being implemented to improve productivity, increase flexibility, have higher levels of automatisation, reduce costs and have better quality in the ASs, if they are not properly implemented and not monitored, it is possible that, instead of a benefit, these technologies could turn into a problem for companies and their ASs (Bortolini et al., 2021; Souifi et al., 2022). Because of the high investment that can be required to implement new technology (in terms of the cost of the infrastructure needed to use the technology, acquiring the skills then to use it and buying and maintaining it), if it then does not perform as it was supposed to, the companies may be discouraged from wanting to use it and will invest in other technologies (Agostini and Nosella, 2019; Palominos et al., 2019; Götz et al., 2020). The noninvestment in new technologies may result in losing the opportunity to benefit from the advantages that technologies could bring to ASs, with the possible consequence of failing to reach their goals (e.g., to minimise the WIP, assemble high-quality products, minimise the inventory level, utilise the workforce effectively and minimise disruption to production).

In general, the researchers who first studied I4.0 technologies were interested in learning how I4.0 technologies perform in specific applications, in the development of new technologies or in the development of new applications and functionalities of the technologies (Cohen et al., 2019a; Cohen et al., 2019b; Veiga et al., 2021). Therefore, further studies are needed now to understand the impact of I4.0 technologies on the design and management of ASs; these studies should create new models, methods and frameworks to understand, for example, which I4.0 technology to use, how to apply an I4.0 technology and when to use an I4.0 technology during the design of an AS and to manage the AS.

Moreover, the current research has aimed to enhance the investment that the Department of Mechanical and Industrial Engineering of NTNU is making by providing some of the I4.0 technologies to the Logistics 4.0 Lab, which is Norway's first logistics laboratory and merges I4.0 technologies with traditional production and logistics systems, enabling researchers, practitioners, engineers, pioneers, students and other enthusiasts to come together and collaborate on the common ground; this can help in developing and improving their knowledge and skills in the use of the technologies. Many I4.0 technologies such as AR, VR, IoT and mobile robots can be found in the Logistics 4.0 Lab. Here, the basic idea was to use one or more of these technologies in collaboration with the production management group to answer the research questions of this study.

1.3. Research scope

The current research study lies within the research area of ASs and examines the impact of I4.0 technologies on the decision areas related to the design and management of ASs. However, a complete discussion of the topics introduced so far is too extensive a task for the present research. Thus, further scoping of the domains is needed.

As shown in the background, an AS can be manual, automatic or hybrid, according to whether the AS activities are performed manually, by robots or both manually and by robots. However, because performing assembly tasks still requires intensive manual activity (Bi et al., 2007), the present research focuses on manual and hybrid ASs of small-to-medium sized products such as hydraulic pumps, engines, actuators, hose reels and so forth. Moreover, because investigating all the decision areas related to the design and management of an AS would exceed the time frame of the current study, only three decision areas have been considered. In fact, the present study focused on how to configure the ALS, the workplace design of an ALS and the control of the ALFS. In particular, for the control of the ALFS, the focuses was on the control of the material management of the ALFS.

Regarding I4.0 technologies, it is known that there are many available technologies that can be studied in an AS. However, the Logistics 4.0 Lab at the Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology (NTNU) came to our aid. In fact, the present research study was conducted with the idea of exploiting the technologies that were already available, without having to purchase new ones. Therefore, in this sense, the Logistics 4.0 Lab limited the possible I4.0 technologies to be studied to only those available internally. In addition, among these technologies were selected those that could help investigate the three decision areas configuration of an ALS, workplace design of an ALS and control of the ALS. Therefore, from the I4.0 technologies available in the Logistics 4.0 Lab, AR, VR and digital twin (DT) technologies were selected and analysed.

The scope of the research study is summarised as follows:

The current study focuses on three decision areas (configuration of an ALS, workplace design of an ALS and control of the ALS) related to the design and management of a manual/hybrid AS4.0 that assembles small/medium products. During the study of the three decision areas, we considered the three I4.0 technologies of AR, VR and DT.

1.4. Research objectives and questions

Motivated by the challenges and research problem and following the research scope outlined above, the current study aims to support and create new knowledge for the academy and managers and practitioners who want to design and manage AS4.0.

To do so, the first main goal was to understand the state of the art of AS4.0 and propose possible future research opportunities in AS4.0 that represent, respectively, the first two main outcomes of the current study. Therefore, we performed a systematic literature review (SLR). From this SLR, we understood how I4.0 technologies impact the decision areas of an AS and derived nine future research opportunities that can generate many research questions related to the design and management of AS4.0.

However, because there was no time to explore all the possible future research opportunities and unanswered questions regarding this topic, the objective is limited to providing a better understanding and knowledge of the following:

- The factors that are relevant for modelling dynamic reconfigurable configurations of an ALS and the impact of I4.0 technologies on these factors
- The use of VR, together with a motion capture system to design the workplace of an ALS
- The use of DT for the control of the material management in an ALFS

Therefore, from the research objectives, the following research questions were defined to guide the research process:

RQ1: How can AS4.0 configurations be affected by Industry 4.0 technologies?

The configuration of an ALS is related to how the workplaces where the resources that will perform the assembly tasks will be arranged in the space allocated for the creation of the AS. Nowadays, due to the change in the market demand companies should model dynamic reconfigurable configurations for their ALSs that can help them assembly different products day by day without hindering the performance of their ALSs. The modelling of the configuration of the ALSs should not be made randomly, but it should be based on some factors that companies need to know if they want to make the best decision. These factors are the ones that not only determine the configurations of the ALSs but can also determine how dynamic reconfigurable can be these configurations. In addition, the implementation of I4.0 technologies in ALSs can have an impact on these factors thus facilitating the design of dynamic reconfigurable configurations of ALSs. However, at the moment, no studies have investigated this topic. Therefore, the first research question aims to discover and define the factors that are relevant for modelling dynamic reconfigurable configurations of an ALS and then to understand how I4.0 technologies impact these factors. In addition, to validate our results, we analysed the impact of AR on the discovered factors.

RQ2: How can ergo-efficient AS4.0 workplaces be designed?

The second research question aims to create a framework for guiding the designer of ALSs to create ergo-efficient workplaces using VR together with a motion capture system. The framework consists of five steps that are thoroughly explained, leaving no doubt in the minds of the designers who will use it to design the workplaces in their ALSs. In addition, we integrated in the framework the age of the operators working in the workplace in two different modes: a dynamic mode that considers age in terms of operators' experience in the workplace and a static mode that considers age in terms of two formulas, one calculating the age-based multiplier for muscle strength and the other the age-based multiplier for reduced joint flexibility.

RQ3: How can material management be controlled in AS4.0?

The third research question aims to introduce a DSS that can guide managers and practitioners in deciding whether to adopt a DT solution to control the material management in their ALFS compared with two other solutions that are commonly adopted in this regard (traditional Kanban and e-Kanban). In addition, the DSS can also guide managers and operators to change the current solution they have for controlling materials management in their ALFS.

1.5. Thesis outline

The present thesis is divided into two parts. The first part (I) contains the main report, while the second part (II) includes the collection of published papers from this thesis. Hence the thesis report is developed on the research carried out and described in the supplementary papers. It also provides an overview of the research process and synthesises on the contributions of the independent publications into a coherent argument.

Part I is organised as follows:

Section 1 is the introduction part. It describes the issues encountered in practice and the reason for research in this area. Furthermore, it describes the research problem investigated and defines the research objectives and questions addressed through the current study. The section finishes by explaining the scope and structure of the study.

Section 2 presents the theoretical background of the research. It starts with the definition of the AS and of its subsystems, explaining their decision areas at the strategic, tactical and operational levels. Next, the most common I4.0 technologies are introduced and defined. To conclude the section, together with the definition of Assembly System 4.0, we introduce some of the benefits that, according to the literature, I4.0 technologies can bring to AS.

Section 3 introduces the research design. It provides a full description of the research methodologies employed, as well as thoughts on key methodology-related decisions made over the course of the research. Finally, the topic of research quality is examined in terms of the four accepted requirements of research quality.

Section 4 presents and discusses the results and findings of the study. It presents the key outcomes addressed by the research questions and discusses them. The first subsection explains the SLR done to study the state of the art of AS4.0, which gave, as an output, the future research opportunities that inspired the three research questions. In the rest of the subsections, we then answered the three research questions, one subsection per question.

Section 5 outlines the research study and provides the final remarks. Furthermore, the limitations of the research are noted, as well as recommendations for further research.

Figure 1 illustrates the outline of the thesis and compares it with the commonly used introduction, methods, results, discussion and conclusion (IMRaD) structure.

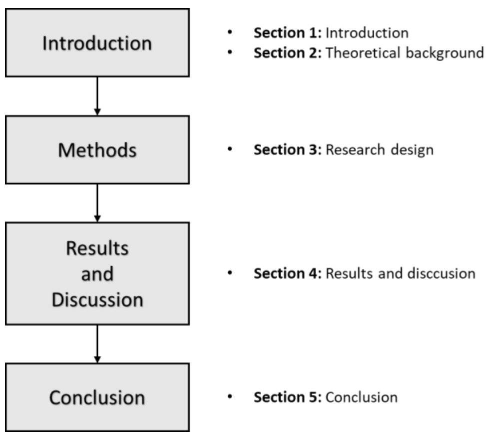

Figure 1. Thesis outline

Part II contains the supplementary papers, which are the papers created to communicate the findings of the current research study. It consists of five published papers (Papers 1 to 5) and one paper that is under the review process (Paper 6):

1. Dolgui, A., Sgarbossa, F. and Simonetto, M., 2022. Design and management of assembly systems 4.0: systematic literature review and research agenda. International Journal of Production Research, 60(1), pp.184–210. (***Paper 1***).
2. Simonetto, M. and Sgarbossa, F., 2020, August. Introduction to material feeding 4.0: Strategic, tactical, and operational impact. In IFIP International Conference on Advances in Production Management Systems (pp. 158–166). Springer, Cham. (***Paper 2***).
3. Simonetto, M. and Sgarbossa, F., 2021, September. Straight and U-shaped assembly lines in Industry 4.0 Era: Factors influencing their implementation. In IFIP International Conference on Advances in Production Management Systems (pp. 414–422). Springer, Cham. (***Paper 3***).
4. Simonetto, M., Peron, M., Fragapane, G. and Sgarbossa, F., 2020, October. Digital assembly assistance system in Industry 4.0 era: A case study with projected augmented reality. In International Workshop of Advanced Manufacturing and Automation (pp. 644–651). Springer, Singapore. (***Paper 4***).
5. Simonetto, M., Arena, S. and Peron, M., 2022. A methodological framework to integrate motion capture system and virtual reality for assembly system 4.0 workplace design. Safety Science, 146, p.105561. (***Paper 5***).
6. Simonetto, M., Saporiti, N., (under review). Traditional Kanban, e-Kanban or Digital Twin: A Decision Support System for material management solution. Computers & Industrial Engineering. (***Paper 6***).

2. Theoretical background

This section introduces the relevant theoretical background that frames and supports the current research study. Here we present, the topics of AS (Subsection 2.1), Industry 4.0 technologies (Subsection 2.2) and Assembly System 4.0 (Subsection 2.3). In Subsection 2.1, we present the traditional ASs in which no I4.0 technologies are implemented. In this subsection, we explain the parts that form an AS with the activities performed in each part. Then, we illustrate the decision areas at three levels—strategic, tactical and operational—that companies have to know while designing and managing traditional ASs. Second, in Subsection 2.2, we present the topic of I4.0 by explaining what it is and which I4.0 technologies managers and practitioners can implement in their companies. Finally, in Subsection 2.3, we present the AS4.0 by discussing what I4.0 technologies can be implemented in it.

2.1. Assembly Systems

An AS is composed of the following two parts (Battini et al., 2009):

- The ALS
- The ALFS

An ALS is a type of production system in which various tasks are executed at one or more workplaces to create the final product (Rekiek et al., 2002; Dolgui and Proth, 2010; Akpinar et al., 2017; Zhong and Ai, 2017). The main components of an ALS are the workplaces in which the operators perform the tasks, and the components can be stored. Based on how workplaces are placed within the space designated for the ALS, ALSs can be designed in different configurations, such as a single line (SL), a two-sided line, a US line, a system with rotary table, a SL with FW, a US line with WW and so on (Becker and Scholl, 2006; Battini et al., 2011; Battaïa and Dolgui, 2013). However, the SL is the most frequently utilised configuration (Rabbani et al., 2011; Mukund and Ponnambalam, 2016), and in fact, all types of configurations can be reconfigured into or treated as a line in terms of how they operate. Moreover, ALSs can be manual, automatic or hybrid, here based on whether the assembly activity is performed only by human workers, only by robots or by both, in which human workers are supported by robots (Levitin et al., 2006; Gil-Vilda et al., 2017; Weckenborg et al., 2019; Zhang et al., 2019). As reported in Section 1, we are interested in manual and hybrid ASs.

Two main activities are executed in an ALS: assembly and control. Assembly is the capstone process for product realisation, where the components and subassemblies are combined to make the finished products (Hu et al., 2011). Assembly encompasses all the assembly and subassembly processes and equipment required to (i) bring together, configure, align, orient and adjust components and materials to form the end-product and to (ii) physically attach parts, materials and components, such as screwing, riveting, stapling, nailing, gluing, wrapping, interlocking, tying, fusing, sewing, welding, soldering, bonding, pegging, coupling, laminating, insertion, sealing and similar activities (Bi et al., 2007). Control, instead, is related to monitoring the quality and performance of the ALS (Hu et al., 2011; Battini et al., 2011).

An ALFS, instead, is responsible for the transportation, preparation and management of all the components to the ALS that are needed to perform the assembly process (Battini et al., 2009; Sali and Sahin, 2016). The main components of an ALFS are the warehouses in which the components are stored, all the containers of the components and all the devices and operators that are responsible for managing and transporting the components. The right component must be delivered in the right quantity, in the right container and at the right moment to the right ALS.

To achieve this, the three main activities of an ALFS are: transportation, preparation and material management (Schmid and Limère, 2019). Transportation involves the process of moving all the components or parts from point A, where they are stored, to point B, where they are needed, while preparation relates to the processes of handling and repacking parts into the load carriers used for the corresponding line feeding policy (Battini et al., 2009; Zuin et al., 2018; Adenipekun et al., 2022). Finally, material management includes all the processes related to the storage of components and products (Battini et al., 2010).

To provide an AS that can achieve its goals, the two subsystems must be correctly designed and managed. To do this, numerous distinct decision areas have been established in the literature, as summarised in Table 1.

Table 1. Decision areas at different levels of a traditional AS

Time horizon	Level	Assembly Line Subsystem (ALS)	Assembly Line Feeding Subsystem (ALFS)
Long term	**STRATEGIC**	• Configuration of the system • Level of automation	• Configuration of the system • Level of automation
Medium term	**TACTICAL**	• Workplace design • Assembly line balancing	• Feeding policy selection • Scheduling
Short term	**OPERATIONAL**	• Sequencing • Control of the ALS	• Routing and material/information management • Control of the ALFS

These decision areas may relate to various levels, such as strategic, tactical or operational. Strategic decisions have a long-term (measured in years) influence on the company's operations, whereas tactical decisions have a medium-term (weekly) impact, and operational decisions are made daily and have a short-term impact.

At the strategic level, decisions are made regarding the configuration of the system and level of automation for both ALSs and ALFSs. This means that companies must select the product family to be assembled and estimate how many resources the family will require, how many ASs will be required (e.g., one flexible system for the entire product family or several more dedicated ones), the shape of their ASs and the type of equipment, that is, whether the various tasks associated with these systems will be executed manually, automatically or both (Bassan et al., 1980; Cormier and Gunn, 1992; Roodbergen and Vis, 2006; Wänström and Medbo, 2009; Battini et al., 2011; Fragapane et al., 2021).

At the tactical level, companies may first carry out workforce dimensioning (Dolgui et al., 2018), determining how many workers are necessary to perform the work in the worst-case scenario (large demand, complex product). Then, this information—together with time-and-motion and ergonomic analyses—can be used for designing workplaces for the ALSs before assigning these tasks to the workplaces using assembly line balancing algorithms (Lindenmeyer, 2001; Boysen et al., 2008; Battaïa and Dolgui, 2013; Zülch and Zülch, 2017). The decisions at this level in the ALFS first relate to how to transport the various components to the ALS (Battini et al., 2009; Caputo and Pelagagge, 2011; Caputo et al., 2018), workforce dimensioning and, then, to the scheduling problem of who needs to deliver them (Mei et al., 2005; Dang et al., 2014).

At the operational level, the AS must function properly and, hence, must be controlled. When the product, production or demand changes, there may be reconfiguration issues. To decide and regulate this process, several types of data are collected from the AS, such as the sequence of goods produced in the ALS, the quantities of components to store in various warehouses and the routes utilised to transport these components to the ALS (DeCroix and Zipkin, 2005; Hu et al., 2008; Boysen et al., 2011; Gebser et al., 2018).

2.2. Industry 4.0 technologies

Introduced for the first time in 2011 at the Hannover Fair in Germany, Industry 4.0 (I4.0) is the term used to refer to the Fourth Industrial Revolution (Rainer and Alexander, 2014). In fact, after the first three industrial revolutions (mechanisation, electrification and digitalisation), where in a period of nearly 200 years, companies went from mechanical looms driven by steam engines to having programmable logic controllers that enable the use of automation systems, we are now in the 'digitalisation era' thanks to the implementation in the industrial environment of new technologies that can communicate with each other and collect data in real time (Lasi et al., 2014; Rainer and Alexander, 2014; Buer et al., 2018). The connection between various pieces of technology and the possibility to have real-time data promise increased flexibility, higher levels of automatisation, better quality and improved productivity in manufacturing systems such as ASs (Thames and Schaefer, 2016; Zhong et al., 2017). Therefore, Industry 4.0 technologies can impact how products are made and, at the same time, may also have an impact on customers' perceptions of product value because the products will have higher quality, will be produced faster and possibly have a greater variety (de Sousa et al., 2018).

Based on the literature, the technologies responsible for the Fourth Industrial Revolution, known as Industry 4.0 technologies, are the IoT technologies, CPSs, data analysis, cloud computing, collaborative robots (cobots), AR, VR, mobile robots, cybersecurity, blockchain and AM (Stock and Seliger, 2016; Dalenogare et al., 2018; Ghobakhloo, 2018).

The term IoT technologies indicates all the objects, systems and processes that are exchanging data through the Internet (Morlet et al., 2016). In addition to the IoT, the fusion of the physical and the virtual world is a further important component of Industry 4.0 (Lu, 2017); this fusion is made possible by CPS, which are technological systems that integrate cyberspace with physical processes and objects to transform the machines and devices of production and ASs into a network so that real-time data are available (Lee et al., 2015). Once real-time data are available, they need to be processed to create useful information that can help in making decisions, such as the prioritisation of production orders, optimisation of tasks, maintenance requirements and so forth to increase the performance. Data analysis aims at analysing these raw data to extract useful information and convert it into effective knowledge, to improve process understanding and to support decisions (Ge et al., 2017). All the real-time data and information can be stored, managed and shared thanks to the cloud. The National Institute of Standards and Technology (NIST) defined cloud computing as 'a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction' (Mell and Grance, 2009). Cloud computing encompasses both the applications offered as services over the Internet and the hardware and system software in data centres that deliver these services.

Companies are always looking for solutions that can assist their operators in the execution of different activities. These solutions are collaborative robots (cobots), AR, VR and mobile robots. Cobots are powerful devices that actively cooperate with the operators during the execution of specific tasks, providing a powerful source of automation and assistance for specific activities (Fast-Berglund et al., 2016). AR refers to the integration of additional computer-generated information into a real-world environment (Paelke, 2014), while VR allows for the creation of a three-dimensional world in which users can interact with three-dimensional objects in real time by using their natural senses and skills (Riva, 2002). Mobile robots can be defined as 'industrial robots that use a decentralised decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area' (Fragapane et al., 2021).

Today, a huge number of 'things' can be connected through the Internet or among themselves to create a fully interconnected industrial networked environment, that is, a cyberspace, across companies. Therefore, it is necessary to ensure secure, safe and reliable communication so that any decisions and actions made in the cyberspace by companies are based on dependable and properly authorised information (Mehnen et al., 2017; Ghobakhloo, 2018). To do so, companies can rely on cybersecurity, which aims at protecting the cyberspace (which includes both information and infrastructures) from any cyber-threat or -attack (Lezzi et al., 2018).

Blockchain is defined as 'a decentralized database technology that is tamper-proof and ensures consistent transactions across many users' (Yetis et al., 2022). Blockchain may be used as a ledger to establish trustworthy and autonomous relationships between various components of companies, suppliers and even customers (Ghobakhloo, 2018). In fact, with consensus, immutability, security and smart contracts, blockchain improves the efficiency of the systems in which it is used (Ouyang et al., 2019).

Finally, AM is the 'process of joining materials to make objects from 3D model data, usually layer upon layer' (ASTM 2010). It is considered an essential ingredient in the new paradigm of I4.0 (Dilberoglu, 2017) and is known also as three-dimensional printing (3D printing).

2.3. Assembly Systems 4.0

The combination of AS with I4.0 technologies has led to what is referred to as Assembly System 4.0 (AS4.0) (Bortolini et al., 2017; Cohen et al., 2019b). Therefore, as in an AS, in an AS4.0, the ALS and ALFS will be present, but in this case, their activities, are shown in Subsection 2.1, can be supported or executed by one or more I4.0 technologies (Figure 2). However, not all the I4.0 technologies described in the previous subsection are used in ASs. In fact, the I4.0 technologies that are used in AS4.0 are IoT technologies, CPSs, data analysis, cloud computing, cobots, AR, VR, mobile robots and AM (Bortolini et al., 2017; Cohen et al., 2019a; Cohen et al., 2019b).

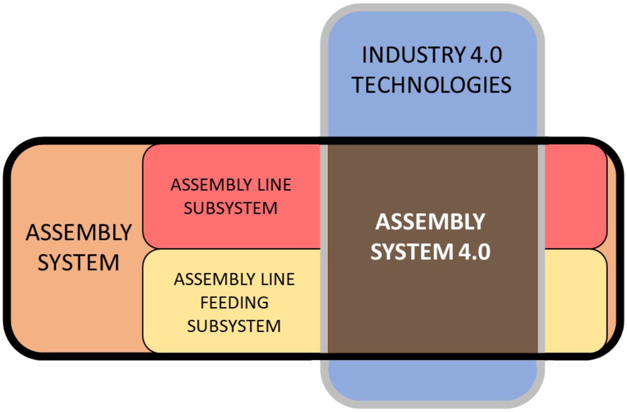

Figure 2. The parts of an Assembly System 4.0

In fact, IoT technologies can help companies collect data from all the activities and actors in an AS, for which knowledge of their status and behaviour can be useful to keep the AS under control and provide opportunities to improve its performance (Alavian et al., 2020; Baumann et al., 2020). Hence, in an ALS, sensors can be applied to operators (e.g., motion capture systems to collect over the time data of the position and orientation of the operator's different limbs in a common reference system (Oyekan et al., 2017)), workplaces and in all the equipment used during the execution of the various assembly tasks (Oyekan et al., 2019; Peruzzini et al., 2020). For the ALFS, sensors can be applied again to operators, to containers used to store components and to all the transportation devices, such as forklifts, trolleys, mobile robots and so forth used to move the components within the AS (Chien et al., 2017; Zhao et al., 2018). The data that can be collected can be related, for example, to the status of the assembly activities, the status of the products that are being assembled, the location of the components in the AS, the number of components in the containers in the AS and environmental factors such as the temperature inside the AS. In addition, the connection of different components of the AS can create a CPS of the AS giving the connected actors the opportunity to communicate with each other and have a better understanding of what is happening not only in the specific position of the AS in which they are located, but also throughout the entire AS (Sgarbossa et al., 2020). This can help in reducing the mistakes made during the execution of different activities, improve the quality and reliability of the activities and create ASs that are synchronised with the requirements of the customers and the capacity of the AS. However, to achieve all these benefits, it is necessary that the data collected from the IoT technologies are saved and analysed to be transformed into useful information before then being delivered to the final users. Data analysis is responsible for analysing the data and transforming them into information, such as the amount of components to be stored in warehouses, when it is time to deliver the components, the number of products assembled in a certain period of time, the time when it is necessary to start assembling a new product, which products can be assembled based on the current components stored in the warehouse and so forth (Storti et al., 2018; Yao et al., 2018; Adams et al., 2021; Zangaro et al., 2021). There are no limits on the information that can be generated; the important thing is to understand what information is relevant for the AS (Cattaneo et al., 2018). To send this information in their ASs, companies can decide to use cloud computing, which is not only a 'place' where data from the AS can be saved, but also providing the opportunity to synchronise all of the actors in the AS with the same information in real time thanks to the possibility of executing cloud computing apps on practically any device, including PCs, laptops and smartphones. Moreover, the cloud computing apps can also give the opportunity to do data analysis directly from the cloud (Alexopoulos et al., 2016; Guo et al., 2020). Therefore, with cloud computing, the performance of the ASs can be watched and managed everywhere around the AS and in real time, with the option of taking action if something is not operating properly or needs to be changed (Nuzzi et al., 2020; Ruppert and Abonyi, 2020; Tao et al., 2020).

By introducing workplaces with collaborative task execution by human workers and cobots, the advantages of both automated and manual ALS can be realised in a hybrid ALS (Weckenborg et al., 2020). Moreover, cobots can be installed on top of mobile robots and can be used in warehouses to help operators pick up and place components in containers (Fager et al., 2020; Fager et al., 2021). Regardless of the application in which the cobots are used, it is important that adequate control systems are designed and implemented to avoid possible collisions with the operators (Malik and Bilberg, 2019). In this regard, AR and VR can give valuable help in preventing collisions. In fact, in real time, AR can show operators who are working together with cobots the areas in which the cobots will be active, enabling them to avoid being in that position and, thus, avoiding potential collisions (San Martín and Kildal, 2019; Gruenefeld et al., 2020; Lee et al., 2021). VR, on the other hand, can be used to recreate the area where the operators will work together with cobots in a virtual environment. Through recreating a high-fidelity copy of the area, even operators who have no previous experience with cobots will have the opportunity to learn how to work together with them before doing so for real in the AS (Brough et al., 2007; Etzi et al., 2019). Moreover, AR and VR can be used for other applications in the AS (Ong et al., 2008; Seth et al., 2011; Ong and Nee, 2013). For example, AR can be used to guide the operators in the execution of the different assembly and maintenance tasks, reducing the time to execute the tasks and errors made during their execution (Hořejší, 2015; Longo, Nicoletti and Padovano, 2017). By creating virtual environments that recreate the real AS, VR can, for example, be used to train the operators who will work in the AS and to design or make changes to the design of the AS (Brough et al., 2007; Grajewski et al., 2013; Gorecky et al., 2017). VR can also be used to remotely control mobile robots that are moving around the AS performing tasks (Chen and Chen, 2014). However, mobile robots are generally autonomous and can, unlike other transportation devices such as forklifts, offer opportunities to create new guide paths, improving the performance of the ALFS in terms of both time and safety (Elhoseny et al., 2018; Moysis et al., 2020; Panda et al., 2020). Moreover, mobile robots can be used not only to transport simple containers, but also to move entire shelves within the AS (Yoshitake et al., 2019; Gharehgozli and Zaerpour, 2020) or transport different types of objects by linking two or more mobile robots together, depending on the object being transported (Groß and Dorigo, 2009).

Finally, in the ALS, some components may be produced directly by AM in the workplaces, especially in the case of parts needed in small quantities, thus avoiding the need for their transportation and storage in workplaces or warehouses (Cohen et al., 2019b).

While in Table 1 it is possible to see the decisions that need to be made to design and manage an AS, these decisions are related to what we call traditional ASs, where the technologies responsible for the Fourth Industrial Revolution are not implemented. Assembly System 4.0 may need new decisions, in addition to those of traditional ASs; or the decisions of a traditional AS may change based on the technologies applied in AS4.0. However, at the moment, to the best of the author's knowledge, there are no studies that have tried to investigate this topic. Therefore, to fill this gap, one of the results of the present research study was recreating a table like Table 1 but for AS4.0. Thus, the present study has created two tables, one for the ALS and one for the ALFS of an AS4.0 (Subsection 4.1, Table 3 and Table 4).

3. Research design

This section presents and explains the research design of the current study (Figure 3). First, the research methods adopted to perform the study are described (Subsection 3.1). Second, the four requirements to ensure research quality (construct validity, internal validity, external validity and reliability) are presented (Subsection 3.2).

3.1. Research methods

Knowing the research methods used in the elaboration of a scientific document, such as a thesis dissertation, is of primary importance for understanding its validity and quality (Borrego et al., 2009; Queirós et al., 2017). Research methods can be divided into qualitative and quantitative methods. If qualitative methods seek to comprehend a complex reality and the meaning of actions in a specific context, quantitative methods instead seek precise and trustworthy measurements that allow for statistical analysis (Reswick, 1994; Queirós et al., 2017).

In the present study, both types of methods have been investigated. In fact, two qualitative methods (SLR and exploratory research) and two quantitative methods (experimental research and simulation modelling) provided the main outcomes of the study. After allowing us to understand the state of the art of AS4.0 and its future research opportunities, the SLR helped derive the three research questions. Exploratory research and experimental research helped answer the first research question (**RQ1**). Experimental research and simulation modelling helped answer the second (**RQ2**) and third (**RQ3**) research questions, respectively.

3.1.1. Systematic literature review

An SLR can make an important contribution to the advancement of research; it aims to give a historical perspective on the relevant study topic and an in-depth assessment of independent research activities (Mentzer and Kahn, 1995). In particular, an SLR is a review of precisely defined questions that employs a methodical and evidence-based approach for discovering, selecting and assessing secondary data. This method varies from others in its transparency, inclusiveness and explanatory and heuristic character (Tranfield et al., 2003). Moreover, as a scientific inquiry, an SLR should be valid, reliable and repeatable (Xiao and Watson, 2019). This is the reason why the steps applied to select the works analysed in an SLR need to be clearly defined (Seuring and Gold, 2012). Therefore, an SLR, compared with other types of literature reviews, allows for a more objective overview of the search results and eliminates bias and error issues (Buchanan and Bryman, 2009). The SLR's primary purpose is to facilitate theory development, organise research being conducted and propose areas for further investigation (Webster and Watson, 2002).

The literature on the design and management of AS4.0 is not yet well structured and investigated. Hence, an SLR was a suitable approach to organise and unify knowledge within this field.

Therefore, in the present research study, an SLR not only helped to provide an overview of AS4.0, but also served to identify future research opportunities. Moreover, the future research opportunities inspired the research questions investigated here (Figure 3). Following the guidelines outlined by Tranfield et al. (2003), the SLR consisted of five steps. In the first steps, the relevant keywords for the research were identified and then combined to generate the query used during the research process performed on the Scopus database. During the second step, the refinement, limitations on the period of research, on the document type and on the language of the papers to study were delineated. Thus, the research was limited to only articles and reviews written in English in the period from 2005 to 2020. A combination of the keywords with these first limitations gave us an initial selection of 16,849 papers, which was reduced to 9,424 after we removed duplicates and considered only journals with a Scimago Journal Rank (SJR) greater than or equal to 0.5. The third and fourth steps—creating the inclusion and exclusion criteria and performing a second refinement, respectively—helped reduce the number of papers from 9,424 to 140. In these two steps, it was possible to remove all the papers that were related to topics outside the scope of the review and those that appeared relevant from the abstract but which turned out to be outside the scope once read in their entirety. Finally, in the fifth step, the snowball search, 17 papers were added. By the end of this step, 157 papers had been selected for inclusion in the SLR.

The entire process of the SLR, the selection of the papers to arrive at the final 157 papers and the analysis of these papers to arrive at the results was carried out using Excel.

3.1.2. Exploratory research

Exploratory research is often qualitative in nature, and it is a methodology approach that analyses previously unstudied research questions (Tegan, 2022). In fact, exploratory research is conducted when problems are in their early stages, when the topic or issue is novel or when data collection is challenging for certain reasons (Babbie, 2007). Therefore, exploratory research can be seen as the preliminary research to clarify the exact nature of the problem to be solved. It is used to guarantee that more research is considered throughout an experiment, as well as setting the research goals, gathering data and focusing on certain issues that would be difficult to notice without exploratory research (Wikipedia, 2021).

According to Tegan (2022), if you have a general notion or specific question that you want to investigate but no underlying knowledge or paradigm with which to do so, you can conduct exploratory research. This was the situation of the first research question (RQ1) of the present research study. In fact, when investigating the literature, there was no precise knowledge of what factors are relevant to understand when a company needs to decide on the configuration of its ALSs; because of this, there was also no knowledge related to the impact that new Industry 4.0 technologies have on these factors.

Therefore, in the current study, the exploratory research not only allowed us to define the seven factors relevant to ALS configuration decision making, but also gave us the opportunity to then understand whether and how new I4.0 technologies impact these factors. Moreover, because it is in the nature of exploratory research to help in proposing new ideas (Swedberg, 2020), this research opened the door to promising new opportunities. In fact, now that the factors and impact of the I4.0 technologies on factors are known, it would be interesting to quantify both the threshold values of the factors that determine the choice of one ALS configuration over another and the numerical values related to how the technologies have changed these thresholds.

The entire process of the exploratory research, which consists of the classification of the papers to define the factors and understand the impact of the I4.0 technologies on those factors, was carried out using Excel.

3.1.3. Experimental research

Experimental research is a type of study that rigidly follows a scientific research design. It involves testing or attempting to prove a hypothesis by way of experimentation (Pollfish, 2022). Therefore, during the experiment, researchers gather evidence that may be used to support or deny this hypothesis and that should help them make better decisions; hence, the present study is also known as hypothesis testing or deductive research approach. In general, experimental research has three categories that researchers might implement, which are pre-experimental research design, quasi-experimental research design and true experimental research design (Pollfish, 2022). A pre-experimental study design involves observing a group or groups once the elements of cause and effect are established. As a result, pre-experimental research is a necessary first step in justifying the presence of the researcher's involvement. A quasi-experimental design, such as a true experiment, seeks to demonstrate a cause-and-effect link between an independent and dependent variable (Voxco, 2022). However, unlike a true experiment, a quasi-experiment does not rely on random assignment. The subjects are instead assigned to groups based on non-random criteria. A true experimental design is a statistical method for determining a cause-and-effect link between many factors (Voxco, 2022). This is one of the most precise types of research design, providing sufficient evidence to demonstrate the presence of correlations.

Therefore, knowing that experimental research is best suited for exploratory research, in which the goal y is to examine cause-and-effect relationships (Bhattacherjee, 2022), we decided to adopt it in two of our studies. In the first one, which was moved by the fact that the next step of exploratory research can be experimental research, we were interested in understanding the impact of AR on the factors relevant to determining the configuration of an ALS (RQ1). In the second one, we were interested in understanding if the methodological framework that we developed is valid (RQ2). Although, generally, experimental research is considered to be time-consuming and expensive to carry out (Berinsky et al., 2012), we were lucky to have some students who voluntarily participated in carrying out the studies. In particular, a total of 15 students participated in the AR studies and one PhD student participated in the experiment to validate the methodological framework.

Furthermore, because experimental research must be carried out in a controlled environment, we conducted the two experimental studies in the Logistics 4.0 Lab at the

Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology (NTNU), where there were no disturbing elements. During the first experiment to develop the AR solution, we used a Kinect camera, the Webcam Zone Trigger Pro motion recognition software, work instruction programme (HTML file) and a projector. For the second experiment, to validate the methodological framework, we used the software Siemens Jack™ to model the 3D environment, Synertial mocap as the motion capture system and the HTC VIVE™ as the VR device. Moreover, in both the experiments, when it was necessary to do some calculations, we again used Microsoft's Excel software.

3.1.4. Simulation modelling

'Simulation modelling and analysis is the process of creating and experimenting with a computerised mathematical model of a physical system' (Chung, 2003). Simulation models may be either stochastic or deterministic (Harrison et al., 2007). Stochastic models feature probabilistic components, which means that the behaviour of a model in any given instance is influenced by chance. Monte Carlo techniques are commonly used in stochastic simulations. Deterministic models instead contain no probabilistic elements, providing the same outputs every time, so they only need to be run once for a specific model. According to Pedgen et al. (1995), the simulation of stochastic and deterministic models is performed for the following reasons: gaining insights into a system's operation, developing operating or resource policies to improve system performance, testing new concepts and/or systems before implementation and gaining information without disturbing the actual system. Furthermore, in general, simulation models consist of the following components: system entities, input variables, performance measures and functional relationships (Maria, 1997).

In the present study, simulation modelling was applied to answer the third research question (RQ3), where we were interested in understanding when a DT-based solution can be adopted to control the material management in an ALFS compared with a traditional Kanban or e-Kanban solution. Simulation modelling was chosen as the methodology because DT is still an emerging technology, especially in the case of materials management, and the physical development process of a DT-based solution requires an a sizeable investment (Gabor et al., 2016; Singh et al., 2021). Therefore, first, a general problem, together with the assumptions and all the parameters of the problem, was defined. Then, to solve the problem, three models were developed: the DT-based model, the traditional Kanban model and the e-Kanban model.

Each model attempts to faithfully replicate what is usually carried out to control the materials management in an ALFS when that specific solution has been adopted. Finally, the three models were simulated to arrive at the end at the creation of the DSS. The DSS gives the opportunity to support managers and practitioners in understanding which of the three alternatives is the best material management solution to adopt in their ALFS.

Regardless of the simulation model, all simulations were carried out using the statistical software RStudio and functions of the library ‘simmer’ (Ucar et al., 2019). Moreover, if there was the necessity to perform some calculations that were not particularly complicated, we used Excel software.

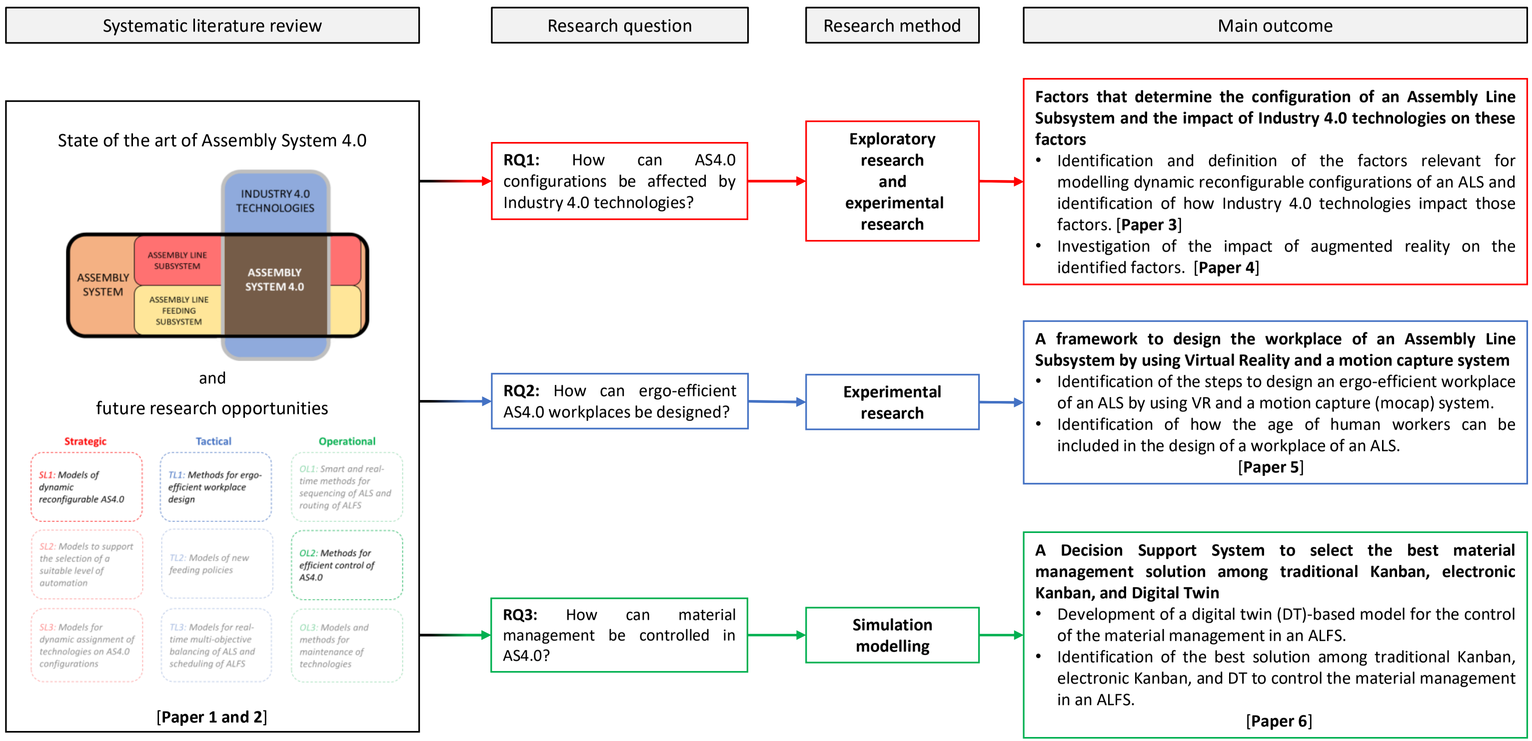

Figure 3. The research design of this research study

3.2. Research quality

In the present research study, qualitative and quantitative methods were applied. According to Karlsson (2016), Halldorsson and Aastrup (2003) and Voss et al. (2002), to determine whether qualitative and quantitative research can be judged to be of good quality, it must satisfy four requirements: construct validity, internal validity, external validity and reliability. Therefore, the following subsections explain how these four requirements were considered during the research process to produce good quality research that is reliable and ethical and can be used by other researchers and practitioners.

3.2.1. Construct validity

Construct validity assesses whether the right operational definitions for the ideas under consideration have been established (Voss et al., 2002). To appropriately account for construct validity, Yin (2017) suggested two essential aspects: (i) offer precise definitions of what is to be studied and (ii) demonstrate that the operational definitions do truly represent what is supposed to be examined.

In present study, the introduction section has provided a clear description of the scope. Definitions and explanations have been presented in both the research study and all appended papers. Furthermore, we attempted to maintain a clear chain of evidence, which, according to Yin (2013), indicates that readers should be able to trace the derivation of the results from the collected data. Therefore, to achieve this, as far as feasible, the reasons for each step, the information from each step and the decisions made at each step were documented and are reported in this study.

For the experimental research and simulation models, verification and validation techniques were used to ensure that the research reflected what was intended.

3.2.2. Internal validity

Internal validity entails revealing the right causal links while not ignoring the other factors that may explain these correlations (Karlsson, 2016). In other words, if it is determined that X occurred as a result of Y, ignoring the fact that X occurred also as a result of Z, the internal validity is poor. Internal validity is more appropriate as an evaluation criterion, particularly in exploratory and causal research, but not always in descriptive studies (Croom, 2009; Yin, 2017).

If the question of internal validity does not arise for the descriptive and exploratory research, one of the key techniques used to verify the internal validity of the experimental research is theoretical replication. In fact, in the experimental studies, which compared different application solutions in ASs, the expected results were formulated based on the literature before data collection. Following this, the empirical findings were then compared with this prediction.

For the simulation study, the system's behaviour and identification of causality were the main curiosities that drove the entire research. In this case, causality was established by adjusting each independent variable individually and then evaluating the causal effects on the dependent variables. Thus, simulation is suitable for investigating causal relationships (Croom, 2009; Bertrand and Fransoo, 2016).

3.2.3. External validity

External validity considers whether the findings from the study's data and environment are generalisable to larger groups and contexts (Cook et al., 1979).

In particular, to assess whether a study has external validity, one should ask whether the results apply to production environments and companies whose circumstances differ from those of the studied cases. This question allows others to make judgements regarding whether the research findings are transferable to other situations. As a result, to give the reader this opportunity, the goal of the present research study is to offer detailed information on all of the situations and cases studied.

Although the generalisability of a research study is not always easy to determine because each case has its own particularities (Yin, 2013), researchers should be adept at removing these peculiarities and creating a general case that can refer to as many situations as possible. After the general case, they can then focus on their specific case.

3.2.4. Reliability

The extent to which research may be duplicated and provide the same results is referred to as its reliability (Voss et al., 2002). The goal is to reduce bias so that another researcher may replicate the study and acquire the same results and conclusions.

Various strategies have been used to ensure reliability. First, presenting the research design and outlining the methodology utilised in the current research study, as well as each attached publication, makes it easier for researchers to repeat all the studies.

Furthermore, the fact of having several researchers participating in the study process and examining the data will eliminate any bias from a single researcher.

4. Design and management of Assembly Systems 4.0

This section presents and discusses the results and findings.

Following the research design (Figure 3), we began the study by performing an SLR. With the SLR, we obtained two main outcomes: the state of the art of AS4.0 (divided in two parts) and proposal of possible future research opportunities in AS4.0. Moreover, from three of the nine proposed future research opportunities derived the three research questions (**RQ1**, **RQ2**, and **RQ3**) we could obtain the rest of the main outcomes. The results are presented in Subsection 4.1 and are based on Papers 1 and 2.

To answer **RQ1** (How can AS4.0 configurations be affected by Industry 4.0 technologies?), we performed exploratory research and experimental research. Because of the exploratory research, we derived two main outcomes, including the factors relevant to determining the configuration of an ALS and impact of I4.0 technologies on these factors. Because of the experimental research instead investigating the impact of AR on the identified factors, we derived the last main outcome related to RQ1. The results and findings are presented in Subsection 4.2 and are based on Papers 3 and 4**.**

Furthermore, to answer **RQ2** (How can ergo-efficient AS4.0 workplaces be designed?), we performed experimental research. Because of the experimental research, we could verify the validity of the five-step methodological framework identified to design ergo-efficient workplaces of an ALS using VR and a motion capture system and to identify how the age of human workers can be included in the design of a workplace of an ALS representing the first and second main outcomes related to RQ2. The results and findings are presented in Subsection 4.3 and are based on Paper 5.

Finally, to answer **RQ3** (How can material management be controlled in AS4.0?), we performed simulation modelling. Because of the simulation modelling, we had first to develop a DT-based model to control the material management in ALFS that represents the first main outcome related to RQ3, and then, we developed a DSS to identify what is the best solution to control the material management in an ALFS between traditional Kanban, electronic Kanban and DT that represents the second main outcome related to RQ3. The results and findings are presented in Subsection 4.4 and are based on Paper 6.

4.1. State of the art of Assembly Systems 4.0 and future research opportunities

In the theoretical background section (Section 2), after presenting all the I4.0 technologies that can be adopted by companies (IoT technologies, CPSs, data analysis, cloud computing, collaborative robots (cobots), AR, VR, mobile robots, cybersecurity, blockchain and AM), we pointed out the ones that are more suitable for creating AS4.0 according to the authors who first introduced the topic of AS4.0 (Bortolini et al., 2017; Cohen et al., 2019a; Cohen et al., 2019b). However, these researchers have mainly focused on the introduction of such technologies or on part of them, their proof-of-concept development, analysis of their characteristics and their performance rather than studying how the I4.0 technologies are implemented in the different activities (assembly, control, transportation, preparation, material management) performed in an AS, studying the decisions at the strategic, tactical and operational levels that companies must make when implementing I4.0 technologies in their ASs. Therefore, an SLR was conducted to fill this gap, from which two main outcomes were derived. The first main outcome of the SLR refers to the state of the art of AS4.0 and is composed of two parts the I4.0 technologies in AS activities and the decisions that need to be made in AS4.0 at the strategic, tactical and operational levels. The second main outcome of the SLR instead refers to the future research opportunities that can open many research streams related to the design and management of AS4.0.

I4.0 technologies in AS activities. The first part of the first main outcome derived from the SLR is presented in Table 2. The table illustrates the I4.0 technologies based on the different AS activities in which they have been implemented. From this result, one I4.0 technology, the AM, was found to be a possible disruptive technology in ASs and is currently not applied in any of the ASs activities. Indeed, based on our SLR, the technologies of the AS4.0 are collaborative robot, mobile robots, AR, VR, IoT technologies and cloud computing and data analysis. For the ALS, the technologies are divided into the two activities of assembly and control, while for the ALFS, they are divided into the three activities of transportation, preparation and material management. It should be noted that the family of IoT technologies include sensors, CPSs, DTs, motion capture system and wearables. Table 2. I4.0 technologies for an AS, here based on ALS and ALFS activities.

Table 2. I4.0 technologies for an AS, here based on ALS and ALFS activities

	ALS		ALFS		
Technology	Assembly	Control	Transportation	Preparation	Material management
Collaborative robots	X			X	
Mobile robots			X	X	X
Augmented Reality	X	X		X	
Virtual Reality	X	X			
IoT technologies	X	X	X	X	X
Cloud computing and Data Analysis	X	X	X	X	X

Table 2 shows that there are two sets of technologies (IoT/cloud computing and data analysis) that are employed in all AS4.0 activities. Because of the nature of I4.0, this result is to be expected. In fact, IoT technologies let businesses collect all accessible data from AS4.0. These data must then be stored and shared, and cloud computing is quite useful in this aspect. Cloud computing can provide both the resources required to save and transform these data into information using data analysis techniques and then deliver them to the users who require them.

The technologies VR and mobile robots are only used in the activities of the ALS and ALFS, respectively. Although this finding was expected for the usage of mobile robots, it was not for VR. In fact, even though VR may be utilised in simulations, such as the study of human employees operating in the same environment as mobile robots, we could not locate any work addressing its usage in an ALFS.

The last information possible to obtain from the table is about AR and cobots. These technologies are used in both ALSs and ALFS. In particular, cobots are employed in ALF preparation activities, where they are used to do picking and kitting, while AR is used to instruct and coach human assembly workers and monitor assembly quality.

The decisions of an AS4.0 at the strategic, tactical and operational levels. Once we understood in which activities the technologies are applied in AS4.0, the study moved to the second part of the first main outcome derived from the SLR, which consists of understanding what decisions companies need to make when they decide to implement one or more of the I4.0 technologies to their AS. These decisions are divided based on the different levels (strategic, tactical and operational) at which they need to be made and on the subsystem of an AS in which they are applied (ALS, Table 3, and ALFS, Table 4). Moreover, the decisions for an AS4.0 are also related to the decisions areas of a traditional AS (see Table 1 above).

Table 3. Decision areas divided into different levels for each I4.0 technology in an ALS

Term	Decision areas		Industry 4.0 Technologies in Assembly Line Subsystem (ALS)				
			Collaborative robots	Augmented Reality	Virtual Reality	IoT technologies	Cloud computing and Data Analysis
Long term	Strategic	*Configuration of the system*	• Type of cobot	• Decision of which AR instructions create	• Decision of which VR instructions create	• Type of IoT technologies	• Data to storage and analysis
		Level of automation	• Type of cobot • Skills to use the cobot	• Type of AR devices • Skills to use the AR devices	• Type of VR devices • Skills to use the VR devices	• Type of IoT technologies • Skills to use the IoT technologies	• Type of Cloud Computing system and/or Data Analytics techniques • Skills to use these technologies
Medium term	Tactical	*Workplace design*	• Workplace design	• How to create and share the instructions	• Workplace design	• Workplace design	• Information to create and share • How to create the information
		Assembly line balancing	• Balancing of the assembly line with the cobots	• Number of AR devices	• Number of VR devices	• Number of IoT tecnologies	• Number of information to create
Short term	Operational	*Sequencing*	• Sequencing of the operations	• Real-time information sharing → assembly instructions	• Real-time information sharing → assembly environment and instructions	• Real-time control of the quality of the assembled products, machines, workers, and environment	• Real-time sharing and displaying of the information
		Control of the ALS	• Control of the system	• Control of the system	• Control of the system	• Control of the system	• Control of the system

Table 4. Decision areas divided into different levels for each I4.0 technology in the ALFS

			Industry 4.0 Technologies in Assembly Line Feeding Subsystem (ALFS)			
	Decision areas		**Mobile robots**	**Augmented Reality**	**IoT technologies**	**Cloud computing and Data Analysis**
Long term	**Strategic**	*Configuration of the system*	• Warehouse design • Type of mobile robots • Design the guide path	• Decision of which AR instructions create • Type of AR devices	• Type of containers	• Data to storage and analysis
		Level of automation	• Type of mobile robots • Skills to use the mobile robots	• Type of AR devices • Skills to use the AR devices	• Type of IoT technologies • Skills to use the IoT technologies	• Type of Cloud Computing system and/or Data Analytics techniques • Skills to use these technologies
Medium term	**Tactical**	*Feeding policy selection*	• Feeding policies	• How to create and share the instructions	• Positioning of the IoT technologies	• Information to create and share • How to create the information
		Scheduling	• Scheduling of the mobile robots • Number of mobile robots	• Number of AR devices	• Number of containers in the warehouses and in the ALS	• How to share the information
	Operational	*Routing and material/information management*	• Routes of the mobile robots	• Real-time information sharing → sequencing of kitting and picking information	• Real-time control of the capacity of the container	• Real-time sharing and displaying of the information
Short term		*Control of the ALFS*	• Control of the system	• Control of the system	• Control of the system	• Control of the system

The decisions can be summarised as:

Strategic. When we talk about the configuration of the system in an AS4.0, we are referring to what is necessary to know before deciding which technology would be best to implement in the AS. For example, the integration of a cobot into an AS can change the spaces that are necessary to allow the robot to work alongside humans; if a company wants to create instructions to train their human workers in a virtual environment without the need for a real one, the firm may prefer to use VR. In contrast, if the company wants to guide their human workers during the execution of their tasks within the environment where they work, AR may be the best solution (Song et al., 2016; Elhoseny et al., 2018; Yao et al., 2018; Mateus et al., 2019; Stadnicka and Antonelli, 2019; Danielsson et al., 2020; Miller et al., 2020). Moreover, the decisions made regarding the types of containers and the types of warehouses in which these will be used may influence the kind of sensors that can be applied to them and the transportation devices that can transport them. In view of all the data that can be collected, companies also now need to decide on the level of automation of their AS (Kolbeinsson et al. 2019; Fragapane et al., 2020; Peron et al., 2020). This is because the different forms of data that can be collected require different sensors and techniques to analyse them. Moreover, regarding the type of information generated by the data analysis, the selection of the device that will work the best is critical. This information can be as simple as just numbers or text, but it can also be more complex, such as pictures or videos. This choice depends not only on the type of information to deliver, but also on who will receive it and which tasks must be performed. For example, in the case of large products, wearable devices will be more preferable than fixed ones more useful in the case of small products assembled in standard workstations. Furthermore, the main purpose of using such technology will also affect its implementation and, hence, the level of automation of the ASs. The selected technology will influence the skills that will be required to use it. The company then needs to know whether it already has someone with these skills or whether it will have to hire or train someone. In the case where the company can rely on internal resources with these skills, technology selection will be facilitated, as well as its implementation. This will also increase the general technological knowledge of the whole company in the case where these resources share their expertise. Furthermore, even if a company is not planning to implement any new technology in its AS4.0, a strategic decision may be to hire skilled human workers, with previous experience in I4.0 projects (Dolgui et al., 2022). These workers are valuable resources that could assist and guide the company toward the possible implementation of I4.0 technologies.

Tactical. When the technologies have been chosen, the company needs to design the workplace in which they will be used and determine how they will be used (Havard et al., 2019; Faccio et al., 2020). Some forms of technology, for example, VR and motion capture systems, can help in designing the workplaces where other technologies will be used. Indeed, VR provides the possibility of creating virtual environments, where human workers toward motion capture systems can interact with the virtual elements and where the technologies, such as cobots and mobile robots, can be modelled. This facilitates the study of different workplace designs. As a result of the virtual environment, different alternatives between the human workers and technologies can be studied before their implementation in real workplaces. This helps create optimal workplaces where technologies and human workers can interact with optimal results (Choobineh et al., 2012; Yoshitake et al., 2019; Gharehgozli and Zaerpour, 2020). The feeding policies determined by the company can also influence the design of the workplace because the transportation of a container, like a pallet, may require a different space when it is delivered to the workplace when compared with the transportation of a shelf. A time analysis and decision aid may be necessary to identify the numbers of cobots, workers, AR devices or mobile robots required to execute the different tasks in the AS. In conjunction with this time analysis, it may be necessary to evaluate the ergonomic impact of the technologies while they are being used as a way to understand where and when it is best to use them. The time analysis and ergonomic impact can be evaluated because of the sensors applied in the technologies and by the human workers, such as IoT sensors or wearable devices. Another possibility is the combination of cameras that monitor the movements of the technologies and human workers as a result of computer vision algorithms. At this level, a company is aware of which data it must collect and now needs to know where to install the sensors to collect these data. The sensors need to be installed in protected and proper places to reliably and safely collect the required data. Therefore, the significant amount of data that companies can collect from the sensors need to be analysed and validated (Papakostas et al., 2016; Plantar et al., 2017; Wu et al., 2018). This should be done because next step is to decide what information the company is interested in creating from the collected data and how this information will be created. The final decision also relates to the issue of the final recipient of such information (Papakostas et al., 2016; Plantar et al., 2017; Wu et al., 2018). It is important to create specific information for each user to avoid possible misunderstandings, which can result in the execution of incorrect activities or decisions.

Operational. At this level, the technologies have been implemented and are working. The employees now need to know how to do their jobs, and the company needs to control them to ensure that they are doing them to the best of their ability (Faccio et al., 2019; Alavian et al., 2020; Baumann et al., 2020). The daily activities that are assigned to cobots need to be sequenced based on the products that they are required to produce, and the routes of the mobile robots must be generated according to the paths that they need to take. The AR and VR equipment must also receive the information necessary for the human workers to carry out their activities. This information needs to be sequenced based on what activities the human workers will carry out when they are using the technology, and it needs to be easily comprehensible and personalised. Indeed, there can be a negative impact in the case of incorrect information, but also if the information is not understandable or clearly visible to the user (Tarallo et al., 2018; Oyekan et al., 2019; Chen et al., 2020a; Chen et al., 2020b; Negri et al., 2020). Therefore, a good control loop of accuracy and usability is important for continuously improving their utilisation. Moreover, the correct information at the appropriate time and place not only needs to be sent to the AR and VR devices, but also to all the actors in the AS4.0 that require it. This needs to be carried out efficiently while avoiding a possible loss of information during the communication process. Cloud computing can provide a way of sharing all this information, without the need for physical connections, across all of the devices in the AS that have the capacity to give them in output (Liu et al., 2017; Nuzzi et al., 2020). All of this information can be generated using data analysis techniques and algorithms, and these need to be checked periodically to ensure that the parameters that they are using are still valid; alternatively, they may need to be updated, for example, because of variations in customer demand. These techniques and algorithms also need to be updated if new techniques or algorithms that are more efficient are developed or if they fail to work properly. It is not only the software aspects of the technologies that need to be checked: the hardware parts of technologies, such as mobile robots, cobots, AR and VR devices, also need to be periodically maintained and updated to avoid problems during the execution of their tasks (Zhuang et al., 2018; Nikolakis et al., 2019a; Nikolakis et al., 2019b; Malik and Brem, 2020). For example, the malfunctioning of the batteries that power the mobile robots affects their performance in terms of speed and autonomy, thereby having a negative impact on the performance of the AS4.0. Checking the hardware can help to avoid not only losses in the performance of the AS4.0, but also in its security. Therefore, it is clear that appropriate maintenance measures are important for strictly controlling the reliability and availability of the hardware of the technologies.

Future research opportunities. Table 3 and Table 4 provide the results leading to the second main outcome of the SLR study and can hopefully inspire future researchers in the field of AS4.0 to address new research challenges that go beyond the study of the mere use of these technologies. As seen from Figure 4, for each of the levels of strategic, tactical and operational, three future research opportunities have been identified. These nine future research opportunities are now described.

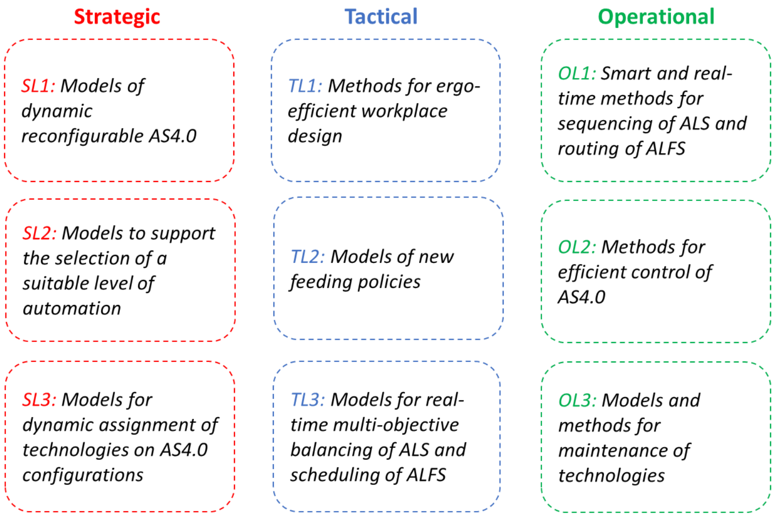

Figure 4. Future research opportunities for Assembly System 4.0

4.1.1. Future research opportunities at the strategic level

Research opportunities SL1: Models of dynamic reconfigurable AS4.0

From the SLR, we observed that mobile robots and cobots were the two most researched technologies. One aspect in our analysis that was not deeply investigated was related to the high level of reconfigurability that can arise because of these two technologies, especially from the use of mobile robots. In a reconfigurable system all the equipment, human workers or material handling systems should be rapidly added, removed, modified or interchange in response to changing needs and opportunities. Because of their flexibility, mobile robots can facilitate companies in creating AS4.0 configurations (primarily networks rather than line configurations) that change dynamically based on the current demand. In fact, using mobile robots as a workplace in which human workers perform the assembly tasks can give the opportunity to increase or decrease the number of workplaces that are needed based on the demand, and the same mobile robots can also be used to transport all the components that the human workers need for each task (Battaïa et al., 2018). Moreover, a mobile robot can be equipped with a cobot to create a collaborative mobile robot that can pick and transport components and then execute assembly tasks based on the same components. Although these approaches can be easily adopted to create different AS4.0 configurations, it is essential to understand what is the best configuration in terms of performance and cost, here based on the situation under study. However, to do so, first, it is necessary to know what are the factors impacting the decision of the configuration of an AS to choose and how I4.0 technologies impact these factors. Once this is understood, future studies should focus on mathematical and simulation modelling of the different configurations created by the different I4.0 technologies. These models will allow researchers to improve the knowledge related to the factors that can affect the reconfigurability of the system. Sensitivity analyses will also be useful in studying how these parameters can change the reconfigurability and performance of the different configurations. In the end, decision support systems, like decision trees and evolutionary algorithms, can be created to support decision makers in determining what is the best configuration to adopt based on their needs.

Research opportunities SL2: Models to support the selection of a suitable level of automation

I4.0 technologies can be used to execute a task or collect and share data, for example, to assist operators or support managers. Hence, the choice of a piece of technology is not only related to the help that it can give in terms of the physical and cognitive aspects of the execution of a task, but also to the data that can be collected and shared with it. A huge amount of data can be collected and sent to the AS4.0, and new models are needed to support decision makers regarding how to automatise the AS4.0. These models can provide a methodological toolbox that can guarantee a structured implementation of the technologies to ensure a suitable level of automation for AS4.0. For example, the decisions that need to be made on the most suitable amount of information to give to the operator through AR or assistive technologies (which relates to the level of collaboration between operators and collaborative robots) or on the configuration of the systems can be made by managers based on the available data. To create these models, further research is required to deepen our knowledge of the case where multiple technologies work together to complete different tasks. Simulations and experiments are needed to validate these models. The results from these methods, together with the possibility to do sensitive analysis, give the opportunity to evaluate different cases with advanced data analytics tools that can create decisional support systems. Companies can benefit from these results because they will help them simplify the decision process of the level of automation to adopt in their AS4.0.

Research opportunities SL3: Models for dynamic assignment of technologies on AS4.0 configurations

We have seen that, at this level, companies have to choose the configuration and level of automation of their AS4.0. Here, this can mean that the choice of a configuration compromises the possibility of using a specific technology and instead that the technology is most appropriate for another kind of configuration. Moreover, the performance of the AS4.0 is correlated to the combination of configurations and technologies, with synergic effects arising in some cases. Therefore, at this level, to determine the goals of the AS4.0 that the companies want, it is necessary to have a guide that supports decision makers in the correct assignment of the different technologies to the configurations under analysis. The decision of the assignment of the technologies on the different configurations will facilitate other decisions, such as, for example, the number of devices to buy and skills that are necessary in the different configurations. To understand if a technology is good or not for a specific configuration, future research should consider its behaviour and performance in different configurations. Case studies, experiments and simulations represent opportunities to collect the necessary data to create new decisional support systems that can guide companies in better deciding which configurations to implement for the different technologies. It will also be important to study the behaviour and performance of more technologies together and the interactions between the technologies and human workers to see if their implementation together generates issues in the configuration or not.

4.1.2. Future research opportunity at the tactical level

Research opportunities TL1: Methods for ergo-efficient workplace design

When a human worker is involved in the execution of activities in the AS4.0, they should be able to do these without worrying about the workplace in which these activities take place. To enable this, the workplace needs to be optimised, and VR can be used to help create virtual environments that replicate the real AS, hence allowing a user to design and study a range of configurations of workplaces without needing a physical model. These virtual solutions need to be further investigated, and new parameters, such as the ages of the human workers or integration of additional technologies into virtual environments, should be evaluated. Different human characteristics may require different workplace design solutions to facilitate high levels of ergonomic comfort for manual processes and to increase efficiency. The data collected from human workers while they are executing their activities can be used to adapt the workplace based on the tasks that need to be executed within the workplace and characteristics of the human worker executing them. Motion capture (mocap) systems can be used to collect these data. A mocap system gives the opportunity to create a virtual copy of the object under study by utilising sensors or cameras to recreate its movements. Experiments are first needed to determine the relevant parameters for optimising a workstation, and case studies will then be required to verify whether these parameters are correct, hence designing a workplace that is not just optimal in terms of performance but is also efficient in terms of human well-being. In relation to the acceptance of technology, further studies could provide insights into the factors affecting success. Data analysis and artificial intelligence techniques can be useful during this step.

Research opportunities TL2: Models of new feeding policies

The use of mobile robots, with or without a cobot, can open up the possibility of creating new feeding policies because if these are used to move shelves, each level of the shelves can be designed to store different components in different ways. For example, a kit can be stored at one level and only one type of component can be stored at another level, so the shelf may be delivered to one or more workplaces. Instead, if mobile robots are used in conjunction with a cobot, these collaborative mobile robots can be used to pick the individual components from warehouses or supermarkets and transport them to the ALSs that need them. To study these new opportunities, advanced modelling and simulations and, then, real case studies will be needed to validate the results of the models. Moreover, AR can be used to support the human workers involved in feeding tasks by giving them instructions, such as which component to pick, where to put the components and how many components to pick. When AR is used together with mobile robots, the two technologies need to be integrated. This means that the AR instructions should not only able to change based on the demand for products. but also based on the characteristics of the mobile robots used to execute the feeding policies. In addition, these AR instructions need to change based on the components that the human workers have and must be visible and in the correct position for the particular type of mobile robot used. Further investigation and testing through experiments that replicate real scenarios can better highlight the strengths, weaknesses and potential advantages that the use of AR with mobile robots can generate in terms of developing new feeding policies.

Research opportunities TL3: Models for real-time multi-objective balancing of ALS and scheduling of ALFS

The balancing of the new ALS needs to take into account not only the assignment of the different tasks within the different workplaces, but also the technologies used in the ALS. However, there is yet to be research on how these technologies can affect line balancing. For example, the choice to adopt AR to support operators in executing the tasks is not yet well investigated, particularly regarding the impact on the balancing of the ALS. In any case, the use of AR is very interesting because it can help to reduce line balancing effort for the ALS by creating flexible, dynamic and self-balancing ALSs in which the number of workplaces may change based on the current demand from customers. Hence, if demand is low, a single operator may be able to do all the tasks in one workplace, here thanks to the use of AR, whereas if demand grows, the number of workplaces can increase and the AR instructions will need to be divided between the workstations. One avenue for future research would be to investigate the number of AR devices needed and the ways in which the instructions that they display to human workers needs to change. The various types of mobile robots, which may or may not have a cobot mounted on them, allow for new tasks to be carried out in the ALS and ALFS. For example, we saw that a mobile robot with a cobot can pick up a component from the warehouse, transport it to the ALFS and then execute a task based on this component in the ALS. The new dynamic network configurations that have become possible require new assembly line balancing methods that consider the evolutionary aspects of such configurations, with multiperiod and multiobjective models that can be applied in real time to adapt the workload of the workstations without affecting the work of the operators. In this case, economic, performance and ergonomic objectives should be considered together.

A mobile robot can be used solely as a workplace or transportation device. Different mobile robots can carry out different tasks, giving rise not only to new opportunities, but also to a more complex problem in relation to scheduling these mobile robots. A company needs to optimise the use of its mobile robots based on the tasks that they can do, so new scheduling models need to be created that can consider all the possible tasks that these mobile robots can carry out. These models first need to be studied through simulations and, then, with experiments or case studies to verify the results. A connection between the different actors in an AS4.0, here thanks to all the sensors and, hence, the collected data, can allow for synchronised assembly line balancing and scheduling to simultaneously optimise both the assembly and activities needed to deliver the components. Future investigations into methodologies for dynamic and synchronised assembly line balancing and scheduling of the AS4.0 are needed to allow companies to use their technologies in an optimal way.

4.1.3. Future research opportunity at the operational level

Research opportunities OL1: Smart and real-time methods for sequencing of ALS and routing of ALFS

ALSs need to know the sequence of products that they have to assemble on a daily basis, and mobile robots need to know the routes to follow so that they can arrive at their destinations. Algorithms developed in the future to solve these problems will need to take into consideration the new information generated by the AS4.0 in a predictive and prescriptive way, which will involve not only reacting to the changes required, but also anticipating them and adapting in a proactive way. For example, a new sequencing algorithm may consider the fatigue of human workers when deciding which products to assemble or which workers should execute the tasks to make them. If the human workers are tired, it may be possible to sequence products that are easy to assemble or to let the workers take a break to recover. Sequencing can be done at the same time as routing when the products to be assembled are determined with the goal of minimising the routes travelled by the mobile robots. Sequencing should also take into account the quantity of components stored in the warehouses and supermarkets, that is, to optimise inventory management by reducing stocked quantities by as much as possible. Sequencing and routing can be synchronised to allow the products in an ALS to be assembled using only the components closest to that ALS. To achieve this, the routing of the mobile robots must consider their positions in real time; only the mobile robots closest to the components will be used to transport them to the ALS. This synchronised sequencing and routing can reduce the travelling time of the mobile robots and can also increase the productivity of the ALS because the components are delivered more quickly.

Research opportunities OL2: Methods for efficient control of AS4.0

Today, for the first time, it has become possible to control the quality of products, assembly activity and all the activities of an AS4.0. This has been facilitated by the huge amounts of data that can be collected from an AS4.0 if its activities are monitored, including data from each step of the assembly tasks, from the products being assembled, from the mobile robots while they are working and so on. After collection, these data need to be understood and analysed so that companies can use them. Data analysis techniques can be applied to these data to give useful information as the output. New machine learning and artificial intelligence algorithms that transform data into information can be developed by studying the different activities of the AS4.0. Simulations will be useful in understanding the performance of the methods, and experiments with real scenarios should then be carried out. It is important that the right data are collected to ensure the success of these methods and to give valid results, and more research is needed to identify the factors that make a data analysis technique reliable. Surveys of practitioners can help in developing an understanding of the factors that can increase reliability. More reliable are the results of a data analysis technique and more precise can be the control of the AS4.0. At the same time higher can be the benefits that can be generate from these analyses. In the material management activity, for example, the adoption of data analysis techniques can open the opportunity to optimise the stock of materials in the warehouses and workplaces and, at the same time, help optimise the flows of these materials in the AS4.0 in a dynamic and real-time way, such as dynamic Kanban systems, dynamic replenishment and integrated replenishment policies. For a dynamic and synchronised stock and flow of the material, new objective functions can be defined to improve the performance of material management in an AS4.0. Benefitting from all these data and information, it is possible to model all, or parts of, the AS4.0 to create its DT. The DT of the AS4.0 gives the opportunity to control in real time what is happening in the AS4.0 and simulate what can happen in the future using predictive analysis models. Indeed, it allows us to see, for example, how mobile robots work in a single day and then simulate their performance for an entire week. This simulation can be useful for understanding whether the mobile robots will decrease their performance or not after a period of continuous work. Although DTs have significant potential, it is important to understand what it is relevant to monitor. Therefore, future studies can be orientated towards understanding which digital copies are the most important to create based on the characteristics of the AS4.0. Case studies, experiments and interviews with the practitioners can help create frameworks to follow when creating the digital copies while simultaneously verifying their reliability.

Research opportunities OL3: Models and methods for maintenance of technologies

As discussed in the previous section, both the software and hardware aspects of these technologies need to be controlled and updated. All of the sensors in the AS4.0, the mobile robots and the AR devices must operate without problems over their lifetimes. For example, the sensors must collect all of the appropriate data without missing any, and the mobile robots must run at a certain speed to execute their tasks. The development of new models and methods for the maintenance of these technologies, both predictive and proactive, should be a subject for future study. These models and methods can help avoid a loss of performance of the AS4.0 because of hardware problems with the technologies. It is important that these methods recognise when the performance of a particular technology is reduced, even if the problems are not evident, and when it must be replaced by a new model. Technology must also be replaced when it becomes obsolete. New data analysis techniques should be developed by creating predictive analytics models to predict when both of these situations are likely to occur. The information created by these techniques can then be sent to the technologies that are recognised as obsolete or that are not working properly to make them stop working. Once they stop, they can be evaluated to understand whether to fix or dispose of them.

4.1.4. The investigated future research opportunities

However, investigating all the identified future research opportunities would exceed the research time frame. Therefore, the results presented in the current research, as already depicted in Figure 3, and highlighted here in Figure 5, have been derived from only one future research opportunity per level: strategic (SL1), tactical (TL1) and operational (OL2). The selection of the three future research opportunities is not casual. In fact, as already written in the research motivation subsection (Subsection 1.3), it stemmed from the idea of investigating three of the decision areas related to the design and management of an AS and enhancing the Logistic 4.0 Lab in the Department of Mechanical and Industrial Engineering at NTNU using some of its I4.0 technologies.

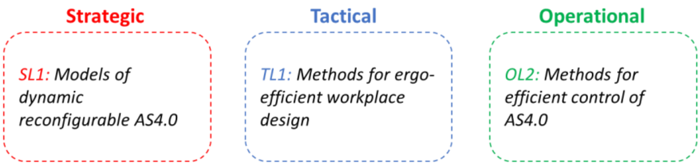

Figure 5. The future research opportunities investigated in this study

One research question for each of the three future research opportunities of Figure 5 has been identified. These are not to be considered as the only possible research questions that can fulfil the three future research opportunities selected in the current study but as three among all the possible research questions that can be generated to satisfy them. This is not to diminish the importance of the present work but rather to emphasise how many more research possibilities can be created through the current study.

The three research questions investigated in the rest of the section, which are linked with the future research opportunities to which they refer (see Figure 3 and Figure 5) and with the reference subsection where they are answered, are as follows:

SL1 - RQ1:	How can AS4.0 configurations be affected by Industry 4.0 technologies?	→ Subsection 4.2
TL1 - RQ2:	How can ergo-efficient AS4.0 workplaces be designed?	→ Subsection 4.3
OL2 - RQ3:	How can material management be controlled in AS4.0?	→ Subsection 4.4

Each subsection (4.2, 4.3 and 4.4) contains the following:

- The reasons why the research questions were created, which are the research gaps that were intended to be filled based on the future research opportunities investigated (Figure 5)
- The main outcomes that help answer these questions

Although there is a connection between the subsections (4.2, 4.3 and 4.4), each subsection is developed to be understood without the need to read the previous one. In fact, each subsection is developed with the intention of allowing any reader to fully understand the research conducted, whether they are interested in knowing the answers at all the research questions (thus following all the 'branches' of the research design of Figure 3 after understanding the status of AS4.0) or if they want to know only the answer at one specific research question (thus following only one 'branch' of the research design of Figure 3 after understanding the status of AS4.0).

4.2. Factors affecting the configurations of Assembly Line Subsystems with Industry 4.0 technologies

This subsection aims to answer the first research question, **RQ1**, which has been derived from SL1, Models of dynamic reconfigurable AS4.0 configuration:

How can AS4.0 configurations be affected by Industry 4.0 technologies?

In recent years, companies have faced great changes in customers demands (Battaïa et al., 2018). In fact, customers are no longer passive clients who buy only the products that companies offer them; they are now more often active clients who ask for personalised, customised products that are closer to their needs and desires (Pollard et al., 2008; Kucukkoc and Zhang, 2017). If companies decide to accept these requests from their customers, they must be ready to manage the production of more complex product models (Otto and Li, 2020), and configuration of their ALSs should be dynamic reconfigurable (Battaïa et al., 2020). In fact, dynamic reconfigurable configuration of ALSs can be model with a certain level of flexibility, which can involve the reconfiguration of human workers, technologies and equipment, to be able to face the rapid change in market conditions (Hashemi-Petroodi et al., 2020a; Hashemi-Petroodi et al., 2020b; Yelles-Chaouche et al., 2020). Companies such as Sew Eurodrive, Porshe an Audi are already trying to model dynamic reconfigurable configurations of their ALSs, and to do this, one of the first decisions to be made concerns the configuration of the ALS to be adopted (Ilika, 2017; Porsche, 2019; Sew Eurodrive, 2022). However, this strategic decision is not easy to make, so it is important for companies to know which factors characterise the different configurations as these are also responsible for determining how dynamic reconfigurable a configuration can be. Although in the literature it is possible to find some qualitative guidelines about when to model one ALS configuration with respect to another (Battini et al., 2011) and a work that gives an idea of factors that can be considered is the one of Aase et al. 2004, the factors that need to be taken into consideration to model dynamic reconfigurable configuration of ALSs have still not been well identified and defined. Therefore, through exploratory research, we first identified and defined the factors that need to be taken into consideration when one wants to model dynamic reconfigurable configurations of ALSs and identify how Industry 4.0 technologies impact these factors.

The factors that are relevant for modelling dynamic reconfigurable configurations of an ALS. Thanks to the exploratory research of the literature, in which we were interested in detecting how companies can model dynamic reconfigurable configurations of their ALSs, we derived the first main outcome of this subsection, which is related to the identification and definition of the relevant factors that companies need to know when they have to model the configuration of their ALSs. The knowledge of these factors is of considerable importance when companies want to model dynamic reconfigurable configurations since based on their values it is possible to know if is possible or not to model dynamic reconfigurable configurations of ALSs. The factors are the following:

1. ***Cycle time:*** indicates the time elapsed between completions of two consequent units (Battini et al., 2011).
2. ***Number of tasks:*** the number of different activities that each operator must do in each workstation; it is a measure used to indicate the problem size for combinatorial problems such as the assembly line balancing (ALB) problems (Mastor, 1970).
3. ***Network density:*** calculating network density entails dividing the number of actual precedence relationships by the theoretical maximum number of relationships that could exist for a problem of that size. Extreme network density values of 0.0 and 1.0 correspond to flexible and rigid assembly sequences, respectively (Aase et al., 2004). For a more complete description of network density factors, see Johnson (1981).
4. ***Products variety:*** is the number of different products assembled in an assembly line. The performance of the assembly lines may be different depending on the number of different products variety to be assembled (Hu et al., 2011; MacDuffie et al., 1996). The higher this number is, the more likely it is that more experienced operators will be requested to assemble them (Johansson et al., 2016).
5. ***Volumes variety:*** is the difference between the quantity to produce a product one day and quantity to produce the same product the following day (Li and Gao, 2014).

For example, one day of product A can produce 100 pieces and the next day only 50. This can mean that a different number of operators are requested to assemble the same product in the two different days based on the different quantities that need to be assembled each day (Şahin and Kellegöz, 2017).

6. Quality: is the quality of the final assemble products that come out from the assembly line. To represent the quality in an assembly line, it is possible to count the number of products that come out from the line with or without defects (Monden, 1993). The more products that come out with defects, the worse the performance of the line will be.

7. Complexity of tasks: is the complexity of each task of the assembly process. This is the experience that each operator has in the assembly process. It is possible that an operator with more experience can complete a task in less time than an operator with less experience or that they can complete more tasks than another operator with less experience (Mossa et al., 2016). The operator's experience can be represented in a quantitative way, for example, by the number of years that an operator is working, time working in the same company or the number of hours that they have worked doing the same activities (Lin et al., 2007).

The impact of I4.0 technologies on the factors. Because the impact of I4.0 technologies on the aforementioned factors is unknown and this impact on the factors could facilitate modelling of dynamic reconfigurable configurations, modelling an ALS configuration may become even more complex when I4.0 technologies are implemented into ALSs (Shtub and Dar-El, 1989; Boysen et al., 2008; Cohen et al., 2017). However, now that the factors that companies need to be aware of to model dynamic reconfigurable configurations of their ALSs are known, it is possible to investigate how the I4.0 technologies impact them. From the SLR, it was found that the I4.0 technologies used in ALS are collaborative robots, AR, VR, IoT technologies and cloud computing and data analysis. However, when it is time to model the configuration of the ALS, VR does not have an impact. In fact, the exploratory research we conducted has led to a result for each I4.0 technology as to whether they decrease or increase the value of the different factors, but no result was found for VR (Table 5). Table 5 represents the second main outcome of this subsection, which is also the response to **RQ1**.

Table 5. The impact of Industry 4.0 on the factors

	Industry 4.0 technology			
Factor	***Collaborative robot***	***Augmented Reality***	***IoT technologies***	***Cloud computing and Data analysis***
Cycle time	Decreases	Decreases/ Increases	Decreases	Decreases
Number of tasks	/	/	/	/
Network density	/	/	/	/
Products variety	Increases	Increases	Increases	Increases
Volumes variety	Increases	/	Increases	Increases
Quality	Increases	Increases	Increases	Increases
Complexity of tasks	Decreases	Decreases	Decreases	Decreases

From the table, for example, it is possible to see that collaborative robots, improving the performance of the ALS (Bloss, 2016; Fast-Berglund et al., 2016), giving the opportunity to decrease the 'Cycle time' or the IoT technologies and cloud computing and data analysis can increase the 'Quality' of the final products analysing, here because of data analysis techniques, such as machine learning algorithms, the data collected from sensors that control the assembly process (Georgakopoulos et al., 2016; Schmitt et al., 2020). Moreover, it is possible to see that it has been identified that no technology has an impact '/' on the factors 'Number of tasks' and 'Network density'. This is because these two factors are more related with the design characteristics of the product that need to be assembled than to the assembly process to assemble it. Although these abovementioned results are interesting, one finding that stands out from Table 5 is the 'Decreases/Increases' related to the factor 'Cycle time' for the technology 'AR'. This finding indicates that the true impact of this technology on 'Cycle time' is not yet well understood. In fact, current studies using AR to assist human workers in performing assembly activities have yielded conflicting results. This might be connected to the human workers' experience with the technology or on how the AR instructions are developed and delivered to the human workers.

Based on the results presented in Table 5, it is possible to derive how the modelling of the configuration of an AS can change if a company decides to implement one or more of the I4.0 technologies. In fact, it is possible that a decrease or increase in one or more of the considered factors may give companies the opportunity to model a configuration that they would not have been able to model if they had not implemented I4.0 technologies. In particular, we focused on two of the most adopted configurations: the SL and US line (Bagher et al., 2011; Rabbani et al., 2012; Mukund and Ponnambalam, 2016). A SL configuration is represented by a sequence of workplaces in a line, as shown in Figure 6a. Simply rearranging the SL into a U-shaped line, it is possible to obtain the US line, as shown in Figure 6b. Usually, in SL, operators perform their tasks staying in one designated workplace, thus being FW configurations. In US, instead, operators can move across the workplaces to assemble the finished products and, thus, are WW configurations (Calzavara et al., 2021). Therefore, the results shown in Figure 7 that are related to SL and US can be generalised for FW configurations and WW configurations, respectively.

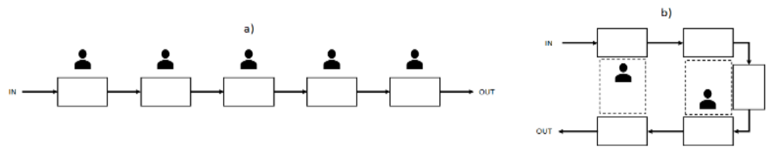

Figure 6. Straight-line configuration (a) and U-shaped line configuration (b)

Because technologies create the same impact for the various factors, in Figure 7, instead of making a table for each technology, we have considered only the two cases where companies have to model the AS configuration, between SL and US, without technologies and with technologies. In this last case, if more than one piece of technology is adopted, the positive or negative impact of each technology is considered to arrive at the final decision of the configuration chosen. In addition, we can see that the choice of configuration to be adopted is also based on the number of workplaces that will form the configurations and number of operators who will work in them.

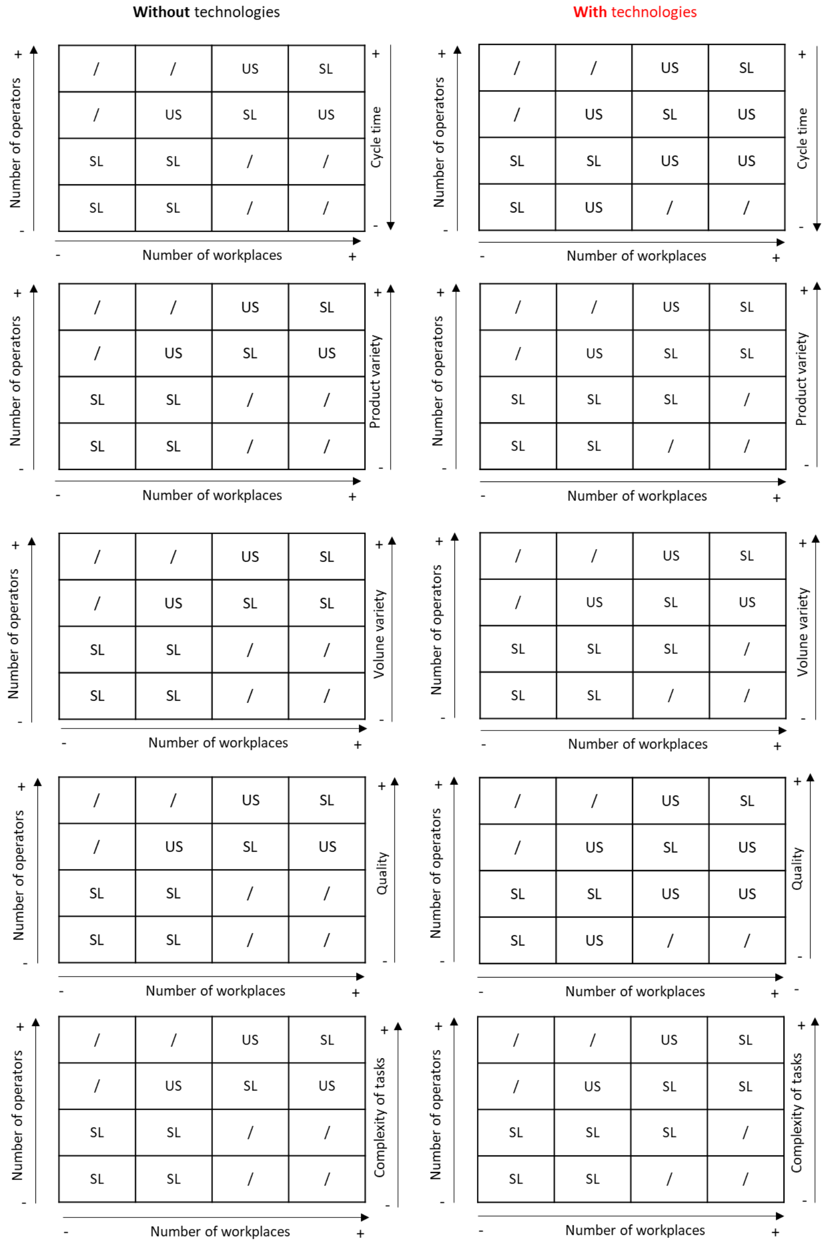

Figure 7. How the choice of the AS configuration changes based on the impact of I4.0 technologies

However, it is worth mentioning that, at the moment, these results are based only on theory and need to be validated through quantitative analyses. In fact, all the threshold values that determine the transition from one configuration to another—in both cases without and with technologies—are not yet known. Therefore, more quantitative studies are needed that can also investigate this; once the threshold values of the factors are known, the ability of I4.0 technologies in creating dynamic reconfigurable ALS configurations will be improved.

The impact of AR on the identified factors. One of the I4.0 technologies that, in our opinion, seems to be very promising for creating dynamic ALS configurations is AR. In fact, this technology gives the opportunity for operators to assemble different products variety during the same day, even if they have never assembled them without making mistakes, or reducing mistakes, thus increasing the quality of the ALSs. However, as shown in Table 5, there is a result that seems to contradict our opinion: the one on factor cycle time. In fact, it is not clear if the adoption of AR can make companies choose an ALS configuration that would be chosen only if the cycle time is higher compared with another. Therefore, to conclude this subsection, following this result, experimental research with an example of a prototype of projected augmented reality (PAR) has been conducted, and the third main outcome of this subsection has been obtained. The PAR was used as assistance system to provide assembly instructions to human workers during assembly activities. The experimental research has been designed to have three different results: 'task completion time', 'quality', and 'mental workload'. With these results, we were able to study the impact of AR on the factors cycle time, products variety, quality and complexity of tasks. Based on Table 5, these are the factors for which AR have an impact.

The prototype of PAR, consisting of a Kinect camera, motion recognition software, work instruction programme and a projector, was developed and installed in the Logistics 4.0 Laboratory at the Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology. To calculate the 'test completion time', 'quality' and 'mental workload' to understand the impact of AR on the factors, a test population consisting of 15 participants carried out a series of assembly tests of two components (Front wing and Side pod, Figure 8) of a LEGO product when being assisted by the instructions provided by the PAR. The 'test completion time' was measured by using a stopwatch. The 'quality' of the assembly activities was measured by counting the number of assembly and picking errors made by the participants. Finally, the 'mental workload' was measured using a simplified NASA-TLX questionnaire.

Figure 8. The Front wing (on the left) and the Side pod (on the right)

For the ‘task completion time’ and ‘quality’, the results showed the following when using the PAR:

- On average, the Front wing was assembled in 34.92 seconds, with an SD = 7.14 seconds, and the ‘Side pod’ in 58.36 seconds, with an SD of 9.45 seconds.
- On average, only one error was made when assembling both the components, that is, the ‘Front wing’ and ‘Side pod’.

However, these results alone do not say much. Therefore, they have been compared with the results obtained from the other two assistance systems. Because in most manufacturing contexts paper-based manuals and workplace-mounted monitors assist human workers, the two factors ‘task completion time’ and ‘quality’ have been calculated also for the case in which paper-based and computer-assisted instructions were used to assemble the two components shown in Figure 8. The results obtained to assemble the two components using all three assistance systems are shown in Figure 9. As Figure 9 and the comments of the participants of the experiments show, it was possible to compare the three systems and contextualise the results of the PAR.

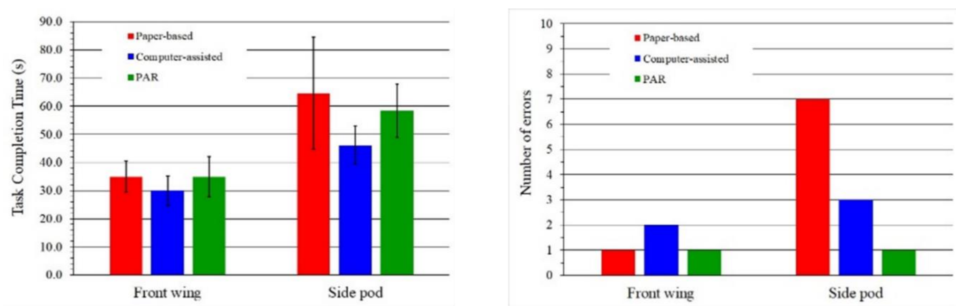

Figure 9. The ‘task completion time’ on the left and ‘quality’ on the right

Looking at the righthand side of Figure 9, the computer-assisted instructions achieved the best results in the ‘task completion time’ compared with the other alternatives (see Figure 9 left). In fact, the ‘Front wing’ was assembled in 29.98 seconds, with an SD = 5.35 seconds, and the ‘Side pod’ in 46.19 seconds, with an SD of 6.79 seconds. When compared with the paper-based manual instructions, the PAR achieved almost the same ‘task completion time’ for the Front wing and achieved a better ‘task completion time’ for the ‘Side pod’. Therefore, the PAR was not best option in terms of ‘time completion time’. This could lead to the conclusion that AR has a negative impact on the factor ‘cycle time’. In terms of ‘quality’, the results show that the PAR system was the best option to assist human workers compared with the other two assistance systems, reducing the possibility of errors during the assembly activity, especially for the more complex assembly task of the ‘Side pod’ (eight different parts to be assembled in eight work steps). In fact, regarding the ‘Front wing’, it was difficult for the participants to make errors, regardless of the assistance system, given the simplicity of the assembly activity (three different parts to be assembled in four work steps). This could lead to the conclusion that AR has a positive impact on the factors ‘quality’ and ‘complexity of tasks’.

After experience with the three different assistance systems (paper-based manual instructions, computer-assisted instructions, and the PAR), the 15 participants were asked what they thought of them. Therefore, all the participants completed a simplified NASA-TLX questionnaire. The questionnaire asked to the participants to give feedback on perceived enjoyment, frustration, perceived ease of use, effort and mental demand for each assistance system; the results are shown in Figure 10. The PAR system obtained the overall best results and scored especially high in perceived enjoinment (86.7%) and ease of use (86%)Figure 10.

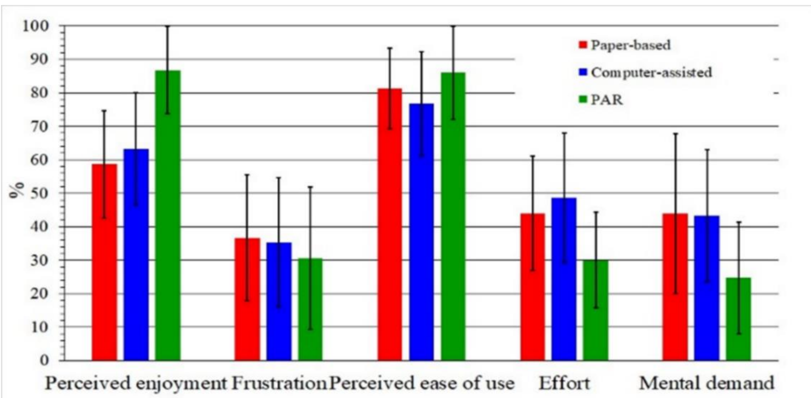

Figure 10. Results of the simplified NASA-TLX

The questionnaire helped us understand more about the impact of AR on the examined factors. The participants said that, although no one had previous experiences whit AR solutions, they did not experience any difficulties related to the use of the PAR while assembling the two components. In fact, the participants found that the PAR was the easiest assistive system to use compared with those proposed and could help in assembling products that someone may have never assembled. Therefore, we can exclude that the results concerning ‘task completion time’ were derived from the participants’ experience with the technology. However, the participants pointed out that how the PAR was developed and delivered were the main reasons because the results related to the ‘task completion times’ were worse than expected. In fact, in each work step, the participants were performing the following actions: pick the part, confirm the picking, assemble the part and confirm the assembly. Thus, there were two confirmation steps that were time-consuming and inevitably had a negative impact on the ‘task completion times’. Therefore, the drawback preventing the PAR developed in this experimental research from being the fastest solution and ensuring better performance for companies in terms of time was that each task must be validated after it has been completed because there was no system able to detect the execution of the assembly process step by step and comprehend when one work was completed and the next was supposed to begin.

Therefore, the results from the experimental research that represent the third main outcome of the subsection were found to be the following:

- For what concern the factor ‘cycle time’, the current study has confirmed the uncertainty found in Table 5 (‘Decreases/Increases’). The reason behind this result was mainly related to how the AR was developed and then delivered to the final users (readers can check Paper 4 for more information). Therefore, if a company wants to use AR in its ALS to reduce time spend on a procedure, it must create a solution that does not present time-consuming steps, such as the ones explained in the abovementioned solution, and that would be user friendly, meaning that even human workers who never experienced AR can use it without problems.
- For the factor ‘products variety’, the results have shown a positive effect found, as shown in Table 5 (‘Increases’). In fact, although the participants never assembled the two components assembled during the experiments, they said that, thanks to the PAR, they were able to do it without any problem. Therefore, if companies decide to use

AR as an assistive system in their ASs, they can also increase the variety of products assembled in their AS.

- Regarding the factor 'quality', there was a positive effect, as shown in Table 5 ('Increases'). In fact, the PAR was able to reduce the assembly and picking errors made by the participants, thus reducing the number of defective assembled products and increasing the 'quality' of the ALS. Moreover, from the experimental research, there was an increased benefit when constructing more complex components, increasing the benefit of using the AR when assembling them (see Figure 9 right).
- Regarding the factor 'complexity of tasks', there was a positive effect found, as shown in Table 5 ('Decreases'). This result is directly connected with the increase in quality of the final products. In fact, the participants felt that, thanks to the AR, the assembly process was easier than when they performed it with the other two assistive systems because, with the AR, everything they had to do was clearly marked and guided, minimising the possibility of making mistakes.

4.3. Framework to design the workplace of an assembly line subsystem by using virtual reality and motion capture system

This subsection aims to answer **RQ2**, which was derived from TL1, Methods for ergo-efficient workplace design:

How can ergo-efficient AS4.0 workplaces be designed?

At the tactical level, once companies have decided the configuration of their ALSs, it is time to design the workplaces in which the operators will perform the assembly tasks (Table 1). Designing a workplace is not an easy process, especially considering the time- and resource-consuming AS workplace design procedures that are conventionally used (e.g., physical mock-ups and computer-aided systems). However, with the advent of Industry 4.0, firms can facilitate this process (Burggräf et al., 2019). In fact, new solutions have started to emerge to accelerate the AS workplace design procedures that use I4.0 technologies. Specifically, the combined use of VR and mocap systems has been considered very promising technologies. VR allows for the creation of a three-dimensional world in which users can interact with three-dimensional objects in real time using their natural senses and skills (Riva, 2002). A mocap system allows for the creation of a digital copy of the operator in real time because of 'a virtual representation of the skeleton and its movements' (Bortolini et al., 2020), facilitating and improving the ergonomic assessments because AS workplace designers have access to the exact movement over time of the position and orientation of the operator's different limbs in a common reference system (Oyekan et al., 2017). The use of VR and a mocap system during the design phase of an AS can eliminate the main constraints of conventional AS workplace design procedures: namely subjective and time-consuming assembly time measurements and ergonomic assessments (Battini et al., 2011; Battini et al., 2014). The combined use of these two technologies enables fast and reliable assembly time measurements and ergonomic assessments. Although many researchers have indicated its potential (Peruzzini et al., 2017; Vosniakos et al., 2017; Michalos et al., 2018; Caputo et al., 2017; Battini et al., 2018), none have suggested a clear methodology to follow when designing AS workplaces using VR and mocap system. Therefore, we first identified the steps to design an ergo-efficient workplace of an ALS using a VR and mocap system; then, we verified its validity through experimental research at the Logistic 4.0 Lab at NTNU. Before and during the steps identification process, we were in contact with the developer of the software tools Siemens Jack™ to get feedback on how best to use their solution and understand the reasons why companies contact them. From the discussions we had, one of the reasons why companies were contacting them was because they were curious about how to design their ALSs using their software tool with VR and mocap system. Although the companies were asking questions about the software and technologies, in the end, most were not interested in buying anything because they did not know how to properly use the technologies. Therefore, it is from the discussions with the software developer that we were inspired to create the methodological framework to design an ergo-efficient workplace of an ALS using VR and a mocap system.

The steps to design ergo-efficient AS4.0 workplaces. The five-step methodological framework can guide the design process of ergo-efficient AS workplaces and represents the first main outcome of this subsection; this framework also answers **RQ2** and is illustrated in Figure 11.

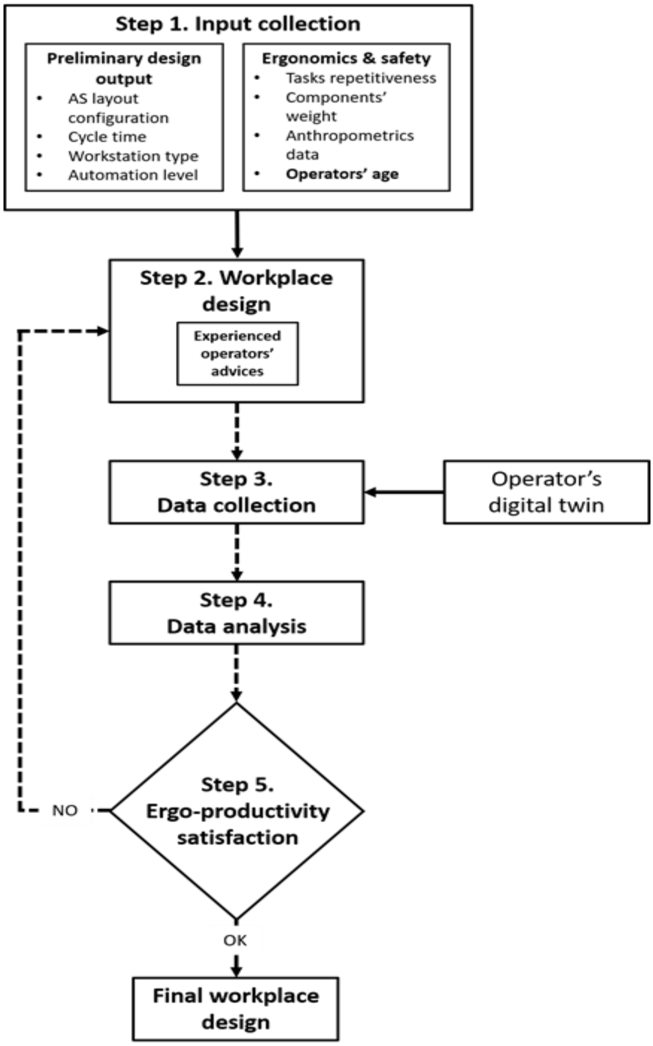

Figure 11. Methodological framework; the dashed arrows represent the steps that may change during the iterative process

Below, the core description of each step is reported. For a detailed description of the steps, the reader is referred to Paper 5.

Step 1 – Input collection

The first step is to gather the input parameters. As previously stated, the methodological framework developed herein is intended to be used in the detailed design phase, so the (i) AS layout configuration, (ii) cycle time (paced/un-paced), (iii) workstation type (i.e., open/closed, parallel/serial, two-sided, ...) and (iv) automation level (i.e., percentage of automation, type of equipment, ...) are all known. Furthermore, those product features that impact ergonomics and safety (e.g., component weights) are discovered during this design phase. Moreover, the operators who will operate on the AS workplace under construction are well known, as are their anthropometric data and age.

Step 2 – Workplace design

Once the inputs have been gathered, the AS workplace design can begin. Unlike the traditional AS workplace design approach, which requires physical mock-ups, the workplace is developed virtually, by utilising a 3D modelled environment. Many distinct options may be quickly produced and evaluated without the need to construct a physical mock-up for each one. As previously noted, this has significant time and cost savings benefits.

During this phase, it is fundamental that the AS workplace designers are assisted by experienced operators. Indeed, as is known from the literature, operators experience a gradual decline in both physical and cognitive abilities as they age (Shepard, 2000; Bouma, 2013; Bures and Simon, 2015), and experienced operators can provide useful advice to AS workplace designers regarding taking these aspects into account. Furthermore, throughout this phase, it is critical that AS workplace designers and experienced operators take a holistic approach, viewing productivity and operator well-being as two complementing components rather than as two distinct aspects. The AS workplace layout, in fact, influences both productivity and operator well-being throughout the assembly process.

It is worth mentioning that, although numerous software tools are available to create a 3D environment, only those that can communicate with the mocap system and VR (e.g., Siemens Jack™) may be utilised. The interface with the mocap system is vital because it allows for the exact replication of the operator's real-world movements in the 3D modelled environment.

Step 3 – Data collection

Data gathering can begin after the virtual workspace has been completed. In this step, an operator must be outfitted with a mocap system and VR. The operator will be immersed in the 3D-designed world and able to move and interact with it. In this approach, the operator can simulate the assembly process without the necessity for a real mock-up.

Step 3 involves creating a DT of the operator carrying out the virtual assembly process. In this way, it is ensured that the anthropometric data of the operator's DT corresponds to those from the operator who will perform the actual virtual assembly process. Moreover, in this step, it is recommended that the operator chosen to carry out the virtual assembly process is representative in terms of the anthropometric data of the operators who will work on the AS workplace under development.

Step 4 – Data analysis

Once the data have been obtained, they must be analysed with respect to productivity and ergonomics. Productivity can be measured by using time-related parameters (e.g., task execution times), whereas ergonomics can be measured by using ergonomic indices (RULA, REBA, NIOSH, OWAS, etc.). During the data analysis step, in order to optimise the outcomes, the AS workplace designers are required to divide the whole assembly process into the different assembly tasks that constitute it. Thus, each assembly task has to be associated with its own data (mocap-based recording and ergonomics-relevant data). As a result, each assembly activity must be coupled with its own data (mocap-based recording and ergonomics-relevant data). In this way, AS workplace designers may assess the productivity KPIs (Key performance indicators) and ergonomics index ratings for each assembly activity.

During the ergonomic assessments, it is crucial that the age of the operator is explicitly considered. In particular, it is advised to use a preventive approach, in which the age of the oldest operator who will work on the AS workplace under development is considered because the operator utilised for virtual assembly does not have to be the oldest operator who would work on the AS workspace under development; it might be a younger coworker. The reason for this is derived from the second outcome of this subsection, which will be explained later.

Step 5 – Ergo-productivity satisfaction

The productivity KPIs and ergonomic scores obtained from the previous step serve as an input in this step: ergo-productivity satisfaction. This is a decision step in which the AS workplace designers must determine whether the productivity KPIs and ergonomic scores are adequate (in terms of the company's requirements, legal restrictions and so on). If they are, this is the final AS workplace design; if not, the user must return to Step 2. It should be emphasised that, if the user must return to Step 2, until the operator performing the virtual assembly procedure changes, the operator's DT, which comes in at Step 3, is not need to be created (or updated) every time an iteration occurs.

To conclude with the first main outcome of this subsection, the results of a practical example of how to use the methodological framework have been reported. A simple but representative case study was carried out at the Logistic 4.0 Lab at NTNU. Specifically, we applied the methodological framework for redesigning an AS workplace where a medium size pump, which is shown Figure 12, comprising 25 components assembled through 17 tasks was produced (readers can refer to Paper 4 to see more about this case study).

Figure 12. Pump assembled in the case study

The case study was carried out by a second-year PhD student (27 years old) who designed, based on his experience, the initial workplace; from now on, we will refer to this workspace as the 'as-is configuration', which is where the pump was supposed to be assembled. Once the workplace was ready, the PhD student carried out the assembly process, during which the data necessary to measure the task execution times and REBA index were collected according to Step 3 and then analysed according to Step 4 of the methodological framework. Specifically, we considered the task execution times and REBA index as the productivity KPI and ergonomics index, respectively. Moreover, for the purpose of showing the importance of considering the age of the operators in the ergonomic assessments, we considered a fictitious case where the age of a second case study operator was 60 years old. This second case is called fictitious because, unlike the first operator, there was no real person who performed the assembly tasks at the workplace, but we considered only the age to calculate the REBA index. In fact, the ages of the operators (27 years and 60 years old) were explicitly considered in the ergonomics assessment by means of the age-based multipliers $f_{strength}$ and $f_{flexibility}$, which are going to be explained later as part of the second main outcome of this subsection. From the study of the 'as-is configuration', here considering both the ages (27 and 60), it has been possible to calculate the total task execution time and total average REBA score, as shown in Table 6. Moreover, because of the study of these two KPIs, for each task executed, it has been possible to identify the tasks that reduced the productivity (i.e., tasks with low value-added ratios) and operators' well-being (i.e., tasks with high ergonomic risks).

Table 6. Total task executed time and total average REBA score of the 'as-is configuration' of the AS workplace

	Task execution time (s)	Average REBA score	
		Age = 27	Age = 60
Total	758.6	4.12	4.97

After collecting this information, we then proceeded with the redesign of the AS workplace, here according to the methodological framework developed herein. The workplace has been redesigned based on the advice of an expert, a full professor; then, the same two KPIs were calculated by assembling the same product but this time in the redesigned workplace, as shown in Table 7.

Table 7. Total task executed time and total average REBA score of the 'redesign configuration' of the AS workplace

	Task execution time (s)	Average REBA score	
		Age = 27	Age = 60
Total	641.6	3.74	4.24

Therefore, comparing the results form Table 6 and Table 7, it is possible to see that, because of the use of VR together with a mocap system and following the framework we developed, the total task executed time (758.6 s vs. 641.6 s) and total average REBA score (4.12 vs. 3.74 for the 27-year-old operator and 4.97 vs. 4.24 for the 60-year-old operator) in the redesigned configuration were lower than in the as-is configuration. These results have confirmed the validity of the developed methodological framework in designing ergo-efficient AS workplaces using VR together with a motion capture system.

The inclusion of the age of human workers in the design of an ALS workplace. In Step 4 of the methodological framework, it is recommended that during the ergonomic assessment the age of the operator be explicitly considered. However, how to consider this is still overlooked in the literature, with only Wolf and Ramsauer (2018) proposing a solution. Therefore, what is presented next is a tentative method to fill this gap, here also representing the second main outcome of this subsection.

The age of the operator in the design process of ergo-efficient ALS workplaces can be considered in two different modes:

- The first mode is more dynamic and involves the most experienced 'senior' operators who work in the ALS. Experienced operators, because of the experience they gained over the years, can provide advice that can simplify and speed up the design procedure (Di Pasquale et al., 2020); during Step 2, they can suggest to the AS workplace designers whether (i) the operators need to be supported by new equipment (e.g., lifter, automatic screwdrivers, collaborative robots, etc.), (ii) where it is better to place the components and (iii) the environmental conditions (e.g., lighting) that need to be adapted or not based on their age.

  We can define this mode as dynamic because different experienced operators can give different suggestions on (i), (ii) and (iii), even if they have the same years of experience in the ALS. However, the fact that the suggestions are not all the same can be a positive. In fact, during the iterative design process, if a suggestion during Step 2 (workplace design) did not give a positive result, it can be changed to another during the next interaction.
- The second mode is more static and required 'only' two formulas. These two formulas are derived from the work of Wolf and Ramsauer (2018).

  The first formula, as reported in Equation (1), was developed by fitting data from the literature on variations in muscle strength with age to evaluate an age-based multiplier ($f_{strength}$):

  $$f_{strength}(\%) = 0.00058 \cdot age^3 - 0.08478 \cdot age^2 + 3.24439 \cdot age + 62.92006 \quad (1)$$

  The second formula, as reported in Equation (2), was developed by fitting the joints flexibility reduction data reported in Table 1 of Wolf and Ramsauer's work (2018); it evaluate the age-based multiplier for joints flexibility reduction ($f_{flexibility}$), which is needed when the ergonomic indexes contain assessments on joint flexibility (e.g., allowable joint angle limits in the REBA index):

$$f_{flexibility}(\%) = -0.00019 \cdot age^3 + 0.034286 \cdot age^2 - 2.538095 \cdot age + 145 \quad (2)$$

By considering these age-based multipliers in the ergonomic assessments in Step 4, it is ensured that the age of the operator is explicitly considered.

Because in the formulas age is represented only as a number, it does not matter if the operator who physically performed Step 3 (data collection) is the oldest operator working in the ALS. In fact, the decision of the age of who will perform Step 3 will depend on a trade-off between the workforce characteristics (in terms of technological skills) and the assembly process under consideration (i.e., whether the assembly process is affected timewise by the age of the operator). However, it is recommended that, in moment of the ergonomic assessment (Step 4), and, thus, the moment to use (1) and (2), the age of oldest operator that work in the ALS should be considered in the formulas. The reader is referred to Appendix A of Paper 5 to see an example of how the formulas here have been applied. We can define this mode as static because it considers age as a number, so the results obtained using the same age at different interactions of the design process will always be the same.

It is important that, during the design process of the ALS workplaces, both modes, dynamic and static, are considered.

Because of the methodological framework proposed in Figure 11, companies have a simple but effective guide to follow when they are looking to design ergo-efficient workplaces in their ALSs using VR and a mocap system. The methodological framework allows for the maximisation of both production and operator well-being through a holistic approach. In fact, it does not focus only on productivity: it also makes it possible to consider the current labour market because it allows for the inclusion of ageing employees and their related advantages, along with their downsides, in the AS workplace design approach.

4.4 Decision support system for the selection of the best material management solution among traditional Kanban, electronic Kanban and digital twin

This subsection aims to answer **RQ3**, which was derived from OL2, Methods for efficient control of AS4.0:

How can material management be controlled in AS4.0?

At the operational level, companies must control their ASs (Table 1). In particular, in the current study, we were interested in the case in which companies must decide how to control the material management in their ALFS by considering the scenario where components are stored at the workplaces in bins (which is one of the most frequently adopted (Battini et al., 2009)). Based on the literature, different material management solutions have been developed over the years that take into consideration this scenario. The first material management solution was represented by the traditional Kanban (Huang and Kusiak, 1996), in which the replenishment of components at the workplace is controlled by physical cards applied to the bins: once the bins are empty, the Kanban card is removed and sent manually to the supermarket warehouse to request new components (Singh et al., 1990; Junior and Godinho Filho, 2010). The traditional Kanban solution, then, evolved into the electronic Kanban (e-Kanban) solution, where the need for replenishment of the component at the AWs was still triggered manually but in a digital way (e.g., by pressing a button or by scanning a barcode or QR code, etc.) (Kouri et al., 2008). Although there are pros in adopting Kanban and e-Kanban solutions, these are accompanied by a common limitation that is represented by the fact that the inspection of empty bins and requests for the replenishment of components need to be manually executed from the operators, resulting in inefficiencies (e.g., loss of Kanban cards, delayed triggered of replenishment, etc.). To overcome these inefficiencies, researchers and practitioners have been evaluating the potentialities provided by certain I4.0 technologies (e.g., sensors, computer vision, DT, etc.) for the development of new material management solutions (Bortolini et al., 2017; Cohen et al., 2019b; Dolgui et al., 2022). Among these technologies, DT appears to be the most promising and disruptive. A DT is '*an integrated simulation technology, which aims at developing a model of the environment that has to be fed with real-time data, to provide high fidelity of the overall system*' (Saporiti et al., 2020); a DT-based material management solution allows knowing in real time the status of the components in the bins, which can automatically trigger the replenishment of components, hence simulating what can happen in the near future in terms of the status of components in the bins and forecasting when is the best moment to carry out replenishment (Qi and Tao, 2018).

However, despite the importance of the material management activity, managers and practitioners must choose the proper material management solution to adopt in their ASs. This was confirmed by the managers from Bossard (2022), a company that provides components and digital solutions for the management of components. During discussions with them, it emerged that most of their customers decided on the solution to control the material management in their ALFS by following their own experience rather than proper guidelines or tools that can tell them what is the best solution to choose based on their situation. Therefore, we have developed a DSS that can guide managers and practitioners in choosing the most convenient material management solution among traditional Kanban, e-Kanban and DT-based material management solutions to adopt in their ALFSs.

To develop the DSS, a three-step procedure must be followed:

- Step 1: development of three simulation models, one per each material management solution considered (traditional Kanban, e-Kanban and DT-based solutions).
- Step 2: parametrical analysis, from which it is possible to have an output of man hours and average inventory level required for different scenarios (where a scenario corresponds to a certain combination of parameters adopted in the models). Specifically, we varied the parameters' mean demand of final products Q and standard deviation of the demand σ, the distances between the supermarket warehouse and the assembly area d and the number of assembly lines L and assembly workplaces W, which are the parameters that are commonly considered when companies choose the material management solution to adopt in their ASs (Houti et al., 2017; Urru et al. 2018; Sapry et al. 2020). From the parametrical analysis, we obtained 243 different scenarios per each material management solutions considered.
- Step 3: development of the DSS that, given the unitary cost of the stocks of components, suggests the most convenient material management solution, here based on the investment and operational costs for each scenario considered.

For a detailed explanation of the DSS development, the reader is referred to Paper 6. Below are only reported the results required to reach the main outcome of this subsection.

The DT-based model. Because the only example of a DT-based solution for material management that can be found in the literature was the one proposed in the conference proceedings by Kim et al. (2021), the first main outcome of this subsection concerns the development of a DT-based model.

In the DT-based model, the DT is responsible for the determination of the best moment (best time interval) when a feeder must go to replenish the components in the workplaces. In fact, the DT monitors in real time the availability of components in the bins through the use of sensors and scales. In this way, once a bin falls under the desired replenishment level, a signal is immediately sent to the DT. When this situation occurs, the DT activates a system, which performs a simulation based on the current state of the workplaces. This analysis can simulate the assembly processes and forecast the consumption of components in a very precise and accurate way. The DT stops the simulation whenever a component reaches a status of prestarvation, that is, when it is very close to the starvation point. The starvation point is reached when, in the bin, there are enough components to assemble a maximum of two products. Then, the DT records the stopping time and collects all the signals of replenishment that occurred in the simulated period. Finally, the DT communicates to the feeders the time in which they will have to perform the replenishment, as well as what bins will need to be refilled. The process of the developed DT-based model is depicted in Figure 13.

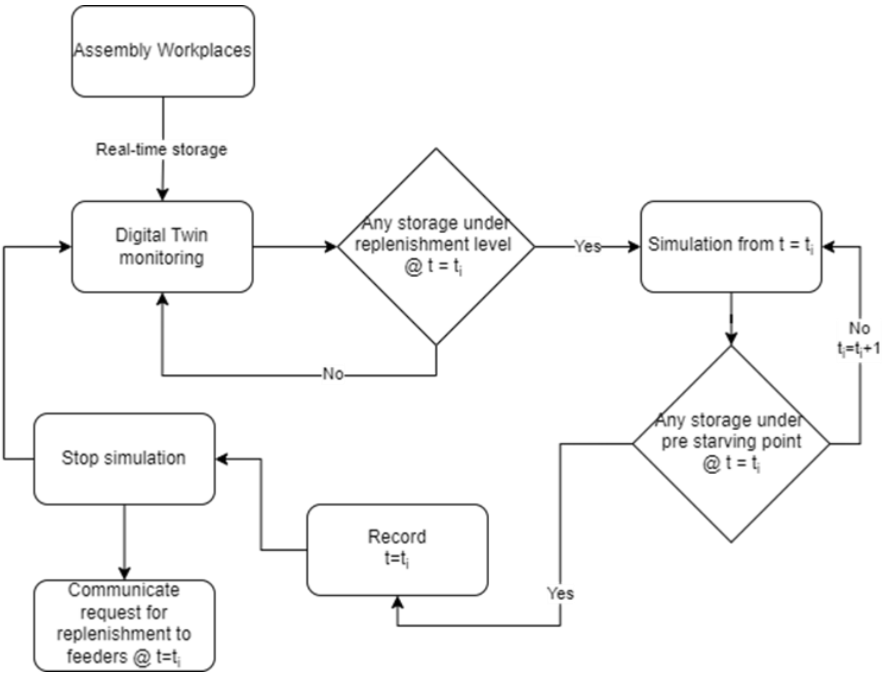

Figure 13. Digital twin-based model process representation

In this way, the DT-based model determines the best replenishment time (best time interval), which will be variable and depend on the current state of the system, as well as on the demand profile. In this way, the operators in the workplaces, compared with the cases of traditional Kanban and e-Kanban, do not perform any non-value-added activity linked to the replenishment of the workplaces as it is completely managed by the DT (i.e., the inspection of empty bins and requests for the replenishment of components is not manually executed by the operators).

The decision support system (DSS). Once the DT-based model has been determined and simulated, together with the results of the simulations of the other two material management solutions (traditional Kanban and e-Kanban), it was possible to develop the DSS. The DSS represents the second main outcome of this subsection, which also answers **RQ3**.

The aim of the DSS is to support managers and practitioners in identifying the most convenient material management solution, here based on investment and operational costs, between traditional Kanban, e-Kanban and DT-based solutions, depending on their situation in terms of the mean demand of final products Q and standard deviation of the demand σ, the distances between the supermarket warehouse and assembly area d, and number of assembly lines *L* and assembly workplaces *W*. The DSS was built to be a tool that is easy to read and interpret. In fact, if we consider in all the figures below (Figures 14, 15 and 16) the same case where σ = 10%, d = 20, L = 2 and W = 4, we have companies that should choose a different material management solution based on the unitary cost of stocks © in their ALFSs, as shown in Table 8.

Table 8. Decision of the material management solution in different scenarios based on the unitary cost of stocks c

	Mean demand of final products		
Material management solution	**Q = 10 pcs/h**	**Q = 20 pcs/h**	**Q = 40 pcs/h**
Traditional Kanban	0.01 €/pc < c ≥ 0.70 €/pc	0.01 €/pc < c ≥ 0.30 €/pc	0.01 €/pc < c ≥ 0.10 €/pc
E-Kanban	0.70 €/pc < c ≥ 8.10 €/pc	0.30 €/pc < c ≥ 3.10 €/pc	0.11 €/pc < c ≥ 1.90 €/pc
DT-based solution	c > 8.10 €/pc	c > 3.10 €/pc	c > 1.90 €/pc

Moreover, the DSS has been analysed to draw some considerations that can be made when analysing the impact of the single parameters of the scenarios.

First, considering the demand parameter, ceteris paribus, a rise in the demand level negatively affects the convenience of the traditional Kanban solution, as supported by Houti et al. (2017). Indeed, the mean value of the extent of the convenience range of the traditional Kanban solution drops from 1.08 €/pc, when considering the lowest level of demand, to 0.27 €/pc, when considering the highest level of demand (-75%). The same behaviour can be noticed also for the convenience of the e-Kanban solution (-60.4%). On the other hand, the convenience of a DT-based material management solution is generally higher when considering a remarkable level of demand (+36.4%).

Second, considering the standard deviation of the demand parameter, the convenience of the traditional Kanban solution follows the same behaviour of the first parameter, but with a more moderate impact when considering the change in value, which can be noticed when comparing the highest standard deviation with the lowest (-4.6%). For the convenience of the e-Kanban solution, it presents the highest level in correspondence to the highest variability, while the lowest level can be associated with the middle value of the standard deviation parameter.

The DT-based solution presents the highest level of convenience when considering a middle value of standard deviation, while it shows the lowest level in correspondence to the highest value of variability. However, as for traditional Kanban solution, the impact of the standard deviation of the demand on the convenience of the e-Kanban and DT-based solutions is quite limited.

Third, considering the parameter linked to the distance between the supermarket warehouse and assembly area, both for the traditional Kanban and e-Kanban solutions, the highest level of the convenience extent is reached at the middle level of distance. In the case of a DT-based solution, this value is reached at the lowest value of distance. However, in this situation, the impact of this parameter on the convenience of the material management solutions is quite limited.

Fourth, the last two parameters, that is, the number of AWs and number of lines, affect the convenience of the material management solutions in a very similar way. Indeed, regarding the traditional Kanban solution, the convenience is negatively influenced by the rise in the number of AWs and lines at -78.6% and -80%, respectively. A similar behaviour can be noticed when considering the convenience extent of the e-Kanban solution, with a negative influence associated with a rise in the number of AWs and lines equal to -61.6% and -63.25%, respectively. In the case of DT-based solution, the behaviour is completely the opposite. Indeed, an increment in the value of AWs and lines can be associated with a rise in the convenience of this solution by 35% and 37%, respectively.

Finally, to enhance the results of the study and understand the statistical relevance of all the parameters exploited to develop the DSS, an analysis of variance (ANOVA) has been carried out, as shown in Table 9.

Table 9. ANOVA p-value results

	Material management solution		
Parameter	Traditional Kanban	e-Kanban	DT
Q	5.72e-12	3.36e-15	1.79e-15
σ	0.958	0.685	0.747
d	0.479	0.937	0.896
W	6.98e-16	3.85e-13	4.11e-14
L	2.46e-16	8.86e-15	1.04e-15

The table shows that the parameters standard deviation of the demand (σ) and the distances between the supermarket warehouse and assembly area (d) do not present a statistically significant impact on the convenience range extent of the DSS at any confidence level. Therefore, because these two parameters were statistically not relevant, they have been excluded from the DSS and its final version, which only considers three parameters that were found to be statistically significant—Q, L and W—as reported in Figure 17.

To conclude this subsection, the DSS can help managers and practitioners thinking about changing the material management solution adopted in their ALFS from a traditional or e-Kanban solution to a DT-based one or in creating a new DT-based solution to control the material management in their ALFS. The DSS has shown that traditional Kanban and e-Kanban solutions are more convenient in environments where the number of workplaces and assembly lines, demand level and average cost of stocks are low and medium, respectively, whereas the DT-based solution is more convenient in environments characterised by a high number of AWs and assembly lines, with a high demand level and with a high average cost of stocks. Moreover, companies should not pay much attention to the standard deviation of the demand (σ) and of the distance between the supermarket and assembly area (d) when planning which material management solution to adopt in their ASs. In fact, although these two parameters are commonly considered when companies have to choose the material management solution to adopt, based on the ANOVA analysis, they resulted as not being not statistically significant when deciding which material management solution to choose among the traditional Kanban and e-Kanban and DT-based solution.

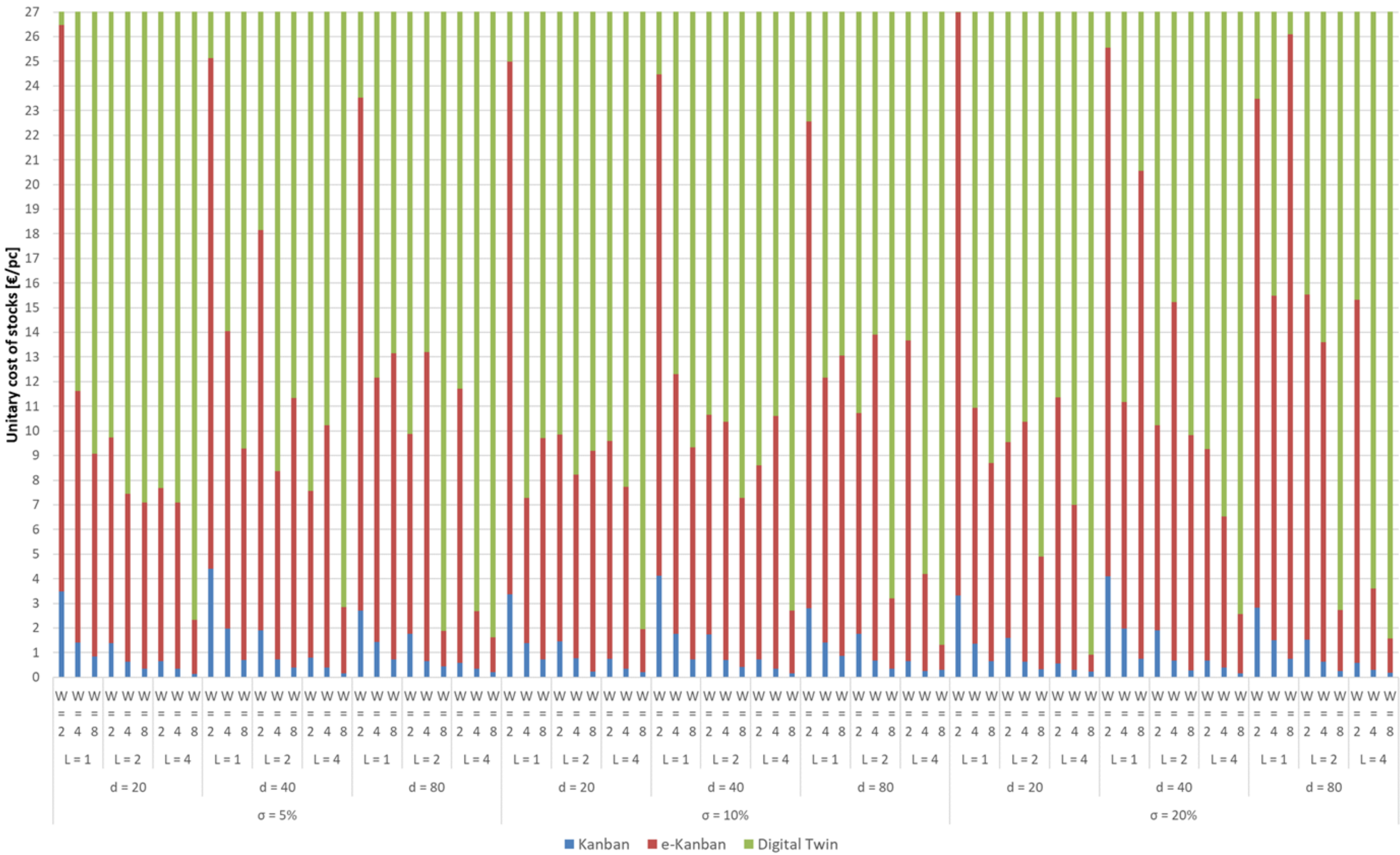

Figure 14. Decision support system (expressed as euro per piece) in the case of Q=10 pcs/h

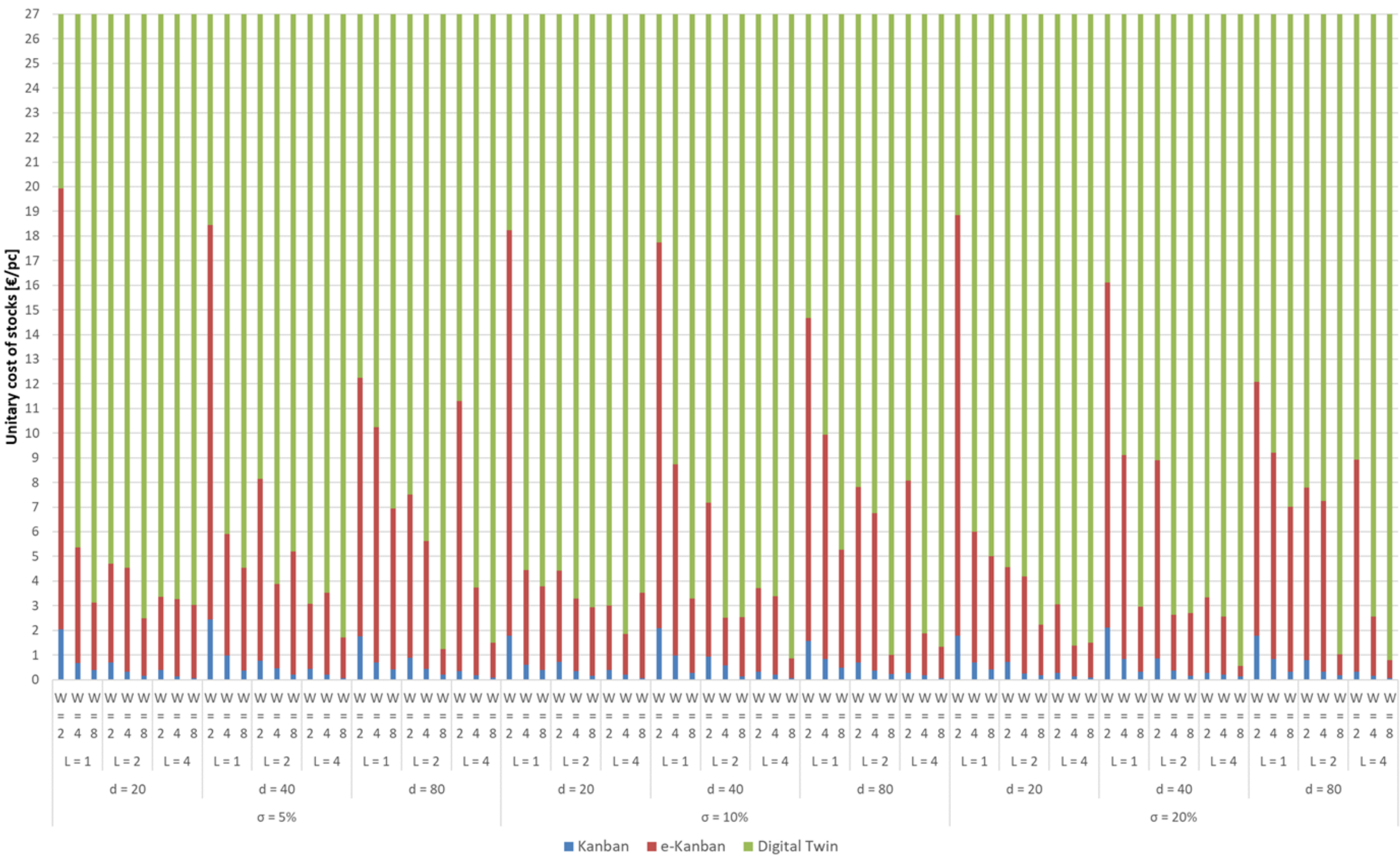

Figure 15. Decision support system (expressed as euro per piece) in the case of Q=20 pcs/h

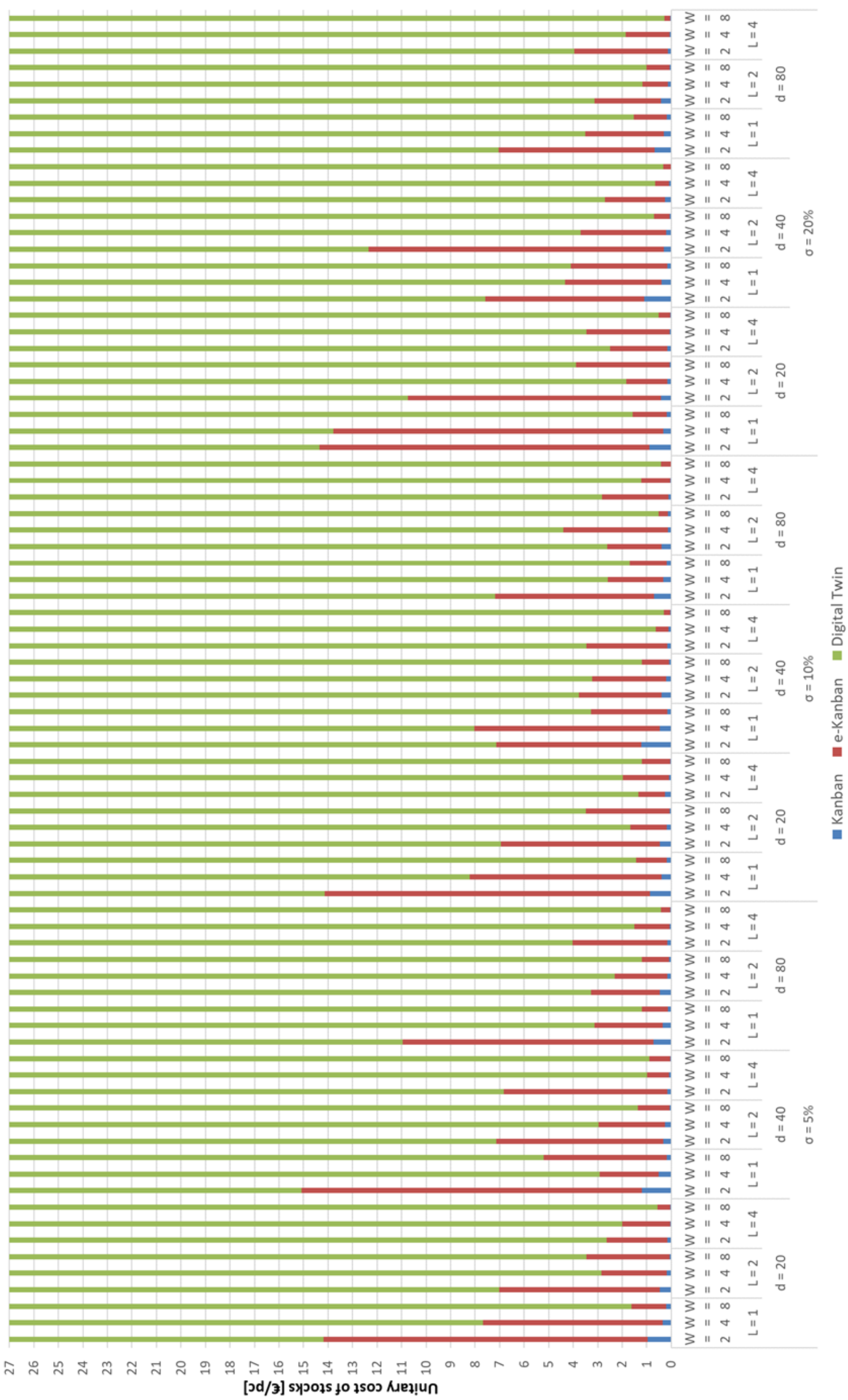

Figure 16. Decision support system (expressed as euro per piece) in the case of Q=40 pcs/h

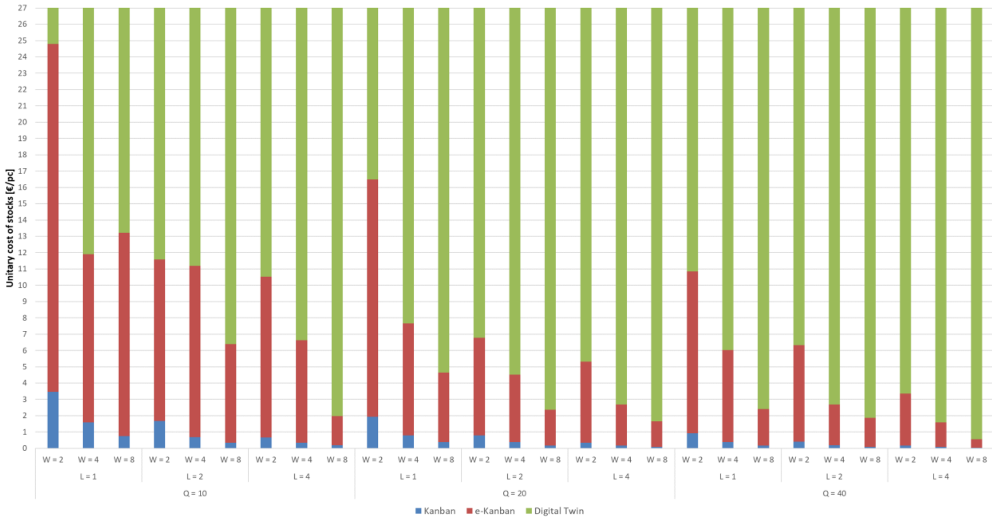

Figure 17. Final DSS after the ANOVA

4.5. General discussion of the results

So how can companies move from traditional AS to AS4.0? How can researchers continue the research stream in the design and management of AS4.0? From the results of the present research study, a few reflections and recommendations can be offered.

Implementing I4.0 technologies in ASs can be problematic for companies (Karadayi-Usta, 2019; Mahmood et al., 2021). However, we believe that companies can significantly benefit from the results that have been presented in the current study (Tables 3 and 4) to ease the implementation of Industry 4.0 in their AS. Tables 3 and 4 can be used as a guide to move from a traditional AS to an AS4.0, here by following the decisions that they will have to make for each technology during all the steps of their implementation (from the strategic to operational level). It is possible that more decisions can be discovered and added to the two tables, especially with the increased knowledge about the implementation of I4.0 in AS4.0.

At the strategical level, the decision of the configuration of the ALS is one of the first decisions that companies must make (Battaïa and Dolgui, 2013; Battini et al., 2011). However, there was still no clear idea of how the configurations should be chosen. Therefore, our investigation identified the relevant factors that companies need to know when choosing the configuration of their ALSs. The identified factors are the ones that also determine if a configuration can be dynamic reconfigurable. Moreover, the present study, in identifying the impact of I4.0 technologies on these factors, has shown how the implementation of I4.0 technologies can open opportunities for companies to choose new ALS configurations that should even be more dynamic reconfigurable. However, at the moment, these results are qualitative in nature, so it is not possible to say precisely when one configuration has to be chosen instead of another and how much dynamic reconfigurable each configuration can be. Therefore, it will be challenging to find the threshold values of the factors that determine when one should choose a configuration instead of another in the case without I4.0 technologies and then to see how the identified threshold values will change when one or more I4.0 technologies are implemented in the ALS.

At the tactical level, companies must design their ALSs. I4.0 technologies can support companies to do design their ALSs (Peruzzini et al., 2017; Vosniakos et al., 2017). In the present study, a methodological framework to design ergo-efficient ALS workplaces using VR and a mocap system has been developed for the first time. This framework can help companies in designing their ALS workplaces by following five simple steps. The strength of the developed methodological framework is that it can be followed using all types of VR devices and all types of mocap systems available on the market, making it accessible to all companies. Moreover, the study has identified how to include the age of human workers in the design of the ALSs' workplaces. The results from the methodological framework were not focusing only on the productivity of the ALS, but also aiming to make it possible to consider the current labour market, including ageing employees and their related advantages and downsides in the ALS workplaces design process. Although the experimental research that was performed to validate the developed framework gave positive results, because of the simple case investigated, there was a need for more complex cases that would not only help to confirm the validity of the framework, but also continuously improve it.

At the operational level, companies need to know how they will control the material management in their ALFS (Battini et al., 2009). I4.0 technologies—especially DT—can open new opportunities to control the material management (Bortolini et al., 2017; Dolgui et al., 2022). However, it deciding to use a DT-based solution is not always going to be the best solution. In fact, if companies consider the costs (investment and operational costs) of their material management solutions, it is possible that other solutions like traditional Kanban or e-Kanban can be more convenient. Therefore, the DSS developed here has aimed to give to companies a tool that allows them to choose the best material management between traditional Kanban, e-Kanban and DT-based solutions. The DSS is not only a tool that is easy to read, but it is also easy to develop. However, at the moment, the results related to the DSS are based only on simulations. Results derived from real case studies can increase the quality and validity of the DSS and can better define the ranges of when one material management solution is more convenient than another.

Finally, researchers interested in this topic will be able to find—primarily through the nine future research opportunities identified—ways to increase the knowledge about the design and management of AS4.0. Even with the relevance of the presented results, the current research study is only a starting point for what can be a prosperous future of research. The continuation of the research on the design and management of AS4.0 can pave the road to the easier implementation of I4.0 technologies in AS.

5. Conclusions

This section summarises the research study and provides contributions to theory and implications for practice. Furthermore, the research limitations are addressed, as well as recommendations for future research.

5.1. Summary

The objective of the current research was to support and create new knowledge for academy and managers and practitioners who want to design and manage AS4.0. In addition, an aim was to propose future research opportunities related to the design and management of AS4.0 to inspire new researchers to continue investigating the topic. To do so, the study focused on three decision areas related to the design and management of an AS (configuration of an ALS, workplace design of an ALS and control of the ALFS) and on three of the I4.0 technologies (AR, VR and DT). Moreover, to develop a richer and more thorough knowledge of the research area, a mixed methods approach was used, integrating components of qualitative and quantitative research:

1. The SLR provided in-depth knowledge about the state of the art of AS4.0 while also contributing possible future research opportunities that inspired the research questions investigated in the present study.
2. Exploratory research enabled the identification and definition of the relevant factors that companies need to know when they have to choose the configuration of their ALSs.
3. Experimental research for investigating the impact of AR in the previous identified factors and for helping the validation of the developed methodological framework to design ergo-efficient workplaces of an ALS.
4. Simulation modelling allowed the analysis of different material management solutions (traditional Kanban, e-Kanban and DT-based solutions) to identify which is the best for controlling the material management in ALFSs.

Therefore, the SLR made it possible to understand what decisions companies need to make when they decide to implement one or more of the I4.0 technologies into their AS, showing nine future research opportunities related to AS4.0. The future opportunities not only inspired the three research questions answered in the present research study, but they can also inspire many other researchers to continue exploring the topic by creating new knowledge.

Moreover, using the other three research methods (exploratory research, experimental research and simulation modelling) in the studies carried out for this research enabled us to answer the three research questions, thus providing the following contributions:

RQ1: How can AS4.0 configurations be affected by Industry 4.0 technologies?

The findings of Paper 3 revealed the factors that companies need to know when they have to model the configurations of their ALSs and the impact of I4.0 technologies on these factors. The seven identified factors are cycle time, number of tasks, network density, products variety, volumes variety, quality and complexity of tasks. The knowledge of these factors is of considerable importance when companies want to model dynamic reconfigurable configurations of their ALSs since their values determine if a configuration is dynamic reconfigurable or not. Regarding the impact of I4.0 technologies on these factors, except for the factors of number of tasks and network density, where no impact was identified, the technologies decreased or increased these factors, hence being beneficial for the ALSs. Moreover, the most interesting result was related to the factor cycle time for AR. Here, it is not clear if AR is able to decrease the cycle time or if it increases it. Intrigued by this result, Paper 4 tried to see if it was possible to have a clearer idea of the impact of AR on the factor cycle time and other factors. Although the findings of Paper 4 have confirmed the uncertainty of this theory, we found that this this uncertainty was more caused by how the AR technology was developed than by the experience that the operators of the ALSs had using the technology. Furthermore, the findings of Paper 4 have shown that AR can help operators assemble products they have never assembled before and that the more complicated the product is to assemble, the greater the quality that can be achieved using AR because AR allows for fewer errors in the assembly process.

RQ2: How can ergo-efficient AS4.0 workplaces be designed?

The findings of Paper 5 revealed the methodological framework that designers should follow if they want to design ergo-efficient workplaces of an ALS using VR together with a motion capture system. The methodological framework consists of five steps: input collection, workplace design, data collection, data analysis and ergo-productivity satisfaction. When arriving at Step 5 (ergo-productivity satisfaction), designers need to see if the productivity KPIs and ergonomic scores obtained from Step 4 (data analysis) satisfy the company's requirements. If they do, the design process ends, and the company puts into place the final ALS workplace design; if not, the designer must return to Step 2 (workplace design). Therefore, the design process proposed by the methodological framework is an iterative process that stops only when the productivity KPIs and ergonomic scores are adequate (in terms of the company's requirements, legal restrictions and so on). Moreover, in the methodological framework, the age of the operators has been considered in two different modes: a dynamic mode that involves the most experienced 'senior' operators working in the ALS and a static mode that involves two formulas: one that calculates the age-based multiplier for muscle strength and the other for the age-based multiplier for reduced joint flexibility.

RQ3: How can material management be controlled in AS4.0?

The findings in Paper 6 have revealed a DSS that can help managers and practitioners thinking about changing the material management solution adopted in their ALFS from a traditional or e-Kanban solution to a DT-based one or who want to create a new DT-based solution to control the material management in their ALFS. The DSS suggests that traditional Kanban and e-Kanban solutions are more convenient in environments where the number of workplaces and assembly lines, the demand level and the average cost of stocks are low and medium, respectively, whereas the DT-based solution is more convenient in environments characterised by a high number of AWs and assembly lines, with a high demand level and high average cost of stocks. Finally, based on the ANOVA analysis, two of the parameters considered (the standard deviation of the demand and the distance between the supermarket warehouse and the assembly area) to develop the DSS were not statistically significant when deciding which material management solution to choose between the traditional Kanban and e-Kanban and DT-based solution.

5.2. Contributions to theory

The current research study has several contributions to theory, which are summarised in the seven main outcomes reported in Table 10.

Table 10. Contributions to theory: main outcomes

Main outcomes	Paper					
	1	**2**	**3**	**4**	**5**	**6**
State of the art of AS4.0	x	x				
Future research opportunities for AS4.0	x	x				
Factors for the modelling of dynamic reconfigurable configurations of an Assembly Line Subsystem and the impact of Industry 4.0 technologies on these factors			x	x		
Identification and definition of the factors relevant for modelling dynamic reconfigurable configurations of an ALS and identification of how Industry 4.0 technologies impact those factors			x			
Investigation of the impact of augmented reality on the identified factors				x		
A framework to design the workplace of an Assembly Line Subsystem by using Virtual Reality and a motion capture system					x	
Identification of the steps to design ergo-efficient workplace of an ALS by using virtual reality (VR) and motion capture (mocap) system					x	
Identification of how the age of human workers can be included in the design of a workplace of an ALS.					x	
A Decision Support System to select the best material management solution among traditional Kanban, electronic Kanban, and Digital Twin						x
Development of a digital twin-based model for the control of the material management in an ALFS.						x
Identification of the best solution among traditional Kanban, electronic Kanban and DT to control the material management in an ALFS.						x

The first and second contribution of comes from the findings of the SLR that support the organisation and unification of knowledge related to the design and management of AS4.0. The decisions that companies have to make when implementing I4.0 technologies in their AS have been identified, together with the need for more research, as summarised in nine future research opportunities, which can open numerous research areas related to the design and management of AS4.0. Three of the future research opportunities inspired the three research questions answered in this research study.

The third contribution is related to the identification and definition of the factors relevant to know when companies want to model dynamic reconfigurable configurations of their ASs. Furthermore, analysing the literature helped understand the impact of I4.0 technologies in the identified factors. The implementation of I4.0 technologies in ASs can play a crucial role when it is time to choose the configuration of the AS and it can help in the creation of dynamic reconfigurable configurations. Based on our results, I4.0 technologies may change the decision regarding which AS configuration to choose compared with the case where no technologies are implemented in the AS. Finally, the fourth contribution, which was derived by experimental research, supported the results discovered from the literature related to AR, here in relation to the impact of this technology on the identified factors. The third and fourth contributions have addressed RQ1.

The fifth contribution helps explain how it is possible to design ergo-efficient ALS workplaces using VR together with a mocap system. The five-step methodological framework can be applied using all VR devices and mocap systems available on the market. Furthermore, the sixth contribution helps identify how to consider the age of operators during the design process of an AS workplace. The fifth and sixth contributions address RQ2.

The seventh contribution is related to the development of a DT-based model for controlling the material management activity in ALFS. Finally, the eighth contribution supports the decision regarding the solution for controlling the material management in an ALFS between the traditional Kanban and e-Kanban and DT-based solutions, hence providing the DSS. The seventh and eighth contributions address RQ3.

5.2. Implications for practice

For managers and practitioners who are responsible of the design and management of ASs, the findings of the present research have several relevant implications. ASs need to achieve and maintain their goals (e.g., have high efficiency, maximise throughput with minimum resources, have high flexibility, rapid change in production volume and type of products to be assembled, minimise the WIP, assemble high-quality products, minimise the inventory level, effectively utilise the workforce and minimise disruption to production) while achieving high profits and keeping costs low. To do this, great potential lies in implementing new I4.0 technologies in the ASs. Therefore, the current research first presented how companies can implement I4.0 technologies in their ASs. The study identified the decisions that companies must make at each level (strategic, tactical and operational) and for each technology possible to implement in ASs. This is an important step to help companies that must make a difficult decision like the one to buy one or more technologies. Second, because companies must use the technologies they purchase, they need to know what the impact of these technologies may be in their ASs. In particular, the current research has focused on the impact that I4.0 technologies can have in the decision of the configuration of the ASs. Therefore, the present research first highlighted the seven factors that companies need to be aware of when they want to model a dynamic reconfigurable configurations of their AS and then gave insights into the impact of I4.0 technologies on these factors. Third, the current research has described the five steps that form the methodological framework that companies can follow to design ergo-efficient AS workplaces using VR. The methodological framework can guide companies deciding to use VR together with a mocap system to design the workplaces of their ASs and that, at the same time, want to take into consideration the age of the operators who will work in those workplaces. Finally, the current study has offered a tool that managers and practitioners can use to decide which solution to choose to control the material management in their ASs. The developed DSS suggests the most convenient solution, here based on investment and operational costs, between traditional Kanban, e-Kanban, and DT-based solutions for controlling the material management in ALFSs.

To sum up, first, we have supported companies in their implementation of I4.0 technologies in their ASs, showing them the decisions that they must make level by level (strategic, tactical and operational) for each technology (Table 3 andTable 4) if they want to reach the goals of the ASs. Second, to give them even more information during the design phase, we explained the impact that each I4.0 technology has on the factors relevant to the decision of which AS configuration to choose (Table 5). Third, we encouraged companies to use VR when designing the workplaces in their ASs; here, they can use our five-step methodological framework that considers the age of operators to design ergo-efficient AS workplaces using VR together with a mocap system (Figure 11). Finally, we have supported companies in the decision of the solution for controlling the material management activity in their ASs. We provided a DSS that they can use to choose the most convenient material management solution, here based on investment and operational costs, among traditional Kanban and e-Kanban and DT-based solutions by considering the demand and layout parameters of their ASs (Figure 7).

5.3. Research limitations

No research is conducted without limitations. This subsection highlights limitations that may be of significant concern.

First, because of time constraints, not all the decision areas related to the design and management of an AS have been investigated. In fact, a longer period would be necessary to study all the decision areas, but the current research had only a three-year period. Therefore, the present study focused only on three (one decision per level: strategic, tactical and operational) of the 12 decision areas related to the design and management of an AS. Moreover, for the same reason, not all the nine future research opportunities identified thanks to the SLR have been explored, here focusing only on the three connected to the three decision areas selected.

Furthermore, not all the I4.0 technologies have been considered. In fact, the I4.0 technologies were chosen from those already available in the Logistic 4.0 Lab of the Department of Mechanical and Industrial Engineering at NTNU to make the most of the resources already available. Moreover, because of time constraints, the present study has also not considered using other I4.0 technologies to address the same problems investigated during the research period.

Moreover, to conclude with the main limitations, no case studies from companies were undertaken. The quantitative results of the research study were derived from experimental research and simulations that, although giving the opportunity to arrive at solid conclusions, were created in a controlled environment without the presence of possible uncertainties that may occur in a real work environment such as an AS.

Finally, in addition to the main limitations, it is necessary to highlight that each study in the appended publications have their own specific limitations. Therefore, if interested, the reader is referred to read the conclusion section of Papers 1 through 6 to know more about the limitations of each work.

5.4. Future research

In this section, some possible future research areas that can be explored related to the design and management of AS4.0 are reported. If interested, the reader should refer to Paper 1 to get a full picture of the future research opportunities related to this topic.

Considering mobile robots and cobots, future studies should focus on the mathematical and simulation modelling of different new configurations that can be created by these two technologies. These models will allow researchers to determine the impact of these technologies on the factors that companies need to know when they must choose the AS configuration. Sensitivity analyses will also be useful to study how these factors can change the configuration and performance of the different configurations. In the end, decision support systems, such as decision trees and evolutionary algorithms, can be created to support decision makers in determining what is the best configuration to adopt based on their needs.

Mobile robots, which can be used with or without a cobot, can open up the possibility of creating new feeding policies. In fact, if cobots are used to move shelves or in conjunction with other cobots, they can be used in applications that were not possible before. Moreover, a mobile robot can only be used as a workplace or transportation device, so new scheduling models need to be created that can consider all the possible tasks that mobile robots can carry out. Because companies need to optimise the use of their mobile robots according to the applications that they have to do or tasks able to do, advanced modelling and simulations and then real case studies are needed to study these new opportunities.

AR can be used not only to support operators, but also to show what is happening in the surrounding environment, especially if there are mobile robots or cobots working within it. Therefore, further investigation and testing through experiments that replicate real-world scenarios can better highlight the strengths, weaknesses and potential benefits that the use of AR can generate both in facilitating the execution of various assembly tasks and in increasing the safety of AS4.0.

In general, a piece of technology can be chosen not only in relation to the help that it can give in terms of the physical and cognitive aspects of the execution of a task, but also based on the data that can be collected and shared with it. Therefore, new models are needed to support decision makers to decide on the right technology to implement in their AS4.0, here based on what they have to do with the technology and level of automation that they want to reach in their AS4.0.

Finally, it should be noted that each study in the appended publications that give us the opportunities to answer our three research questions reports with possible future research opportunities to improve the works we have created, thus creating additional knowledge. Therefore, if interested, the reader is referred to read the conclusion sections of Paper 3 through 6.

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Part II: Collection of papers

Paper 1: Dolgui, A., Sgarbossa, F. and Simonetto, M., 2022. Design and management of assembly systems 4.0: systematic literature review and research agenda. International Journal of Production Research, 60(1), pp.184-210.

Paper 2: Simonetto, M. and Sgarbossa, F., 2020, August. Introduction to Material Feeding 4.0: Strategic, Tactical, and Operational Impact. In IFIP International Conference on Advances in Production Management Systems (pp. 158-166). Springer, Cham.

Paper 3: Simonetto, M. and Sgarbossa, F., 2021, September. Straight and U-Shaped Assembly Lines in Industry 4.0 Era: Factors Influencing Their Implementation. In IFIP International Conference on Advances in Production Management Systems (pp. 414-422). Springer, Cham.

Paper 4: Simonetto, M., Peron, M., Fragapane, G. and Sgarbossa, F., 2020, October. Digital assembly assistance system in Industry 4.0 era: a case study with projected augmented reality. In International Workshop of Advanced Manufacturing and Automation (pp. 644-651). Springer, Singapore.

Paper 5: Simonetto, M., Arena, S. and Peron, M., 2022. A methodological framework to integrate motion capture system and Virtual Reality for assembly system 4.0 workplace design. Safety Science, 146, p.105561.

Paper 6: Simonetto, M., Saporiti, N., (under review). Traditional Kanban, e-Kanban or Digital Twin: a Decision Support System for material management solution. Industrial Management & Data Systems.

Paper 1

Dolgui, A., Sgarbossa, F. and Simonetto, M., 2022. Design and management of assembly systems 4.0: systematic literature review and research agenda. International Journal of Production Research, 60(1), pp.184-210.

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Design and management of assembly systems 4.0: systematic literature review and research agenda

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Design and management of assembly systems 4.0: systematic literature review and research agenda

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ABSTRACT

Assembly systems (ASs) have moved into the era of mass customisation and Industry 4.0 (I4.0). Mass customisation involves a shift from the production of high quantities of the same product to the production of low quantities of a high number of different products. This is changing the way in which companies assemble their products and has introduced a certain number of challenges. For example, there are increases in the numbers of parts to be moved, the quantities of data to be collected, and the skills of the human workers that companies must manage to meet their customers' demand. The adoption of I4.0 technologies can help companies to face these challenges. However, although companies and researchers have studied possible solutions based on I4.0 technologies for ASs and have introduced the concept of Assembly System 4.0 (AS4.0), no studies have tried to understand how these technologies impact on decision areas at the strategic, tactical, and operational levels. In this paper, we attempt to fill this gap through a systematic literature review that not only offers the opportunity to understand the current situation and the state of the art in this field but also gives an overview of possible future research challenges.

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Assembly; feeding; industry 4.0; design; management; state of the art

1. Introduction

In recent years, companies have been faced with changes in demand from their customers (Battaïa et al. 2018). In fact, customers are no longer passive clients who buy only the products that companies offer them but are now more often active clients who ask for personalised, customised products that are closer to their needs and desires (Pollard, Chuo, and Lee 2008; Kucukkoc and Zhang 2017). These customisations may involve, for example, a change in the colour (aesthetic design), the shape (measurement), or the technical characteristics of some components (functionality) (Piller 2005). Hence, if companies decide to accept these requests from their customers, they must be ready to manage the production of more complex product models (Otto and Li 2020) and their assembly systems should be agile and reconfigurable (Battaïa et al. 2018). In fact, a reconfigurable system is designed with a certain level of flexibility, that can involve the reconfiguration of human workers, technologies, and equipment, in order to be able to face the rapid change in market conditions (Hashemi-Petroodi et al. 2020a, 2020b; Yelles-Chaouche et al. 2020; Dolgui et al. 2021).

Products can be customised in different phases of a production cycle (Da Silveira, Borenstein, and Fogliatto 2001; Hu et al. 2011), for example during the design, fabrication, or assembly stages, or at the moment that they are bought by the final customers. In this paper, we focus on the assembly systems (ASs) where the mass customisation is especially performed. Such ASs can be composed of the following two parts: the assembly line subsystem (ALS) and the assembly line feeding subsystem (ALFS) (Battini et al. 2009b).

An ALS is a type of production system in which various tasks are executed, at one or more workstations, to create the final product (Rekiek et al. 2002; Dolgui and Proth 2010; Akpinar, Elmi, and Bektaş 2017; Zhong and Ai 2017). Although they have the word 'line' in their name, ALSs can be designed in different shapes, such as a two-sided line, a U-shape line, a system with rotary table, a fixed position, and so on (Becker and Scholl 2006; Battini et al. 2011; Battaïa and Dolgui 2013). However, the straight simple line is the most commonly used layout (Rabbani, Moghaddam, and Manavizadeh 2012; Mukund Nilakantan and Ponnambalam 2016), and, in

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Table 1. Decision areas at different levels of a traditional AS.

		Assembly Line Subsystem (ALS)	Assembly Line Feeding Subsystem (ALFS)
Long term	STRATEGIC	• Configuration of the system • Level of automation	• Configuration of the system • Level of automation
Medium term	TACTICAL	• Workplace design • Assembly line balancing	• Feeding policy selection • Scheduling
Short term	OPERATIONAL	• Sequencing • Control of the ALS	• Routing and material/information management • Control of the ALFS

fact, all types of layouts can be reconfigured or considered as a line in terms of how they work. Two main activities are executed in an ALS: the process, subassembly and assembly, which is related to the realisation of the final products by integrating together component parts and subassemblies; and control, which is related to monitoring of the quality and performance of the ALS (Hu et al. 2011; Battini et al. 2011).

The ALFS is responsible for the management and delivery of the components to the ALS (Battini et al. 2009b; Sali and Sahin 2016). The right component must be delivered in the right quantity, in the right container and at the right moment, to the right ALS. In order to achieve this, the three main activities of an ALFS are: transportation, preparation, and material management (Schmid and Limère 2019). Transportation involves the process of moving all components or parts from point A, where they are stored, to point B, where they are needed, while preparation relates to the processes of handling and repacking parts into the load carriers used for the corresponding line feeding policy. Finally, material management includes all processes related to the storage of components and products.

These subsystems need to be properly designed and managed in order to give an efficient and flexible AS, and several different decision areas have been defined in the literature, as summarised in Table 1.

These decision areas may be associated with different levels, for example strategic, tactical, or operational levels. Strategic decisions have a long-term impact (measured in years) on the company's operation, while tactical decisions impact operations in the medium term (over weeks), and operational decisions are made daily and have a short-term impact.

At the strategic level, decisions are made on the configuration of the system and the level of automation, for both ALSs and ALFSs. This means that companies must choose the product family has to be assembled and estimate how many resources are required by the family, how many ASs are necessary (for example, one flexible system for the whole product family or several more dedicated ones), the layout of their ASs, and the type of equipment, i.e. whether the different tasks associated with these systems are to be executed manually, automatically, or both (Bassan, Roll, and Rosenblatt 1980; Cormier and Gunn 1992; Roodbergen and Vis 2006; Wänström and Medbo 2009; Battini et al. 2011; Orru' et al. 2019; Fragapane et al. 2021).

At the tactical level, companies may carry out first workforce dimensioning (Dolgui et al. 2018), thus how many workers is necessary to function in worst case (large demand, complex product). Then this information together with time-and-motion and ergonomic analyses are necessary in order to design workplaces for the ALSs, and then assign these tasks to the workplaces using assembly line balancing algorithms (Lindenmeyer 2001; Boysen, Fliedner, and Scholl 2008; Battaïa and Dolgui 2013; Zülch and Zülch 2017). In the ALFS, decisions at this level firstly relate to how to deliver the different components to the ALS (Battini et al. 2009b; Caputo and Pelagagge 2011; Caputo et al., 2018; Arena et al., 2019), workforce dimensioning and then to the scheduling problem of who needs to deliver them (Mei et al. 2005; Dang et al. 2014).

At the operational level, the AS must work correctly, and therefore needs to be controlled. There can be also problems of reconfigurations when the product, production or demand change.

Different forms of data are collected from the AS in order to determine and control this process, for example the sequence of products produced in the ALS, the quantities of the components to stock in various warehouses, and the routes used to deliver these components to the ALS (Agrawal and Cohen 2001; DeCroix and Zipkin 2005; Hu et al. 2008; Battini et al. 2009a; Boysen, Kiel, and Scholl 2011; Gebser et al. 2018).

All these decisions need to be made for the AS in order to be able to generate the varieties of product required to meet customer demand. Despite the efforts of many companies, it is not easy to achieve mass customisation (Piller 2005; Piller 2007; Pollard, Chuo, and Lee 2008). This because companies need to be able to handle the three main elements of elicitation, process flexibility, and logistics if they want to attempt this goal (Radder and Louw 1999; Zipkin 2001; Blecker and Abdelkafi 2006; Roda et al. 2019; Hashemi-Petroodi et al. 2020a).

Process flexibility and logistics can be supported by Industry 4.0 (I4.0) technologies (Lasi et al. 2014; Shrouf, Ordieres, and Miragliotta 2014). I4.0 is the term used to refer to the fourth industrial revolution (Kirazli and Hormann 2015), which offers the opportunity to use new technologies such as collaborative robots (cobots), mobile robots, augmented reality (AR), virtual reality (VR), the Internet of Things (IoT), cloud computing and data analysis, etc. with the promise of increased flexibility, higher levels of automatisation, better quality, and improved productivity (Thames and Schaefer 2016; Zhong et al. 2017).

Companies and researchers are already studying the implementation of these technologies in relation to ASs and have introduced the concept of Assembly System 4.0 (AS4.0) (Bortolini et al. 2017; Cohen et al. 2019b). Bortolini et al. (2017) studied how I4.0 technologies can impact in the AS4.0. In particular, they proposed and described in detail the distinctive characteristics of such technologies in these new systems. With the same purpose, Cohen et al. (2019b) created a road map to understand and investigate the impact of I4.0 technologies on AS4.0, at the three impact levels: strategic, tactical, and operational. On each level they explored the different uses that the technologies can have in the AS4.0 and what is specific for AS4.0 in terms of functionalities and performances.

However, these researchers have mainly focused on the introduction of such systems or part of it, its proof-of-concept development, analysis of their characteristics and their performance, while in limited way they have investigated decisions in strategic, tactical, and operational levels applied to AS4.0, as it will be analysed in the following sections.

Thus, in line with the aims and scope of International Journal of Production Research, which is to disseminate research on decision aid on assembly systems among the others, we want to investigate how I4.0 technologies are likely to change the decision areas of an AS, and to provide an original vision of perspectives and challenges to the readers of IJPR and researchers in the production research field.

We pursue the main contribution of the paper answering the following three research questions: How are Industry 4.0 technologies applied to AS4.0? How do these technologies impact on the decision areas of AS4.0? What are the future needs of research into AS4.0? To answer these questions, we conducted a systematic review of the literature. In Section 2, the methodology used in this study is introduced. In Section 3, we present a descriptive analysis of the selected papers, and we analyse these in Section 4 and summarise the results in Section 5. Section 6 reflects on research challenges, and Section 7 concludes the work.

2. Methodology

In this section, following the guidelines outlined by Tranfield, Denyer, and Smart (2003), we explain the process used to select the papers included in our review. In a systematic literature review, the steps applied to select the works need to be clearly defined, in order to create a process that is easily replicable (Seuring and Gold 2012). For this reason, we describe the decisions that were made in order to create a collection of papers, as follows:

(1) *Keywords:* Based on the literature, two groups of keywords were defined, as shown in Table 2. The keywords in Group A were related to the main topic of these papers, i.e. the ALS and ALFS (Battaïa and Dolgui 2013; Battini et al. 2015; Bortolini et al. 2017; Schmid and Limère 2019). The choice of keywords in Group B was inspired by the work of Winkelhaus and Grosse (2020) and is also supported by the literature on I4.0 (Schwab 2016; Culot et al. 2020) and assembly (Bortolini et al. 2017; Cohen et al. 2019b). We performed the search process, as suggested in Hosseini and Ivanov (2020), based on a combination of keywords. Therefore, we used logical operators 'AND' and 'OR' to create Boolean

Table 2. Groups of keywords related to ASs and I4.0.

Group A	Assembly, Workstation, Feeding, Supermarket
Group B	4.0, Smart, Mass customisation, Individualisation, Human-machine, Assisted operator, Adaptive workplace, Internet of things, IoT, Internet of Services, Cyber-physical, Cybersecurity, Blockchain, Social media, Mobile services, Mobile robot*, Autonomous robot, Cobots, Collaborative robot, Augmented reality, Virtual reality, Big data, Cloud, Exoskeleton, Gamification

keywords combinations as by Hosseini, Ivanov, and Dolgui (2019), '(keyword of group A) AND (keyword of group B OR another keyword of group B)', in order to generate the queries used in the Scopus database.

(2) *Refinement:* We used several different combinations of criteria in the first refinement. We considered articles and reviews written in English as document types, limiting our search from January 2005 to December 2020. Following Winkelhaus and Grosse (2020), we also considered only the subject areas of 'Computer Science', 'Engineering', 'Economics', 'Management', 'Social Science' and 'Decision Science'. From these, we excluded papers in fields that were outside our scope of interest, for example biology, bioinformatics, fusion engineering, and design. A combination of the keywords with these limitations gave us an initial selection of 16,849 papers, which was reduced to 9424 after we removed duplicates and considered only journals with a Scimago Journal Rank (SJR) greater than or equal to 0.5. The SJR is an index used to describe the prestige of a journal (SCIMAGO 2020) and can be used to classify and select relevant journals (Falagas et al. 2008; Delgado-López-Cózar and Cabezas-Clavijo 2013).

(3) *Inclusion and exclusion criteria:* From reading the title, abstract and keywords of the papers, we were able to identify works that addressed the use of the different I4.0 technologies in an AS. We were then able to remove all of the papers that were related to topics that were outside the scope of the review, which were not immediately identified as irrelevant in the first refinement step, e.g. material science, nanotechnology, and chemistry. Finally, we were left with 412 potentially relevant papers.

(4) *Second refinement:* In this step, we read all of the articles in full. This allowed us to remove papers that appeared relevant from the abstract, but which turned out to be outside our scope once we read them in their entirety, for example papers that were related to AR or VR and which showed how the authors created their solutions but not how these were then implemented. Our vision of the domain as well as our appreciation of the scientific levels of papers were also used at this step. After this refinement, 140 papers remained.

(5) *Snowball search:* At this stage, 17 articles were added through a backward snowball search, which was carried out in order to discover relevant papers that were not identified in the first phases. At the end of this step, 157 papers were selected for inclusion in this review.

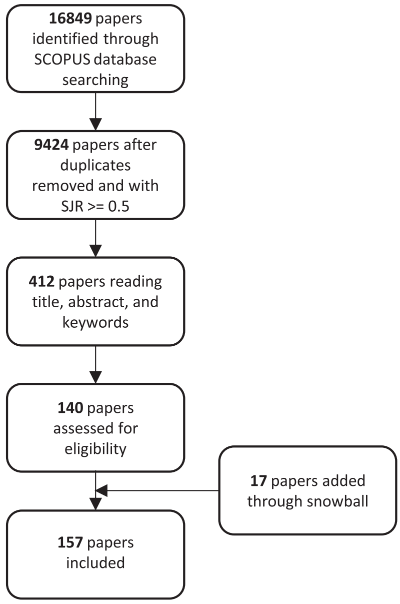

Figure 1. Flowchart of the different phases of the systematic literature review.

Figure 1 summarises the research process and shows the number of papers remaining at each step.

The final set of 157 papers was divided into two groups, representing the two different parts of the AS. In a few cases, the papers dealt with both subsystems, but we decided to assign each one to a specific subsystem based on the main scope of the research. In total, 90 articles were related to the ALS and 67 to the ALFS. As in Kumar et al. (2020), our analysis is decomposed in a descriptive analysis (Section 3) and a content analysis (Section 4) both are based on these two sets of papers.

3. Descriptive analysis

A descriptive analysis of the papers included in this work is conducted in this section, with the aim of presenting some preliminary quantitative results and to motivate our work. These quantitative results are interesting, because they highlight the need for research of this type.

From Figure 2, we can see that the numbers of papers related to I4.0 technologies for ASs start to increase from 2015. In particular, the numbers of papers almost double each year from 2018, indicating an increase in the interest in this topic.

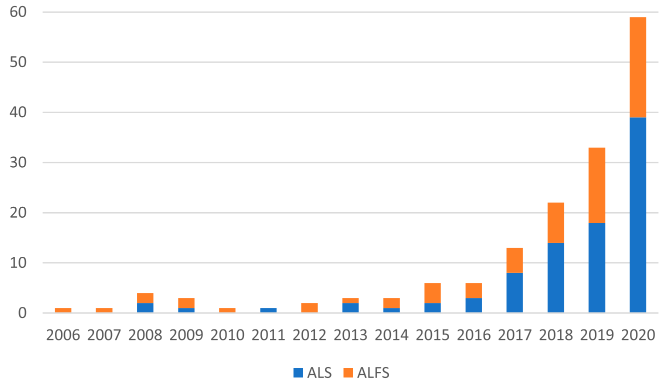

Figure 2. Number of papers examined by year of publication.

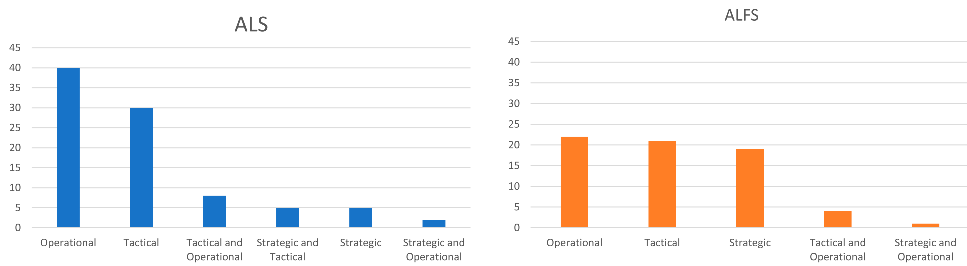

Figure 3. Papers related to the AS, divided by level.

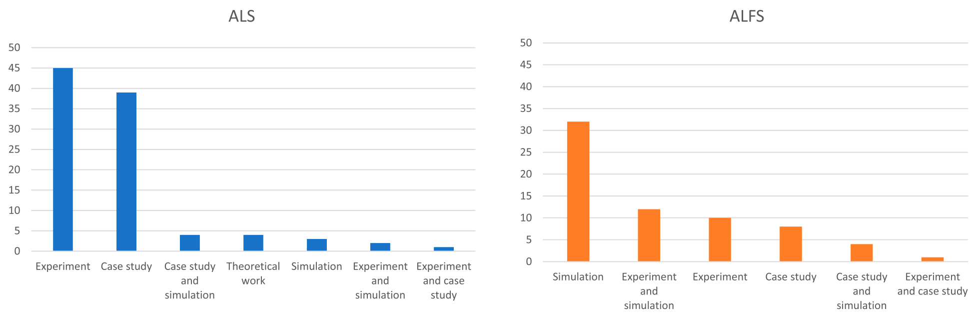

Figure 4. Papers related to the AS, divided by the methodology applied.

Figure 3 shows that the papers related to the ALFS were well distributed over the strategic, tactical and operational levels, while this was not the case for the ALS. For the latter, researchers focused their attention at the operational level, and the topics were mostly related to the quality control of products or performance evaluations of the system.

From Figure 4, it can be observed that almost all of the papers present a case study, experiments or simulations in order to study the technology that they are considering.

Figure 5 shows the I4.0 technologies that are most frequently studied in relation to AS4.0. For the ALS, IoT technologies were the technology most commonly investigated (43 papers), followed by cobots (24 papers), Data Analysis (19 papers), AR (13 papers), and VR (12 papers). The papers related to the family of IoT technologies in our case include sensors, cyber physical systems (CPSs), digital twins and wearables. For the ALFS, we can see that the most widely adopted technologies are mobile robots (53 papers) and IoT technologies (8 papers). In summary, based on this figure, the main technologies related to AS4.0 are cobots, mobile robots, AR, VR, IoT, and cloud computing and data analysis. This categorisation of I4.0 technologies is based on the analysis of the selected papers. Their definitions in the following paragraph will help us in understanding their implementation in ASs and how they impact on decisions at strategic, tactical and operational levels.

Cobots are 'robots intended to physically interact with human workers in a shared workplace' (Djuric, Urbanic, and Rickli 2016). Mobile robots can be defined as 'industrial robots that use a decentralized decision-making process for collision-free navigation to provide a platform for material handling, collaborative activities, and full services within a bounded area' (Fragapane et al. 2021). AR is defined by Carmigniani et al. (2011) as 'a real-time direct or indirect view of a physical real-world environment that has been enhanced/augmented by adding virtual computer-generated information to it'. For Riva (2002) VR is 'A collection of technologies that allow people to interact efficiently with 3D computerized databases in real time using their natural senses and skills'. Xia et al. (2012) state that 'IoT technologies refers to the networked interconnection of everyday objects, which are often equipped with ubiquitous intelligence'. For Armbrust et al. (2010) cloud computing refers 'to both the applications delivered as services over the Internet and the hardware and systems software in the data centers that provide those services'. Oztemel and Gursev (2020) say that data analysis is 'having the capability to handle big amount of data and performing well defined analysis to be able to run the overall system aligned with the manufacturing goals'.

From Figure 5, we can see that there is scientific evidence that the system has changed. However, it is still necessary to study how I4.0 technologies are likely to impact decision areas associated with the design and management of ASs.

4. Content analysis

Krippendorff (2004) defined content analysis as: *[a] research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use.*

Content analysis is a technique that involves specialised procedures; its results should be replicable and valid, and it should help researchers to describe and quantify specific phenomena (Downe-Wamboldt 1992; Krippendorff 2004). In this section, we divide the two sets of papers (on the ALS and ALFS) based on the level (strategic, tactical, and operational) at which they examine these technologies. The main purpose of this analysis is to help us to answer our three research questions, which we repeat here for the reader:

RQ1: How are Industry 4.0 technologies applied to AS4.0?

RQ2: How do these technologies impact on the decision areas of AS4.0?

RQ3: What are the future needs of research into AS4.0?

4.1. Strategic level in assembly system 4.0

A decision made at the strategic level will influence the decisions that can be made at the tactical and operational levels. A wrong decision made at this level can compromise an entire project, and it is therefore important for companies to understand clearly what they want to achieve.

Assembly Line Subsystem: The introduction of new I4.0 technologies such as cobots and assistive technologies to an AS offers the opportunity to create new, more dynamic and flexible configurations. However, it is important to understand how to introduce these technologies into an AS, and whether it is economically beneficial to introduce them. In view of this, two different methodologies for the configuration of a collaborative assembly workplace have been presented by Mateus et al. (2019) and Stadnicka and Antonelli (2019), and an economic evaluation of several different configurations was carried out by Peron, Sgarbossa, and Strandhagen (2020). Mateus et al. (2019) created a four-block procedure that takes into consideration the safety, ergonomics, and performance of the system, whereas the methodology proposed by Stadnicka and Antonelli (2019) instead relies on the implementation of lean methods and tools. Both articles present a case study to demonstrate the validity of the methodologies. Peron, Sgarbossa, and Strandhagen (2020) created a decision tree based on cost models, which was validated through simulation and a case study, to allow the user to understand when it is economically advantageous to create a configuration involving a cobot, AR or both.

The choice of a collaborative human-robot layout requires an understanding of the level of interaction that the human will have with the robot and the skills that will be necessary to make the system work. In order to identify these, Kolbeinsson, Lagerstedt, and Lindblom (2019) proposed several levels of collaboration in their theoretical work, which can help companies that want to shift from automation to collaboration. After studying the state of the art in human-robot collaboration (HRC), Wang et al. (2017) proposed a framework that considered the fundamental elements of an HRC scenario (the actors, work environment, workpieces and operations) to create a symbiotic collaboration between humans and

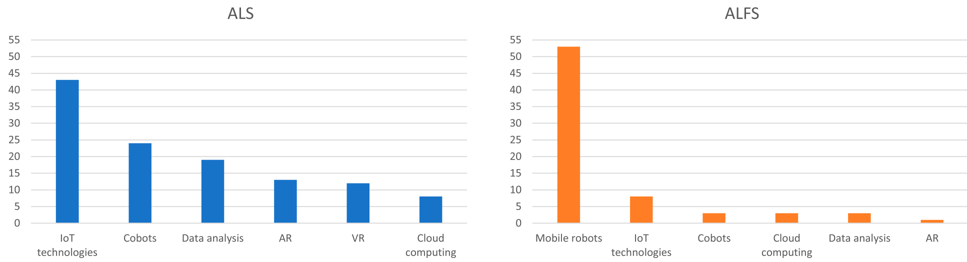

Figure 5. Industry 4.0 technologies for AS.

robots. For Hashemi-Petroodi et al. (2020b), a well-designed human-robot collaboration (HRC) system must consider the three features of resource skills, ergonomics, and resource flexibility. These authors evaluated these features to compare the interaction between humans and cobots in two different scenarios: dual resource-constrained and human-robot collaboration. The cooperation between humans and robots was also carefully investigated by Krüger, Lien, and Verl (2009); through a survey, they studied the organisational and economic aspects of this collaboration. Cyber-physical production systems and human-robot interaction were examined by Yao et al. (2018), and the framework that they proposed was validated based on an assembly case in which a human needed to move heavy parts frequently.

Cobots are not the only assistive technology that can be used in an AS; AR can be used to guide human workers in their tasks, while VR is mainly used for workplace design. However, before implementing these approaches, it is important to know how to use them and whether they will be convenient, and Danielsson, Holm, and Syberfeldt (2020), Miller, Hoover, and Winer (2020), and Marques et al. (2020) therefore attempted to address these two points. Danielsson, Holm, and Syberfeldt (2020) studied the state of the art in relation to the use of AR smart glasses, while Miller, Hoover, and Winer (2020) focused their attention on the Microsoft HoloLens, and tried to mitigate its limitations in terms of input, field of view, tracking and occlusion. They developed a visualisation application in order to overcome these restrictions. Marques et al. (2020) compared three different AR interaction methods for assembly procedures via experiments and a questionnaire. Their results can help in the choice of the best procedure, depending on the aims of the company. The creation of a layout containing an ALS, with or without a robot that can work together with a human, can be facilitated by the development of VR environments. Krishnamurthy and Cecil (2018) created a virtual environment based on data collected by sensors, in which users could interact with the system, and studied different layout alternatives and assembly processes.

Assembly Line Feeding Subsystem: Although other technologies were also applied, mobile robots were the main technology explored in relation to the ALFS. These transportation devices, unlike other equipment such as forklifts, can open up opportunities to create new guide paths using different new methods. Antonelo, Schrauwen, and Van Campenhout (2007) applied a machine learning technique called a reservoir computing network, and Mantegh, Jenkin, and Goldenberg (2010) used harmonic functions and the boundary integral equation method to create different path planning algorithms. A Bézier curve and a genetic algorithm were the approaches applied by Song, Wang, and Sheng (2016) and Elhoseny, Tharwat, and Hassanien (2018), while Unhelkar et al. (2018a) developed a mobile robot that was able to generate its path on a moving floor that was similar to a conveyer belt. Gao et al. (2019) created a new path evaluation function to estimate the localisability of the mobile robots. The importance of spike latency in path planning was highlighted by Koul and Horiuchi (2019), and a global path planning method based on an episodic-cognitive map was presented by Zou et al. (2019). Moysis et al. (2020) reported the performance of their chaotic path planning algorithm, which was enhanced with a pheromone-inspired memory technique. The energy limitations of mobile robots were taken into consideration by Jensen-Nau, Hermans, and Leang (2020) when finding the optimal path based on a Voronoi-based generation algorithm.

The extensive implementation of sensors in mobile robots gives the opportunity to create new path configurations that can guarantee better performance in terms of both time and safety. Indeed, the sensors in mobile robots are controlled by an advanced hardware and control software that allows them to do autonomous operations and communicate with other resources in the dynamic environments in which they perform their tasks (Fragapane et al. 2021). A collision-free path study can be performed in a static environment (Al Al-Dahhan and Schmidt 2020; Das and Jena 2020; Saeed, Recupero, and Remagnino 2020), in a dynamic environment (Qu et al. 2009; Muthukumaran and Sivaramakrishnan 2019; Panda, Das, and Pradhan 2017), or both (Chang et al. 2020). Simulations and experiments were used by these authors to compare their results with other solutions and hence to determine the performance of their models. Al-Dahhan and Schmidt (2020) and Saeed, Recupero, and Remagnino (2020) first found possible solution paths, and then refined them to find the optimal path. In the models created by Muthukumaran and Sivaramakrishnan (2019), Das and Jena (2020), and Panda, Das, and Pradhan (2017), each robot can take the optimal trajectory path without colliding with other robots or obstacles within the environment. Qu et al. (2009) proposed a model that needed to know in advance the environment in which it would be applied, while Chang et al. (2020) proposed a solution that was able to adapt to the unknown environments in which mobile robots perform their activities.

Before implementing a technology, it is essential to understand whether it is convenient to use it and which technology would be best to use, based on what the company aims to do. In view of this, Fragapane et al. (2020) carried out various simulations in an attempt to understand whether or not the use of mobile robots in a material handling system was advantageous. Fager et al. (2019) used experiments in their work to compare paper-based picking, light-based picking and voice-based picking with the use of AR to support picking activities for kit preparation.

The use of IoT and cloud computing can help in creating new configurations for warehouses. Zhou et al. (2019) applied these technologies to collect, store, and share data from different devices in real time in a warehouse, in order to compare two different layout configurations through a simulation.

4.2. Tactical level in assembly system 4.0

At this level, the company has already chosen the technologies that will be used, and now needs to make all the decisions required in order to allow these technologies to work.

Assembly Line Subsystem: The design of a workplace with an ALS may change if a cobot is introduced into it. Faccio et al. (2020) highlighted that it is not only the type of cobot that influences the possible collaboration with human workers and the design of the workstation, but also the characteristics of the products that are being assembled. In their work, Gualtieri et al. (2020) and Prati et al. (2020) presented case studies of the transformation of a manual workplace into a collaborative one, with improvements in its productivity and physical ergonomics. In contrast, Michalos et al. (2018b) presented a method for the transformation of a fully automated line to a collaborative one. This design, with or without a cobot, could be optimised using AR, VR, wearables and sensors. Michalos et al. (2018a) examined the use of VR in a case study with the aim of reducing the time and cost requirements of the process, and achieving the design or redesign of a workplace. Wu et al. (2020) and Yi et al. (2020) proposed two different solutions based on the application of sensors to create a smart workplace. Havard et al. (2019) used both VR and sensors to explore the design of a workplace containing a cobot. The optimisation of a workplace does not only involve the evaluation of production performance, and in order to determine whether it is well designed, an ergonomic evaluation may also be necessary. Enomoto, Yamamoto, and Suzuki (2013), Azizi, Yazdi, and Hashemipour (2019), and Peruzzini et al. (2020a) used VR to design workplaces in which the ergonomic parameters of assembly tasks were respected. Gao, Shao, and Liu (2016), Plantard et al. (2017), Wu et al. (2018), Xiao et al. (2018) and Bortolini et al. (2020) instead applied sensors to collect different forms of data in order to design an ergonomic workplace.

The data collected from time-and-motion and ergonomic analyses of an AS can then allow for the assignment of tasks within a workplace. Papakostas et al. (2016) created a software application that could assign assembly tasks in an AS based on the data available at the moment of the request. Huo et al. (2020a) and Huo, Zhang, and Chan (2020b) developed two real-time monitoring systems that were capable of reassigning tasks based on the states of the different resources in the AS. A lack of data can lead to the incorrect assignment of tasks. Fantoni et al. (2020) created a method of automatic time measurement that could precisely determine the duration of each task. An architecture based on four layers that could help to collect and share data, thus offering the opportunity to flexibly re-assign these tasks if necessary, was proposed by Qian et al. (2020).

The balancing of an AS that implements several cobots requires a knowledge of which tasks can be executed by the cobots and which cannot. A method of assigning tasks to humans or robots based on their skills, regardless of workload balancing, was presented by Bruno and Antonelli (2018), and Bilberg and Malik (2019) created a digital twin for the same purpose. Two models for the assignment of tasks with the aim of minimising the cycle time were put forward by Weckenborg et al. (2020) and Çil et al. (2020). Dalle Mura and Dini (2019) and El Makrini et al. (2019) proposed two frameworks that also took into consideration the ergonomics of the human workers when allocating human-robot assembly tasks.

Human workers can be trained before executing their tasks in the workplace using VR and AR (Yuan, Ong, and Nee 2008; Zhang, Ong, and Nee 2011; Hoedt et al. 2017). Galambos et al. (2015) used VR to replicate a work environment in which humans could be trained by interacting with the system. The effects of oral, paper-based and AR-based instructions during assembly tasks were studied and compared by Vanneste et al. (2020). An analysis of literature on workforce reconfiguration strategies in assembly lines, also considering the human-robot collaboration, is given in (Hashemi-Petroodi et al. 2020a).

The introduction of technologies such as IoT, wearables, and cloud computing to AS processes may require new frameworks or guides to enable an understanding of how to achieve this. Guo et al. (2020a) tried to cover this gap by presenting step-by-step guidelines for the implementation and transformation of an AS to a AS4.0. Tan et al. (2019) instead explained how it was possible to successfully implement a CPS in an AS.

Assembly Line Feeding Subsystem: After the choice to adopt mobile robots has been made, companies need to understand and determine how many of them are needed. Choobineh, Asef-Vaziri, and Huang (2012) estimated this number for a fleet of mobile robots. The quantity required can be influenced by the feeding policies used by companies to bring the components to the ALS, and the use of mobile robots offers the opportunity to apply a range of different feeding policies. Boysen, Briskorn, and Emde (2017), Yoshitake, Kamoshida, and Nagashima (2019), Gharehgozli and Zaerpour (2020), and Jiang et al. (2020), for example, proposed different algorithms in which mobile robots were used to move entire shelves from a warehouse to an ALS. Groß and Dorigo (2009) studied the possibility of connecting two or more mobile robots based on the type of object that they need to transport. Three different examples with collaborative robots were presented by Andersen et al. (2017), Unhelkar et al. (2018b), and Fager, Calzavara, and Sgarbossa (2020). In the studies by Andersen et al. (2017) and Fager, Calzavara, and Sgarbossa (2020), a cobot was installed above a mobile robot. This solution was used in the former to feed an ALS, and in the latter to pick components from a warehouse for kit preparation. Unhelkar et al. (2018b) instead studied the possibility of using a cobot with single-axis mobility to pick and transport the components needed to feed the ALS.

When a company has the required number of mobile robots and has decided how to feed the ALS, it is necessary to schedule the robots. Lo, Zhang, and Stone (2020) created an algorithm for the scheduling of mobile robots that took into consideration both the tasks executed by the robots and their movements. Bocewicz, Nielsen, and Banaszak (2014), Dang et al. (2014), Caridá, Morandin, and Tuma (2015), Zeng, Tang, and Yan (2015), Petrović et al. (2016), Zhou and Xu (2018), Dang, Nguyen, and Rudová (2019), Lyu et al. (2019), Kousi et al. (2019), Petrović, Miljković, and Jokić (2019), Hari, Nayak, and Rathinam (2020), and Rahman, Janardhanan, and Nielsen (2020) proposed various algorithms for the scheduling of mobile robots. Cloud computing can help in optimising this scheduling. In their work, Nielsen et al. (2017) created a cloud-based application that was responsible for all communication and exchange of data between mobile robots and the other actors in an ALS. The collection of these real-time data enabled scheduling of the mobile robots based on the current situation of the ALS. Wan et al. (2017) proposed a context-aware cloud robotic entity for advanced material handling. This solution offered the opportunity to schedule mobile robots in a more energy-efficient and cost-saving way.

IoT can be applied to help with the design of a warehouse or the space needed by an ALS to stock materials. Lyu et al. (2020) proposed an IoT solution that could optimise the positioning of the containers in a warehouse based on their dimensions, while Xu et al. (2020) created a system that was aware of the number of goods stocked, and those which could be stocked, in a specific space in a warehouse. The IoT can also improve the performance of the warehouses. Lee et al. (2018) demonstrate with a case study how the implementation of sensors in the warehouse generate a positive impact on the warehouse productivity, picking accuracy and efficiency.

4.3. Operational level in assembly system 4.0

At this level, a company must ensure that the technologies are able to work, and more importantly, it must enable them to continue to work as desired. This means that companies need to control not only whether a technology does what they want, but also how it does it. To achieve this, the AS must be constantly monitored, and if something is not working properly it must be fixed as quickly as possible.

Assembly Line Subsystem: Different sensors were used by Huang et al. (2008), Bauters et al. (2018), Li, Ota, and Dong (2018), Faccio et al. (2019), Alavian et al. (2020), Baumann et al. (2020), and Peruzzini, Grandi, and Pellicciari (2020b) to collect data from machines, human workers, products, and various forms of equipment for use in an AS. These data were used to monitor and control the AS, and allowed the user to create a digital copy or digital twin of the all the actors in an AS. Bao et al. (2020) explained how to create a digital twin application, and such applications were reviewed by Cimino, Negri, and Fumagalli (2019), who then presented a case study of a digital twin for energy consumption monitoring. Zhuang, Liu, and Xiong (2018) and Nikolakis et al. (2019a) proposed two different digital twin solutions for monitoring an AS. The data necessary for this monitoring can be also obtained from videos and pictures of the AS, and Tarallo et al. (2018), Oyekan et al. (2019), and Chen et al. (2020c) collected the data used in their studies from an analysis of videos and pictures of assembly activities. These data allowed the authors to monitor and improve the performance of the assembly processes under study.

Once collected, data need to be stored and analysed. Alexopoulos et al. (2016), Alexopoulos et al. (2018), and Guo et al. (2020b) showed how cloud computing could be used not only to collect data but also to analyse them and to share the information created from them. The information generated in this way is important, because it allows a company to be aware of what is happening in an ALS. Liu, Li, and Wang (2015a), Xu et al. (2016), Liu et al. (2017), Nuzzi et al. (2020), Ruppert and Abonyi (2020) and Tao, Leu, and Yin (2020) used information created from the collection of real-time data as a basis for the operation of their solutions and to understand how to improve them.

Although the performance of an ALS can be improved through the introduction of cobots, it is important that these devices are controlled. Mohammed, Schmidt, and Wang (2017) proposed a solution that used images of human operators taken with a depth camera and a virtual model of a robot for monitoring and collision detection. Nikolakis, Maratos, and Makris (2019b) and Malik and Brem (2020) proposed a CPS and a digital twin, respectively, to guarantee the safety of human workers who operate alongside a robot. Two different AR solutions that showed human workers the spaces in which they could perform their tasks without coming into contact with the robots were proposed by Hietanen et al. (2020).

In their work, Liu et al. (2015b) and Wang, Rizqi, and Nguyen (2020b) studied AR and computer vision, respectively, as methods of guiding human workers in real time in the execution of their tasks, while Chen et al. (2020b) used both AR and computer vision: AR as a guide for the human workers, and computer vision to monitor the assembly process. Although human workers can be guided during their activities, they may still make mistakes, and hence several solutions for greater control over the quality of the products, using different sensors and techniques, were proposed by Yu and Wang (2013), Lei et al. (2017), Colledani et al. (2018), Jiang et al. (2019), Chen et al. (2020a), Negri et al. (2020), Runji and Lin (2020), Wagner et al. (2020), Wang et al. (2020a) and Židek et al. (2020). The collection of information about these errors can allow a company to create databases of similar situations, which can then be studied in order to avoid them happening again. For example, Carvajal Soto, Tavakolizadeh, and Gyulai (2019) and Sassi, Tripicchio, and Avizzano (2019) used machine learning and deep learning, respectively, to analyse data collected from quality inspections of assembled products. A machine learning technique was also used by Kucukoglu et al. (2018) to analyse the data collected by a digital glove and hence to reduce quality errors during assembly. Liu et al. (2017) instead used computer vision to inspect the assembly process and to detect redundant objects that could compromise it.

Assembly Line Feeding Subsystem: As soon as a company has decided which mobile robots to use, based on a scheduling process, it then needs to decide on their routes. In view of this, Nishi and Tanaka (2012), Ohnishi and Imiya (2013), and Moussa and ElMaraghy (2019) proposed three different methodologies for routeing mobile robots to enable them to carry out their activities. Two methods that can allow mobile robots to follow certain routes in dynamic environments were proposed by Walker, Garrett, and Wilson (2006) and Posadas et al. (2008).

Armesto et al. (2008), Li et al. (2014), Chien, Wang, and Hsu (2017), Zhao et al. (2018), Bencherif and Chouireb (2019), Filotheou et al. (2020), and Halawa et al. (2020) focused their attention on the localisation of mobile robots in order to control them and to understand whether they were following the correct routes. Tracking the positions of mobile robots can help in increasing the performance of the ALFS, and the addition of other sensors can also improve also its safety. A range of different sensors were therefore applied to mobile robots and their environments by Huang et al. (2015), Indri et al. (2019), Keung et al. (2020), and Luo et al. (2019), to avoid collisions between them.

Mobile robots and human workers involved in transportation and preparation activities cannot do their work if they cannot find the components that they need to transport or pick. Tejesh and Neeraja (2018) implemented a warehouse inventory management system that used sensors to monitor the mobility and storage of products throughout a company. The use of sensors in a warehouse and in an ASL can control the quantities of components present in each container in real time. The data generated by such sensors were used in works by Kartal et al. (2016), Lolli et al. (2017), and Lolli et al. (2019), who applied three different machine learning techniques to analyse the collected data in order to optimise the inventory levels of the warehouses and the ALSs studied.

Table 3. I4.0 technologies for an AS, based on ALS and ALFS activities.

	ALS		ALFS		
Technology	Assembly	Control	Transportation	Preparation	Material management
Collaborative robots	X			X	
Mobile robots			X	X	X
Augmented Reality	X	X		X	
Virtual Reality	X	X			
IoT technologies	X	X	X	X	X
Cloud computing and Data Analysis	X	X	X	X	X

5. Insights

In this section, we aim to answer our first two research questions.

I4.0 technologies applications in AS4.0: The ways in which I4.0 technologies are applied in AS4.0, and hence the answer to RQ1, can be observed from Table 3 which shows these different technologies based on the activities in which they have been implemented. For the ALS, the technologies are divided into the two activities of assembly and control, while for the ALFS, they are divided into the three activities of transportation, preparation, and material management. Table 3, in comparison with the results of previous works, like for example, those that focus more on how these technologies are generally used in AS4.0 (Cohen et al. 2019a; Cohen et al. 2019b), allows us to see where these technologies can create new opportunities or applications in the activities of the AS4.0, and particularly those areas in which they are not being used at the moment.

From Table 3, we can see that there are two groups of technologies (IoT/cloud computing and data analysis) that are used in all the activities of an AS4.0. This result is as expected, due to the nature of I4.0. IoT technologies allow companies to collect all the available data from the AS4.0 (Huang et al. 2008; Lee et al. 2018; Alavian et al. 2020; Xu et al. 2020). These data then need to be stored and shared, and cloud computing is very valuable in this regard (Papakostas et al. 2016; Alexopoulos et al. 2018; Guo et al. 2020b). Cloud computing can simultaneously offer both the resources needed to save and transform these data into information, using data analysis techniques, and then to deliver them to the users who need them (Lolli et al. 2017; Carvajal Soto, Tavakolizadeh, and Gyulai 2019).

Differences were seen for VR and mobile robots, as these two technologies were used only in the activities of the ALS (Galambos et al. 2015; Hoedt et al. 2017; Havard et al. 2019) and the ALFS, respectively (Choobineh, Asef-Vaziri, and Huang 2012; Kousi et al. 2019). Although this result was expected for the use of mobile robots, we did not expect this in the case of VR. In fact, we did not find any work that addressed the use of VR in an ALFS, despite the fact that it can be used in simulations, for example in the study of human workers working within the same space as mobile robots.

The use of cobots and AR was found in both ALSs and ALFSs. In particular, they were used in the preparation activities of ALFs, where they were applied to carry out picking and kitting (Andersen et al. 2017; Kim, Nussbaum, and Gabbard 2019; Fager, Calzavara, and Sgarbossa 2020; Fang and An 2020). In this scenario, a cobot can be installed above a mobile robot so it can do its tasks by following a human worker. For ALSs, it is interesting to note that AR was used to train and guide human assembly workers and to control the quality of the assembly (Westerfield, Mitrovic, and Billinghurst 2015; Michalos et al. 2018b; Hietanen et al. 2020; Vanneste et al. 2020).

I4.0 technologies impact on the decision areas of AS4.0: The ways in which these technologies impact on the decision areas of the AS4.0, and hence the answer to RQ2, can be seen from Tables 4 and 5, which summarise the decisions that companies need to make when they decide to introduce a specific technology to their AS. These decisions are divided based on the different levels (strategic, tactical, and operational) at which they need to be made. They are also related to the decisions made in a traditional AS (see Table 1 above). This allows us to see where each specific decision for each technology fits in with respect to more traditional methods. Tables 4 and 5 also allow us to answer RQ3, which relates to the future needs of research into AS4.0, and this is discussed in the next section.

Strategic: When we talk about the configuration of the system for a technology in an AS4.0, we are referring to what it is necessary to know before deciding which technology would be best to implement in the AS. For example, the integration of a cobot into an AS can change the spaces that are necessary to allow the robot to work alongside humans, if a company wants to create instructions to train their human workers in a virtual environment, without the need for a real one, it may prefer to use VR. In contrast, if the company wants to guide their human workers during the execution of their tasks within

Table 4. Decision areas divided into different levels for each I4.0 technology in an ALS.

			Industry 4.0 Technologies in Assembly Line Subsystem (ALS)				
	Decision areas		**Collaborative robots**	**Augmented Reality**	**Virtual Reality**	**IoT technologies**	**Cloud computing and Data Analysis**
Long term	**Strategic**	*Configuration of the system*	• Type of cobot	• Decision of which AR instructions create	• Decision of which VR instructions create	• Type of IoT technologies	• Data to storage and analysis
		Level of automation	• Type of cobot • Skills to use the cobot	• Type of AR devices • Skills to use the AR devices	• Type of VR devices • Skills to use the VR devices	• Type of IoT technologies • Skills to use the IoT technologies	• Type of Cloud Computing system and/or Data Analytics techniques • Skills to use these technologies
Medium term	**Tactical**	*Workplace design*	• Workplace design	• How to create and share the instructions	• Workplace design	• Workplace design	• Information to create and share • How to create the information
		Assembly line balancing	• Balancing of the assembly line with the cobots	• Number of AR devices	• Number of VR devices	• Number of IoT tecnologies	• Number of information to create
Short term	**Operational**	*Sequencing*	• Sequencing of the operations	• Real-time information sharing → assembly instructions	• Real-time information sharing → assembly environment and instructions	• Real-time control of the quality of the assembled products, machines, workers, and environment	• Real-time sharing and displaying of the information
		Control of the ALS	• Control of the system	• Control of the system	• Control of the system	• Control of the system	• Control of the system

Table 5. Decision areas divided into different levels for each I4.0 technology in the ALFS.

			Industry 4.0 Technologies in Assembly Line Feeding Subsystem (ALFS)			
	Decision areas		**Mobile robots**	**Augmented Reality**	**IoT technologies**	**Cloud computing and Data Analysis**
Long term	**Strategic**	*Configuration of the system*	• Warehouse design • Type of mobile robots • Design the guide path	• Decision of which AR instructions create • Type of AR devices	• Type of containers	• Data to storage and analysis
		Level of automation	• Type of mobile robots • Skills to use the mobile robots	• Type of AR devices • Skills to use the AR devices	• Type of IoT technologies • Skills to use the IoT technologies	• Type of Cloud Computing system and/or Data Analytics techniques • Skills to use these technologies
Medium term	**Tactical**	*Feeding policy selection*	• Feeding policies	• How to create and share the instructions	• Positioning of the IoT technologies	• Information to create and share • How to create the information
		Scheduling	• Scheduling of the mobile robots • Number of mobile robots	• Number of AR devices	• Number of containers in the warehouses and in the ALS	• How to share the information
Short term	**Operational**	*Routing and material/information management*	• Routes of the mobile robots	• Real-time information sharing → sequencing of kitting and picking information	• Real-time control of the capacity of the container	• Real-time sharing and displaying of the information
		Control of the ALFS	• Control of the system	• Control of the system	• Control of the system	• Control of the system

the environment where they work, AR may be the best solution. Moreover, the decisions that are made in regard to the types of containers and the types of warehouse in which these will be used may influence the kind of sensors that can be applied to them and the transportation devices that can transport them. In view of all the data that can be collected, companies also now need to decide on the level of automation of their AS. This because the different forms of data that can be collected require different sensors and different techniques to analyse them. Moreover, on the type of information generated by the data analysis, the selection of the most proper device is very important. This information can be as simple as just numbers or text, but can also be more complex, such as pictures or videos. This choice depends not only on the type of information to deliver but also on who will receive it and which tasks have to be performed. For example, in the case of large products, wearable devices will be more preferable than fixed ones more useful in the case of small products assembled in standard workstations. Furthermore, the main purpose of using such technology will also affect its implementation and hence the level of automation of the ASs. The selected technology will influence the skills that will be required to use it. The company then needs to know whether it already has someone with these skills or whether it will have to hire or train someone. In the case where the company can rely on internal resources with such skills, the technology selection will be facilitated, as well as their implementation. This will also increase the general technological knowledge of the whole company in the case where these resources share their expertise. Furthermore, even if a company is not planning to implement any new technology in its AS4.0, a strategic decision may be to hire skilled human workers, with previous experience in I4.0 projects. These workers are valuable resources that could assist and guide the company toward the possible implementation of I4.0 technologies.

Tactical: When the technologies have been chosen, the company needs to design the workplace in which they will be used and to determine how they will be used. Some forms of technology, for example VR, can help in designing the workplaces where other technologies will be used. Indeed, VR provides the possibility of creating virtual environments where human workers can interact with the virtual elements and also where the technologies, like cobots and mobile robots, can be modelled. This facilitates the study of different workplace designs. As a result of the virtual environment different alternatives between the human workers and the technologies can be studied before their implementation in real workplaces. This helps to create optimal workplaces where technologies and human workers can interact with optimal results. The feeding policies determined by the company can also influence the design of the workplace, since the transportation of a container, like a pallet, may require a different space when it is delivered to the workplace, compared to the transportation of a shelf. A time analysis and decision aid may be necessary at this level in order to identify the numbers of cobots, workers, AR devices, or mobile robots that are required to execute the different tasks in the AS. In conjunction with this time analysis, it may be necessary to evaluate the ergonomic impact of the technologies while they are being used, in order to understand where and when it is best to use them. The time analysis and ergonomic impact can be evaluated due to the sensors applied in the technologies and by the human workers, such as IoT sensors or wearable devices. Another possibility is the combination of cameras that monitored the movements of the technologies and the human workers as a result of computer vision algorithms. At this level, a company is aware of which data it must collect and now needs to know where to install the sensors to collect these data. The sensors need to be installed in protected and proper places in order to reliably and safely collect the required data. Therefore, the significant amount of data that companies can collect from the sensors needs to be analysed and validated. This is because the next step is to decide what information the company is interested in creating from the collected data and how this information will be created. The final decision also relates to the issue of the final recipient of such information. It is important to create specific information for each user in order to avoid possible misunderstandings that can result in the execution of incorrect activities or decisions.

Operational: At this level, the technologies have been implemented and are working. The employees now need to know how to do their jobs, and the company needs to control them to ensure that they are doing them to the best of their ability. The daily activities that are assigned to cobots need to be sequenced based on the products that they are required to produce, and the routes of the mobile robots must be generated according to the paths that they need to take. The AR and VR equipment must also receive the information necessary for the human workers to carry out their activities. This information needs to be sequenced based on what activities the human workers will carry out when they are using the technology and it needs to be easily comprehensible and personalised. Indeed, there is a negative impact in the case of incorrect information, but also if the information is not understandable or clearly visible to the user. Therefore, a good control loop of accuracy and usability is important for continuously improving their utilisation. Moreover, the correct information, at the appropriate time and place, not only needs to be sent to the AR and VR devices, but also to all the actors in the AS4.0 that require it. This needs to be carried out efficiently whilst avoiding a possible loss of information during the communication process. Cloud computing can provide a way of sharing all this information, without the need for physical connections, across all of the devices in the AS that have the capacity to give them in output. All of this information can be generated using data analysis techniques and algorithms, and these need to be checked periodically to ensure that the parameters that they are using are still valid; alternatively, they may need

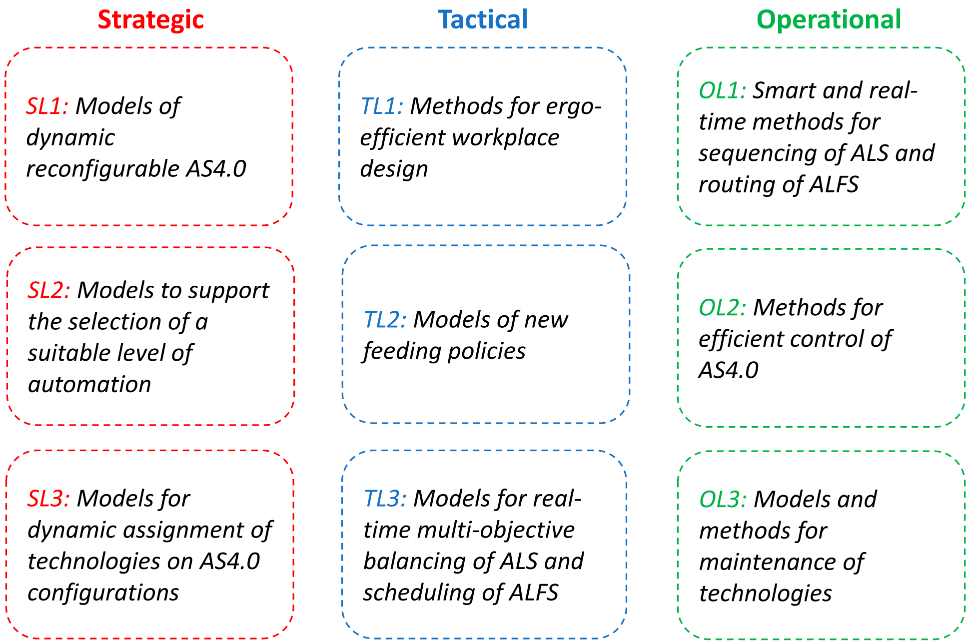

Figure 6. Future research opportunities at the different levels.

to be updated, for example due to variation in customer demand. These techniques and algorithms also need to be updated if new techniques or algorithms that are more efficient are developed, or if they fail to work properly. It is not only the software aspects of the technologies that need to be checked; the hardware parts of technologies such as mobile robots, cobots, AR and VR devices also need to be periodically maintained and updated in order to avoid problems during the execution of their tasks. For example, the malfunctioning of the batteries that power the mobile robots affects their performance in terms of speed and autonomy, thereby having a negative impact on the performance of the AS4.0. Checking the hardware of the technologies can help to avoid not only losses in the performance of the AS4.0 but also in its security. It is therefore clear that appropriate maintenance measures are important for strictly controlling the reliability and availability of the hardware of the technologies.

6. Future research opportunities

In this section, we explore possible future research into AS4.0, reported in Figure 6, to answer our third and final research question, RQ3. In order to achieve this, we use the knowledge acquired from the analysis presented in this work. This represents an attempt to inspire future researchers in the field of AS4.0 to address new research challenges that go beyond the study of the use of these technologies. We use the same classification as in Section 4, with future research opportunities divided based on strategic, tactical and operational levels. At the strategic level, the implementation of emerging technologies is investigated mainly through simulation. Indeed, simulation gives the opportunity to study, before the actual implementation, the benefits of the technologies under investigation, which ones performs better and how they perform and should be used. Given a positive outcome from simulation, the next step is to implement such technologies. The use of simulation allows for the investigation of a potentially infinite number of scenarios with a limited knowledge of the technology and its effects on the system. Consequently, decision makers, practitioners, engineers and managers can be made more aware of the behaviour of the system and its interaction with technologies. Moreover, it is mandatory to validate the simulation results, so some data collected from ad-hoc experiments or observations from previous applications are very helpful as input for the simulation, as well as validating its results.

At this point, at the tactical level, pilots are used to recreate real scenarios where technologies are under investigation mainly through experiments and in some cases with the observation of similar cases in order to tune their implementation by improving their performance.

Simulation can still be used to study different situations starting from the data derived from the experiments. If the results of the experiments are positive, pilots are then extended and industrialised to be integrated with the rest of the facility. Finally, at the operational level, it is possible to study it through observations. These observations give the opportunity to obtain data to see if everything is working as it should be and to create simulations of possible future scenarios based on real data. In this case, experiments can still be used to investigate new ad-hoc solutions and so to feed simulation models with dedicated data. At the operational level, simulation is mainly used in order to exploit the potentialities of digital twins and so of predictive data-analytics, thereby gaining knowledge from data.

6.1. Strategic level

6.1.1. Research opportunities SL1: models of dynamic reconfigurable AS4.0

We observed that mobile robots and cobots were the two of the most frequently studied technologies. One aspect identified in our analysis that was not deeply investigated was related to the high level of reconfigurability that can be enabled from these two technologies, and especially from the use of mobile robots. In a reconfigurable system all the equipment, human workers, or material handling systems should be rapidly added, removed, modified or interchange in response to changing needs and opportunities. Due to their flexibility, mobile robots can facilitate companies in creating AS4.0 configurations (primarily networks rather than line configurations) that change dynamically based on the current demand. In fact, using mobile robots as a workplace in which human workers perform the assembly tasks, can give the opportunity to increase or decrease the number of workplaces that are needed based on the demand and the same mobile robots can also be used to transport all the components that the human workers need for each task (Battaïa et al. 2018). Moreover, a mobile robot can be equipped with a cobot to create a collaborative mobile robot that can pick and transport components and then execute assembly tasks based on the same components. Although these approaches can be easily adopted to create different AS4.0 configurations, it is essential to understand which is the best configuration, in terms of performance and cost, based on the situation under study. Future studies should therefore focus on mathematical and simulation modelling of the different configurations created by these two technologies. These models will allow us to determine the parameters that can affect the reconfigurability of the system. Sensitivity analyses will also be useful to study how these parameters can change the reconfigurability and the performance of the different configurations. In the end, decision support systems, like decision trees and evolutionary algorithms, can be created in order to support decision makers in determining which is the best configuration to adopt based on their needs.

6.1.2. Research opportunities SL2: models to support the selection of a suitable level of automation

I4.0 technologies can be used to execute a task or to collect and share data, for example to assist operators or to support managers. Hence, the choice of a technology is not only related to the help that it can give in terms of the physical and cognitive aspects of the execution of a task, but also to the data that can be collected and shared with it. A huge amount of data can be collected and sent to the AS4.0, and new models are needed to support decision makers in regard to how to automatise the AS4.0. These models can provide a methodological toolbox that can guarantee a structured implementation of the technologies to ensure a suitable level of automation for AS4.0. For example, decisions that need to be made on the most suitable amount of information to give to the operator through AR or assistive technologies (which relates to the level of collaboration between operators and collaborative robots), or on the configuration of the systems, can be made by managers based on the available data. To create these models, further research is required specifically in order to deepen our existing knowledge of the case where multiple technologies work together to complete different tasks. Simulations and experiments are needed in order to validate these models. The results from these methods, together with the possibility to do sensitive analysis, give the opportunity to evaluate different cases with advanced data analytics tools that in the end can create decisional support systems. Companies can benefit from these results since they will help them simplify the decision process of the level of automation to adopt in their AS4.0.

6.1.3. Research opportunities SL3: models for dynamic assignment of technologies on AS4.0 configurations

We have seen that at this level, companies have to choose the configuration and the level of automation of their AS4.0. It can be that the choice of a configuration compromises the possibility of using a specific technology and instead that technology is most appropriate for another kind of configuration. Moreover, the performance of the AS4.0 is correlated to the combination of configurations and technologies, with synergic effects in some cases. Therefore, at this level, to determine the goals of the AS4.0 that the companies want to obtain, it is necessary to have a guide that supports decision makers in the correct assignment of the different technologies to the configurations under analysis. The decision of the assignment of the technologies on the different configurations will facilitate other decisions, such as, for example, the number of devices to buy and the skills that are necessary in the different configurations. In order to understand if a technology is good or not for a specific configuration, future research should consider its behaviour and performance in different configurations. Case studies, experiments and simulations represent opportunities to collect the necessary data to create new decisional support systems to guide companies in better deciding which configurations to implement for the different technologies. It will also be important to study the behaviour and performance of more technologies together and the interaction between the technologies and the human workers to see if their implementation together generates issues in the configuration or not.

6.2. Tactical level

6.2.1. Research opportunities TL1: methods for ergo-efficient workplace design

When a human worker is involved in the execution of activities in the AS4.0, he or she should be able to do these without worrying about the workplace in which these activities need to take place. To enable this, the workplace needs to be optimised, and VR can be used in this instance to help create virtual environments that replicate the real AS, to allow a user to design and study a range of configurations of workplaces without needing a physical model. These virtual solutions need to be further investigated, and new parameters such as the ages of the human workers or the integration of additional technologies into virtual environments should be evaluated. Different human characteristics may require different workplace design solutions in order to facilitate high levels of ergonomic comfort for manual processes and to increase efficiency. Data collected from human workers while they are executing their activities can be used to adapt the workplace based on the tasks that need to be executed within the workplace and the characteristics of the human worker that is executing them. Motion capture (mocap) systems can be used to collect these data. A mocap system gives the opportunity to create a virtual copy of the object that is under study by utilising sensors or cameras to recreate its movements. Experiments are first needed in order to determine the relevant parameters for optimising a workstation, and case studies will then be required to verify whether these parameters are correct, in order to design a workplace that is not just optimal in terms of performance but is also efficient in terms of human well-being. In relation to the acceptance of technology, further studies could provide insight into the factors affecting success. Data analysis and Artificial Intelligence techniques can be useful at this step.

6.2.2. Research opportunities TL2: models of new feeding policies

The use of mobile robots, with or without a cobot, can open up the possibility of creating new feeding policies, since if these are used to move shelves, each level of the shelves can be designed to store different components in different ways. For example, although a kit can be stored at one level, while only one type of component can be stored at another level, the shelf may be delivered to one or more workplaces. Instead, if mobile robots are used in conjunction with a cobot, these collaborative mobile robots can be used to pick the individual components from warehouses or supermarkets and to transport them to the ALSs that need them. In order to study these new opportunities, advanced modelling and simulations and then real case studies will be needed, to validate the results of the models. Moreover, AR can be used to support the human workers involved in feeding tasks by giving them instructions such as which component to pick, where to put the components, and how many components to pick. When AR is used together with mobile robots, the two technologies need to be integrated. This means that the AR instructions should not only able to change based on the demand for products but also based on the characteristics of the mobile robots that are used to execute the feeding policies. In addition, these AR instructions need to change based on the components that the human workers have to pick and must be visible and in the correct position for the particular type of mobile robot that is used. Further investigation and testing through experiments that replicate real scenarios can better highlight the strengths, weaknesses, and the potential advantages that the use of AR with mobile robots can generate in terms of developing new feeding policies.

6.2.3. Research opportunities TL3: models for real-time multi-objective balancing of ALS and scheduling of ALFS

The balancing of the new ALS needs to take into account not only the assignment of the different tasks within the different workplaces, but also the technologies that will be used in the ALS. However, no research has yet studied how these technologies can affect line balancing. For example, the choice to adopt AR to support operators in executing the tasks is not yet well-investigated and in particular the impact on the balancing of the ALS. In any case, the use of AR is very interesting since it can help to reduce line balancing effort for the ALS by creating flexible, dynamic, self-balancing ALSs in which the number of workplaces may change based on the current demand from customers. Hence, if demand is low, a single operator may be able to do all the tasks in one workplace, thanks to the use of AR, whereas if demand grows, the number of workplaces can increase, and the AR instructions will need to be divided between the workstations. One avenue for future research would be to investigate the number of AR devices that are needed and the ways in which the instructions that they display to the human workers need to change. The various types of mobile robots, which may or may not have a cobot mounted on them, allow for new tasks to be carried out in the ALS and in the ALFS. For example, we saw that a mobile robot with a cobot can pick up a component from the warehouse, transport it to the ALFS, and then execute a task based on this component in the ALS. The new dynamic network configurations that have become possible require new assembly line balancing methods that consider the evolutionary aspects of such configurations, with multi-period and multi-objective models that can be applied in real time to adapt the workload of the workstations without affecting the work of the operators. Economic, performance, and ergonomic objectives should be considered together.

A mobile robot can be used solely as a workplace or as a transportation device. Different mobile robots can carry out different tasks, giving rise not only to new opportunities but also to a more complex problem in relation to scheduling these mobile robots. A company needs to optimise the use of its mobile robots according to the tasks that they are able to do, and new scheduling models therefore need to be created that can consider all the possible tasks that these mobile robots can carry out. These models first need to be studied through simulations, and then with experiments or case studies in order to verify the results. A connection between the different actors in an AS4.0, thanks to all the sensors and hence the collected data, can allow for synchronised assembly line balancing and scheduling in order to simultaneously optimise both the assembly and the activities needed to deliver the components. Future investigations into methodologies for dynamic and synchronised assembly line balancing and scheduling of the AS4.0 are needed in order to allow companies to use their technologies in an optimal way.

6.3. Operational level

6.3.1. Research opportunities OL1: smart and real-time methods for sequencing of ALS and routeing of ALFS

ALSs need to know the sequence of products that they have to assemble on a daily basis, and mobile robots need to know the routes to follow to arrive at their destinations. Algorithms developed in the future to solve these problems will need to take into consideration the new information generated by the AS4.0 in a predictive and prescriptive way, which will involve not only reacting to the changes required but also anticipating them and adapting in a proactive way. For example, a new sequencing algorithm may consider the fatigue of the human workers when deciding which products to assemble or which workers should execute the tasks to make them. If the human workers are tired, it may be possible to sequence products that are easy to assemble, or to let the workers take a break to recover their energy. Sequencing can be done at the same time as routeing when the products to be assembled are determined with the goal of minimising the routes travelled by the mobile robots. Sequencing should also take into account the quantity of components stored in the warehouses and supermarkets, i.e. to optimise inventory management by reducing stocked quantities by as much as possible. Sequencing and routeing can be synchronised to allow products in an ALS to be assembled using only the components that are closest to that ALS. To achieve this, the routeing of the mobile robots must consider their positions in real time; only the mobile robots closest to the components will be used to transport them to the ALS. This synchronised sequencing and routeing can reduce the travelling time of the mobile robots and can also increase the productivity of the ALS, since the components are delivered more quickly.

6.3.2. Research opportunities OL2: methods for efficient control of AS4.0

Today, it has become possible for the first time to control the quality of the products, the assembly activity, and all the activities of an AS4.0. This is facilitated by the huge amounts of data that can be collected from an AS4.0 if its activities are monitored, including data from each step of the assembly tasks, from the products being assembled, from the mobile robots while they are working and so on. After collection, these data need to be understood and analysed, in order to allow companies to use them. Data analysis techniques can be applied to these data to give useful information as output. New machine learning and artificial intelligence algorithms that transform data into information can be developed by studying the different activities of the AS4.0. Simulations will be useful in order to understand the performance of the methods, and experiments with real scenarios should then be carried out. It is important that the right data are collected to ensure the success of these methods and to give valid results, and more research is needed to identify the factors that make a data analysis technique reliable.

Surveys of practitioners can help in developing an understanding of the factors that can increase reliability. More reliable are the results of a data analysis technique and more precise can be the control of the AS4.0. At the same time higher can be the benefits that can be generate from these analyses. In the material management activity, for example, the adoption of data analysis techniques can open the opportunity to optimise the stock of materials in the warehouses and workplaces, and at the same time the flows of these materials in the AS4.0 in a dynamic and real-time way, such as dynamic Kanban systems, dynamic replenishment, integrated replenishment policies. New objective functions, for a dynamic and synchronised stock and flow of the material, can be defined in order to improve the performance of material management in an AS4.0. Benefitting from all these data and information, it is possible to model all, or parts of, the AS4.0 in order to create its digital twin. The digital twin of the AS4.0 gives the opportunity to control in real-time what is happening in the AS4.0 and to simulate what can happen in the future using predictive analysis models. Indeed, it allows us to see, for example, how mobile robots work in a single day and then simulate their performance for an entire week. This simulation can be useful for understanding whether the mobile robots will decrease their performance or not after a period of continuous work. Although digital twins have significant potential, it is important to understand what it is relevant to monitor. Therefore, future studies can be orientated towards understanding which digital copies are most important to create based on the characteristics of the AS4.0. Case studies, experiments and interviews with the practitioners can help to create frameworks to follow to create the digital copies whilst simultaneously verifying their reliability.

6.3.3. Research opportunities OL3: models and methods for maintenance of technologies

As discussed in the previous section, both the software and hardware aspects of these technologies need to be controlled and updated. All of the sensors in the AS4.0, the mobile robots, and the AR devices must operate without problems over their lifetimes. For example, the sensors must collect all of the appropriate data without missing any, and the mobile robots must run at a certain speed to execute their tasks. The development of new models and methods for the maintenance of these technologies, both predictive and proactive, should therefore be a subject for future study. These models and methods can help to avoid a loss of performance of the AS4.0 due to hardware problems with the technologies. It is important that these methods recognise when the performance of a particular technology is reduced, even if problems are not evident, and when it must be replaced by a new model. Technology must also be replaced when it becomes obsolete. New data analysis techniques should be created, creating predictive analytics models, to predict when both of these situations are likely to occur. The information created by these techniques can then be sent to the technologies that are recognised as obsolete or that are not working properly to make them stop working. Once they stop, they can be evaluated in order to understand whether to fix or dispose of them.

7. Conclusion

The systematic literature review presented here reveals that despite the benefits that I4.0 technologies can bring to ASs, it is necessary to carry out more research in order to exploit their full potential. Researchers should not limit themselves to studies of how a technology works. Although these are important, they are not sufficient, since this technology will be implemented in a complex environment such as an AS. In an AS, each technology does not operate alone but is integrated into a process that involves several actors, such as human workers, machinery, and other technologies. Each actor has certain tasks to complete, which may require cooperation from two or more other actors. Moreover, companies need to know which decisions they must make when they want to plan to use a technology (strategic level), when they have to decide which technology to use (tactical level), and when they are using this technology (operational level). For these reasons, we first reviewed how these different technologies were used in ASs as part of their activities, and then proposed a future research agenda that can be followed in order to start to reduce the gaps highlighted here. In particular, have seen that the creation of the new AS4.0 requires the study of new advanced solutions at three different levels (strategic, tactical and operational). At the strategic level, one of the most interesting challenges in the AS4.0 is to understand which technologies to use in order to create reconfigurable AS4.0s. It is important to understand first what is required to create a reconfigurable system and then how the technologies can help in developing one. Mathematical optimisation models can be created and then simulated to generate multi-case scenarios that can help the development of decision support systems to help to choose the configuration of the AS4.0 and which technologies to use in it. At the tactical level, the AS4.0 is characterised by the multi-purpose use of the technologies. Therefore, at this level, the challenges are related with the creation of models and methods that can solve multi-objective problems (time, ergonomics, costs, energy and others) that can involve the design of the AS4.0 and their feeding, balancing and scheduling. At the operational level, the major challenges that we individuated are related to the daily control of the technologies in order to make them work and to keep them working with the same efficiency in order to do not compromise the performance of the AS4.0. Therefore, to make this happen, it is necessary to create data-driven models and methods to control and maintain the technologies and the AS4.0. Moreover, the development of predictive analytics models based on the huge amount of data available from sensors that can forecast the behaviour of the technologies and the performances of the AS4.0 can be an interesting challenge for future studies. We hope that researchers who are already studying or intend to study this topic can find useful ideas in this work and will be inspired to create new ones.

DAS statement

'The authors confirm that the data supporting the findings of this study are available within the article'.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Paper 2

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Introduction to Material Feeding 4.0: Strategic, Tactical, and Operational Impact

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Abstract. Mass customization, the process of producing a low-volume high-variety of products, is changing production environments. In Material Feeding (MF) this means a huge increment in the number of parts, and information, that need to be managed during the different MF activities. If companies want to get high performances from their MF activities, they need to be able to manage these changes in the best manner. Industry 4.0 technologies are introducing new opportunities to help companies in the execution and control of the MF activities. It is important for companies to be able to understand how to implement these technologies in their processes and how to take these opportunities. In order to facilitate this, in this paper the concept of Material Feeding 4.0 (MF 4.0) is presented for the first time, as Material Feeding where the Industry 4.0 technologies are introduced. The impact of the identified technologies is studied at a strategic, tactical and operational level.

Keywords: Material Feeding · Industry 4.0 · Assembly system · Strategic · Tactical · Operational

1 Introduction

The demand for customized products is increasing. A high demand of customized products implies that the production and assembly lines require to be fed with an enormous amount of different parts. Material feeding (MF) describes all the activities that are responsible for the provision of components, parts, equipment, etc. to production and assembly systems when needed [1]. If companies want to satisfy the demand of their customers these activities need to be continuously improved and optimized. In this paper the focus will be in the assembly system (AS). MF, in AS, can be performed in different ways, by storing all parts near the assembly line or pre-processing parts and delivering them when needed [2]. In the last years with the so-called Industry 4.0 revolution, both AS and MF are considering the introduction of the technologies that this revolution is offering in their planning and control processes. However, although other works already exist that try to study the effects of these technologies on the AS, [3, 4], still no work exists about their effects in the planning and control processes of the MF systems. Although in literature the terms Supply Chain 4.0 and Logistics 4.0 have been already discussed with a broader perspective, [5, 6], in this paper we focus on the specific process and set of activities related to MF. The idea

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is to understand which are the emerging technologies that can be implemented in the MF activities and how their implementation can impact at three levels: strategic, tactical, and operational. The remainder of this paper is structured as follows. Section 2 provides a review of the existing literature concentrating on the MF activities. Section 3 illustrates and discusses the results obtained from the review of the literature. Finally, in Sect. 4 the paper is shortly summarized.

2 Review of the Existing Literature

Examples of Industry 4.0 technologies in AS are: Internet of Things (IoT), Big data, Cloud Computing, Augmented Reality, Collaborative Robots, and Additive Manufacturing [3]. These technologies affect the performance of the AS activities. In MF it is not yet defined which emerging technologies can be used. The main activities of MF are transportation, preparation, and material management [7]. Transportation implies the process of moving all the components, parts, from a point A where they are stocked to a point B where they are requested. The preparation implies the processes of handling and repacking parts into load carriers used for the corresponding line feeding policy [7]. Material management instead includes all the process related to the storage of components and products. For the storage of components, two of the possible solutions are the central receiving stores and the supermarkets [8]. An extensive review of the existing literature on the subject has been carried out to see what is possible to find about Industry 4.0 technologies that can have an impact on these three activities. We used Scopus database as search engine limiting the research from January 2006 to March 2020, English as language, and journal and conference papers as sources.

2.1 Transportation

In the planning and control of the transportation activity one of the most important decisions is the choice of the transportation devices. Examples of traditional transportation devices are the forklift, tow train, or feeder line [8]. Thanks to the technology development, new solutions have appeared in the last few years [9]. First the Automatic Guided Vehicles (AGVs), driverless vehicles that follow a fixed path in order to move from a point to another [10], and now Autonomous Mobile Robots (AMRs) are getting more popular due to their flexibility [11]. These mobile robots can move without following a fixed path and use cameras and sophisticated software to identify their surroundings and take the most efficient route to their destination [12]. AGVs and AMRs are platforms in which you can implement different additional equipment/resources such as lifting systems and collaborative robot. They can be used as “workstations” to assemble the products [13] or to move shelves from the warehouse to the AS [11]. Based on how companies decide to use them, they will face different problems in order to optimize the performances. For example, if the AGVs/AMRs are used to move the shelves for the picking operations, an example of a possible problem might be when non-completed shelves have to be moved using AGVs/AMRs that usually move complete shelves. A solution to this problem is presented in [14] where the authors proposed a scheduling method to move the shelves even if they are not complete. In [15] a cloud-based architecture that controls and improves the collaboration of the AMRs is presented. Simulations showed that using this cloud-based architecture gives the opportunity to improve energy efficiency and save costs. AMRs seem to be a very prominent technology in order to improve the transportation activity. This is also thanks to the development of more powerful Data Analytics techniques.

2.2 Preparation

In the preparation activity for AS we can find the picking and kitting process [1]. The process of picking can be described as manually seeking a particular item in storage according to a list, taking that object and putting it into a bin/container the appropriate transport vehicle, and bringing the objects to the required location for processing [16]. The kit preparation process instead supplies AS with kits of components. The kits are prepared at a kit preparation workspace apart from the AS [17]. Picking and kitting operation can be facilitated using a AMRs to transport the necessary components from the warehouse to the AS [11]. AMRs are not used only for the transportation. In the last few years many manufacturers have started to develop mobile robots with various functions [9]. If a collaborative robot is integrated with a mobile robot this can be called collaborative mobile robots [18]. In [18] the collaborative mobile robot is used to perform a part-feeding task. The validity of the solution is granted by the successfully performed tests. Another example of a collaborative robot mounted in a mobile robot is presented in [17]. The collaborative robot sorts the components that have been picked by an operator into a batch of kits. The mobile robot gives the opportunity to the collaborative robot to do its operations moving together with the human operator. This is done safely and relieves the human operator of activities associated with sorting components into kits. Kitting preparation in the context of material supply to AS can be performed utilizing augmented reality (AR) [19]. AR is used in single kit-preparation and in batch preparation. The experiment demonstrates how AR is competitive both in terms of time-efficiency and picking accuracy. AR is used also in picking activities. The main improvements that AR can give to picking operations are the errors reduction and time efficiency [16, 20, 21]. The preparation of the different components and parts to deliver at the AS is a very important activity. A mistake in this activity means a reduction in the performances of the AS. The introduction of AR in this activity is made in order to reduce the probability of making mistakes.

2.3 Material Management

Data Analytics techniques, such as data mining algorithms and machine learning algorithm, are becoming more popular and powerful with the advent of Industry 4.0 [22]. These techniques can be used to improve the material management activities of a company. For example, in [23] a machine learning algorithm is proposed to optimize the warehouse storage location allocation. The solution can improve the efficiency of warehouse operations in case of weak correlation between the stock keeping units. Whereas in [24] a positioning big data forecasting model is used in order to predict the trajectory of the mobile robots. This can improve the safety, reliability and stability of the mobile robot navigation. The introduction of mobile robots in the warehouses can mean a change in their design. Mobile robots allow spatial flexibility and expandability. If a warehouse needs more capacity, one simply adds more pods, drives, and stations [11]. In order to manage the inventories of warehouses and ASs it is possible to adopt new smart solutions. Internet of Things (IoT) and Cloud computing can be used to automate inventory systems [25]. An example of a solution that can improve this automation of inventory systems is presented in [26] with the concept of self-optimizing Kanban. Self-optimizing Kanban systems autonomously adjust their capacities as well as the quantity of cards in circulation according to predefined performances. In order to use these systems, it is important to collect all the data of the quantities inside the warehouses in real-time and to use data analytic algorithms to manage the collected data. The data are the most important resource in material management. It is important to know which data need to be collected and how. Once the data are collected, they need to be analyzed in order to obtain valuable information. IoT technologies and Data Analytics techniques will help companies in this MF activity.

3 Material Feeding 4.0

In Fig. 1 we see the results obtained from the review of the literature. From the figure we can see that the most adopted technologies in MF activities are: mobile robots, augmented reality, IoT technologies, Cloud Computing and Data Analytics. These are the technologies that can be present in a MF 4.0 system.

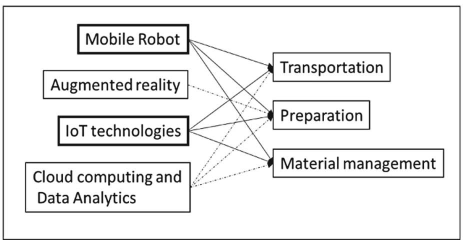

Fig. 1. Industry 4.0 technologies for Material Feeding activities.

Table 1 summarizes where the technologies impact in the different activities at a strategic, tactical, and operational level. The table helps to think about new research challenges that can appear if some of the technologies identified are introduced in the MF system. In order to state the impact of the different technologies at a strategic, tactical, and operational levels in MF 4.0, the scope of every level is shortly explained in the following. Decisions of different levels affect each other and should be considered in an integrated way regarding the intra-organizational decision levels as well as the inter-organizational hierarchy [27]. Due to page restriction, we will use the mobile robots as an example.

Table 1. Decision areas of Material Feeding 4.0. Impact of the different technologies in planning and control.

	Impact level		
Industry 4.0 technology	Strategic	Tactial	Operational
Mobile robots	• Type of mobile robots • Design the guide path system • Warehouse design • Skills to use the sytem	• Feeding polices • Number of mobile robots • Schedulling of the mobile robots • Human-mobile robot interaction	• Routes of the mobile robots • Contol of the system
Augmented reality	• Type of AR devices • Skills to use the AR devices	• Number of workers • Ergonomic of the system	• Real time information sharing → sequencing of kitting and picking information • Control of the system
IoT technologies	• Type of IoT technologies • Type of containers • Skills to use the IoT technologies	• Number of containers in the warehouses and in the AS • Position of the IoT technologies	• Real time control of the capacity of the container • Control of the system
Cloud computing and Data Analysis	• Type of Cloud Computing system and/or Data Analytic techniques • Data to storage and analysis • Skills to use these technologies	• Information to create and share • How to create the information	• Real-time sharing and displaying of the information • Control of the system

3.1 Strategic Level in MF 4.0

Strategic decisions are those decisions that have an influence over the years and a long-term impact on the performance of the MF. Once a strategic decision is made, it is very unlikely to be altered in the short term. They are usually taken at the highest levels of management, include a wide range of uncertainties and carry higher levels of risk. In MF 4.0, the most important decision at this level for all the MF 4.0 activities, is the choice of the technologies to adopt. It is possible to decide gradually which are the technologies to implement in the different activities. Which type of mobile robots to buy will influence all the decisions that a company has to face after their purchase. A mobile robot can be used only as a transportation system or it can be integrated with collaborative robot for picking activities [9, 17]. This together with the flexibility of the guidance system of a mobile robot and its dimensions will influence the design of the possible paths and of the warehouses (central receiving stores or the supermarkets) where it will work [10, 12]. The design of the warehouses can be also influenced by the different types of containers that the mobile robots can transport [11]. The investment that a company makes when it decides to buy the mobile robots is not related only to the purchase of the robots. Someone needs to know how to use them. If the mobile robots are introduced in one or more of the MF activities, it is important to know which skills are needed to use them and what is necessary to do in order to best implement them. This can influence the performance given by the mobile robots. For example, if the company decide to not hire new workers that already know how to use them, it is possible that during the first period, their performance will be lower than the expected. This because a certain amount of time is needed to learn how to use them.

3.2 Tactical Level in MF 4.0

Tactical decisions are decisions and plans that concern the more detailed implementation of the strategic decisions, usually with a medium-term impact on a company. At the tactical level, the decisions about which are the technologies to implement are already made. For the mobile robots this means that the company has decided which type to buy. At this level, for all the MF 4.0 activities, it is important to prepare the different technologies to be used. The first thing to understand is which are the feeding policies to be adopted [1]. The flexibility of mobile robots can change the application of the feeding policies making one policy more convenient than another. For example, it can be more convenient to prepare kits than move entire pallets. Mobile robots are also more flexible with respect to the transported volumes and they can adapt themselves with the variation of the material flow. The chosen policies can influence the number of mobile robots that the company needs and respect with traditional transportation devices it is possible that new algorithms are necessaries to calculate this number. In the scheduling phase of the mobile robots, the company decides when, where and how a mobile robot should act to perform tasks [10]. A new problem to solve during this phase is which mobile robot to use based on the operations needed to perform [9]. This because there are different types of mobile robots that are going to be implemented based on the activities that they must do. In this phase is important to consider also the ergonomic aspect of the system. In fact, the safety precautions that one has to implement can be different in order to use the different type of mobile robots. These can change from a mobile robot that is used only as transportation system from another that works together with human workers, for example when it is used as a workstation or when it helps the human operator in the preparation of the kits [13, 17].

3.3 Operational Level in MF 4.0

Operational decisions are related to day-to-day operations of the companies. They have a short-term horizon as they are taken repetitively. At this level, for all the MF 4.0 activities, it is important to ensure that technology works as best as possible. The vehicle routing problem decides the route a mobile robot should take and the sequence of loads (or jobs) that this vehicle should visit [10]. The routes that a mobile robot can travel are different from those of a traditional transportation devise [8]. The routes change also depending on whether the mobile robots must follow a fixed path or not.

Regardless of the technology, at the operational level it is possible to find the control of the system. This will give the opportunity to continuously improve the MF 4.0 system and to avoid that it stops working. Checking the operation of a mobile robot is more difficult and requires new data to be collected and new knowledge. This is because they are not guided by human workers, and if something is not working properly, no one can be aware of it if a proper control system is not implemented. It is important to create new solutions that can control the mobile robots during the execution of their activities [15]. The data collected from the mobile robots need to be analyzed, and once these data become information these need to be understood before then take any decisions. Not understand the information generated by the execution of the different activities from the mobile robots means not being able to understand if the system is working properly. This means having a system that is not working with the desired performance and that is not possible to change it in order to improve them.

4 Conclusion

This paper focused on the individualization of the most common Industry 4.0 technologies that can be used during the execution of the MF activities. The considered MF activities are transportation, preparation, and material management. This gives us the opportunity to introduce the concept of MF 4.0. MF systems where the different activities are done with the help of the new technologies of Industry 4.0. Moreover, we give some suggestions about the decisions that need to be taken in MF 4.0 with respect to a strategic, tactical and operational impact level. This is only an introduction in the topic of MF 4.0. There seems to be a high potential for future works in this research stream. Future research for example should focus on understanding how to measure the performance of the different technologies implemented in the MF 4.0 activities. This is related to another possible work that is understanding which are the data that need to be collected from the MF 4.0 activities and how to collect them. The technologies are becoming always more powerful and user friendly and their introduction will increase in the next few years. It will be important to know in advance which will be possible issues that companies will face when they decide to implement one of these technologies.

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Paper 3

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Straight and U-Shaped Assembly Lines in Industry 4.0 Era: Factors Influencing Their Implementation

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Abstract. The increasing of products variety is moving companies in rethinking the configuration of their Assembly Systems (ASs). An AS is where the products are being configured in their different variants and its configuration needs to be chosen in order to handle such high variety. Two of the most common AS configurations are the straight-line and the U-shaped line. In this paper we want to first determine and define, through a narrative literature research, which are the factors that are relevant in order to compare these two AS configurations. Additionally, with the advent of Industry 4.0 (I4.0) technologies it is possible that these new technologies have an impact on these factors. For this reason, first, we investigated how I4.0 technologies impact these factors and then we saw how the choice of the AS configuration, between straight-t line and U-shaped line, change based on the impact of the technologies. The seven factors here defined open the opportunity for future research challenges.

Keywords: Assembly system · Configuration · Straight-line · U-shaped line · Industry 4.0

1 Introduction

An AS configuration is a sequence of several workstations organized in a certain way in order to assemble different parts to final products. The assembly process consists of a sequence of typically ordered tasks which cannot be subdivided and should be completed at its assigned workstation [1]. The two AS configurations more used are the straight-lines and the U-shaped lines [2, 3], Fig. 1. A straight-line configuration is represented by a sequence of workstations in a line. Simply rearranging the straight-line into a U-shaped it is possible to obtain the U-shaped line. In both cases, there can be a human worker in each workstation or there can be single workers managing more workstations [4, 5]. However, in U-shaped lines, it is easier for human workers to move from one workstation to another since they can move across both sides of the line, allowing more flexibility and degrees of freedom in the number of workers that can be assigned in these configurations with respect of the straight-line configurations.

Traditionally, a straight-line is suitable for mass-production of standardized products [6]. Because of the growing demand for customized products, in the last few years,

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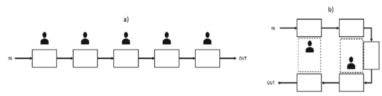

Fig. 1. Straight-line configuration (a) and U-shaped line configuration (b).

the products' variety is increased [7]. The U-shaped line is an example of layout that can handle this increase of variety [8]. However, recently also straight-lines are gained more importance in low volume production of customized products [9]. This can complicate the decision process of which layout configuration to choose. Moreover, the introduction of I4.0 technologies in these configurations can have an impact in this decision.

Industry 4.0 emerges from the synergy of the availability of innovative technologies and the demand by consumers for high quality and customized products and it aims at connecting resources, services, and humans in real-time throughout the production in order to attain an advanced level of operational effectiveness and productivity, as well as a higher level of automatization [10]. Its economic impact is supposed to be huge [11]. It holds the promise of increased flexibility, better quality, and improved productivity [12]. Industry 4.0 technologies are starting to be an integrated part of the AS creating a new generation of AS, the so-called Assembly System 4.0 (AS4.0) [13]. The technologies that can be adopted from AS4.0 can be grouped into Collaborative Robots, Augmented Reality (AR), Internet of Things (IoTs), and Cloud Computing and Data Analysis [13].

In literature is it possible to find some qualitative guidelines about when to choose an AS configuration respect to another [14] and a work that gives an idea of factors that can be considered is the one of [8]. The factors that [8] used are the number of tasks, network density, and the cycle time. However, these are not the only factors that need to be taken into consideration to compare straight-line and U-shaped line. Therefore, we are going to look through a narrative literature review, at which are other factors that need to be taken into consideration when one wants to compare the two configurations.

This research is done in order to answer the following research questions:

1. Which are the factors that have to be considered in order to compare the two AS configurations straight-line and U-shaped line?
2. How Industry 4.0 technologies impact on these factors?

The research wants to help companies that are facing the problem of the increase in product variety, or that are simply thinking in changing their AS configuration, in understanding which are the factors that they need to know in order to be able to compare the two AS configurations. This to facilitate their decision process. The implementation of the right Industry 4.0 technologies can give further help to companies to reach their production performance but can also influence the factors. Therefore, it is important to know if and how the technologies are going to impact on the factors. The remainder of this paper is structured as follows. In Sect. 2 we explained the methodology applied in the paper. In Sect. 3, we answered at the first research question. In Sect. 4, we answered at the second research question and finally, Sect. 5 concludes the work.

2 Methodology

In this paper, to answer at our two research questions, we conducted a narrative literature review. The keywords that we used for the research of the papers are presented in Table 1. We used the Scopus database, searching only result in English as language without limits in the document type and in the year of publications of the papers.

Table 1. The two groups of keywords used in the research

First group of keywords	Assembly*, Assembly system, Line*, Straight line, U shape, U shape*
Second group of keywords	Augmented reality, Cloud computing, Collaborative robo*, Data analysi*, Internet of thing, Assembly*, Assembly time, Quality, * time, Products quality, Products variety

These keywords were used as a single keyword or, most of the time, as a combination of two, or more, words thanks to the operator "AND". For example, one combined research can be: "Assembly*" AND "Collaborative robo*".

3 Factor Influencing the Configuration Selection

In this section with an inductive approach, we derived the relevant factors that a company has to know when it has to decide which is the best configuration for their AS between straight-line and U-shaped line. Here below there is the list of identified factors followed by an analysis of the selected papers which helped us to derived them.

Cycle Time: indicates the time elapsed between completions of two consequent units.

Number of Tasks: it is the number of different activities that each operator must do in each workstation and is a measure used to indicate the problem size for combinatorial problems such as the SALB (Simple assembly line balancing) and UALB (U-shaped assembly line balancing) problems.

Network Density: calculating network density entails dividing the number of actual precedence relationships by the theoretical maximum number of relationships that could exist for a problem of that size. Extreme network density values of 0.0 and 1.0 correspond to flexible and rigid assembly sequences, respectively [8].

Products Variety: is the number of different products that are assembled in an assembly line.

Volumes Variety: is the difference between the quantity to produce of a product one day and the quantity to produce of the same product the following day.

Quality: is the quality of the final assemble products that come out from the assembly line.

Complexity of Tasks: is the complexity of each task of the assembly process.

Following the definitions here above introduced, the papers found by the literature are here presented in order to better explain the different factors.

In straight-line it is not easy as in U-shaped line to adapt to changes in cycle time. This because of the high potential of rebalancing the U-shaped line with a new cycle time and the reallocation of workers [6]. The productivity in straight-line is lower than the one of U-shaped line when network density is high. Indeed, when the network density is low is better to use straight-lines [8]. Straight-lines can guarantee less flexibility in manufacturing volumes respect to U-shaped lines since in U-shaped lines you can increase or decrease the number of operators on the line [15] and the quality of final assembled products is usually better in U-shape lines [2]. The quality in U-shaped is higher thanks to the improved visibility and communication between operators on the line, which facilitates problem-solving and quality improvement [16]. In U-shaped lines usually, a human worker does more tasks than one in a straight-line. As operator responsibilities expand to include more assembly tasks, operators are used more efficiently when using a straight-line configuration [8]. This because more are the different assembly tasks that one human worker must remember and higher will be his mental workload. When a human worker has to walk from a workstation to another one to do his work, the things to keep in mind are not only the time lost by the worker to walk and his physical strain but there is also the possible congestion that can be generate in the line by all the workers that have to move [4, 8]. This congestion can be more problematic in the U-shaped line due to the limited space within the line generating a lost in performance. The walking time of human workers not only influence the physical demand of workers and the congestion of the lines but adding it at the processing time significantly increases the number of workers that are requested in order to execute the assembly tasks [17]. U-shaped lines are a good choice when the workers have to do repetitive actions and avoid keeping wrong postures during the execution of their activities [18]. Moreover, the U-shape lines are more flexible than the straight-lines, balancing by reducing the precedence relations thanks also to the multiskilled workers that perform various tasks in different workstations along the assembly line [19]. U-shaped workers are required to possess more skills than on straight-lines [20].

In order to decide if a configuration is better than another one companies need Key Performance Indicators (KPIs) or objective functions to measure (e.g. costs, flexibility, ergonomics, productivity). Therefore, companies need first to understand how these functions are going to be influenced by the factors and then how to do multi objectives analysis. It will be important to define one or more objective functions and see how these factors impact the decision of the AS configuration. Future works can be indeed related to the definition of these objective functions. Moreover, sensitivity analyses can help to see how the variations of the different factors can change the final decision of which configuration to choose.

4 The Impact of Industry 4.0 Technologies

In this section we are going to investigate the literature to understand how the I4.0 technologies impact the factors defined in the previous section. Collaborative robots do not only improve the performance of the assembly lines [21], but they can also help the human workers in reducing potential occupational risks like awkward postures, mental workload and repetitive actions [22]. This means better ergonomic conditions in the assembly lines. Moreover, collaborative robots can reduce the surface used and so decrease the distances traveled by the human workers [23]. The main improvements that AR can give to assembly operations are the errors reduction and time efficiency. However, researchers have different opinions about these two improvements [24, 25]. There are different opinions also in terms of usability of AR technology. [26] showed how for the participants of their experiments were easier to use paper instructions instead of the AR instructions displayed through Head-mounted display. In [24], experiment's participants instead, in terms of cognitive load, usability and performance, preferred the AR-based instruction than the paper ones. IoT technologies can help companies with the management of the different variants and of the different volumes of products to produce since the consumers can change their orders until the last second and different consumers have different requests [27]. The data collected from the IoT technologies can be analyzed thanks to Data analysis techniques, like machine learning algorithms, and together with the Cloud Computing, that can store data, manage data, and share data and information, the quality of the final products can be guaranteed reducing also the time to do the inspection of the products [28]. These technologies cannot only increase the quality of the final products but can also decrease the amount of scrap parts in a real industrial scenario, consequently saving valuable resources such as energy and raw materials [29] increasing the efficiency of the systems [30].

In Table 2 we can see which are the I4.0 technologies applied in the AS and we summarized the effect of each technology in each factor.

From Table 2 one interesting result that we can see is that there is a technology, AR, that have "Decreases/Increases" as result. This result means that is not well known yet the real impact of this technology with respect to the cycle time. In fact, at the moment the research with this technology regarding this factor are showing different results. This can be related for example to the experience of the human workers in using the technology or on how the AR instructions are designed and presented to the human workers.

Based on the results of Table 2 we created Table 3. Table 3 gives the idea of how the choice of the configuration can change based on the decrease or increase of the factors. In Table 3 we also did the column, based on the review of the literature in the previous section, of the case in which there is no I4.0 technology in the AS.0. This column helps to see that an I4.0 technology can open the opportunity to move to another configuration with respect to the case without technology.

Table 2. Impact of the I4.0 technologies on the factors.

	Industry 4.0 technology			
Factor	Collaborative robot	Augmented reality	IoT technologies	Cloud computing and data analysis
Cycle time	Decreases	Decreases/ Increases	Decreases	Decreases
Number of tasks	/	/	/	/
Network density	/	/	/	/
Products variety	Increases	Increases	Increases	Increases
Volumes variety	Increases	/	Increases	Increases
Quality	Increases	Increases	Increases	Increases
Complexity of tasks	Decreases	Decreases	Decreases	Decreases

Table 3. How the choice of the AS configuration change based on the impact of a I4.0 technology on a factor (U = U-shaped; S = Straight-line; / = not found in literature).

			Industry 4.0 technology			
Factor		Without I4.0 technology	Collaborative robot	Augmented reality	IoT technologies	Cloud computing and data analysis
Cycle time	Low	S	S	/	S	S
	Medium	U/S	U		U	U
	High	U				
Number of tasks	Low	U	/	/	/	/
	Medium	U/S				
	High	S				
Network density	Low	S	/	/	/	/
	Medium	U/S				
	High	U				
Products variety	Low	S	S	S	S	S
	Medium	U/S				
	High	U	U	U	U	U
Volumes variety	Low	S	/	S	S	S
	Medium	U/S				
	High	U		U	U	U
Quality	Low	S	S	S	S	S
	Medium	U/S				
	High	U	U	U	U	U
Complexity of tasks	Low	S	S	S	S	S
	Medium	U/S				
	High	U	U	U	U	U

From Table 3 we can see that, for example, when the quality of the final products increases thanks to the collaborative robots from low to medium, the choice of the configuration of the AS can go to the straight-line configuration instead of the U-shaped line configuration. Indeed, the increase in quality thanks to the collaborative robot gives the opportunity to use the straight-line configuration that usually, without the technology, guarantees a lower quality with respect to the U-shaped line configuration. Of course, it is not only the focus on one factor that defines the choice of the configuration of the AS4.0. Therefore, the combined behavior of these factors with regard to the choice of the configuration can be a matter of interesting future research. Moreover, it will be interesting to do a deeper investigation of the literature to see what it is possible to find about the cases that in Table 3 are now presenting the "/". Especially for all the technologies in the case of the factor "Number of tasks", for the technology "Cloud computing and Data Analysis" for the factor "Network density" and for the technology "Collaborative robot" for the factor "Volumes variety".

5 Conclusion

In this paper, we first determined, based on the literature, the factors that a company has to know when it is time to decide which is the best AS configuration to adopt between the straight-line and the U-shaped line and second we saw how the Industry 4.0 technologies, that can be adopted in these AS configurations, impact in these factors. Being this an exploratory research, our conclusions need to be support by some quantitative results. This is the reason why this work will be used as a starting point for the creation of a mathematical model that will help us validate the assumptions made here.

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Paper 4

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Digital Assembly Assistance System in Industry 4.0 Era: A Case Study with Projected Augmented Reality

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Abstract. Automation has increased more and more in manufacturing companies over the last decades. However, manual labor is still used in a variety of complex tasks and is currently irreplaceable, especially in assembly operations. Assisting and supporting the human worker during potentially complex assembly tasks is very relevant. Clear and easy-to-read assembly instructions, error-proofing methods, and an intuitive user interface for the worker have the potential to not only reduce the cognitive workload of the operator but also increase the productivity, improve the quality, reduce defects, and consequently reduce costs. Industry 4.0 technologies, in particular Augmented Reality and motion recognition sensors, can help companies in reaching these goals. However, there are currently only a few works that show how to implement these technologies with real case studies, especially with the Projected Augmented Reality (PAR). This is the reason why, in this paper an example of prototype of a smart workstation equipped with a Kinect-projector assistance system for manual assembly is presented.

Keywords: Digitalization · Assembly · Industry 4.0 · Projector · Augmented reality · Case study

1 Introduction

In the las few years, manufacturers are dealing with an increasingly demand for customized products [1]. With such a market demand, the variety of products is increasing, dictating the necessity for more flexible and adaptable assembly lines in order to be responsive to the needs of individuals [2]. Zhong and Ai [3] defined assembly lines as continuous production lines, consisting of materials and workstations combined by conveyor belts, contacting workers and machines closely and efficiently. These represent the last phase of production processes and are the place where the products are customized [4].

In assembly lines activities are still performed mainly by human operators due to their characteristics like flexibility, adaptability, decision-making skills, and creativity [5]. Despite these qualities, humans workers can compromise the performance of an assembly system due to the over-workload during the execution of the different

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assembly tasks [6]. This over-workload can be high since the assembly tasks are growing in number due to the increased products varieties and they are getting highly demanded in terms of required skills [7].

In order to help human workers to reduce their workload during the executions of assembly tasks, new solutions have started being introduced thanks to the advent of Industry 4.0. Besides their effects on the human workload, these technologies can also increase the performance of the assembly lines and the quality of the products. An example of such solutions are the Augmented Reality (AR) instructions [8]. These AR instructions compared to the traditional ones, such as paper-based and computer-assisted instructions [9, 10], that can be used as assistance system to guide the human workers during the execution of assembly activities seems to be very promising [11]. Augmented Reality instructions can be presented to human workers through a screen, like a smart phone [12] or a tablet [13], through head-mounted devices, like smart glasses, or through images projected directly in the working area [14]. In the paper we will refer to this last possibility as Projected Augmented Reality (PAR). Despite the high attention that AR solutions have attracted in the last years among researchers and practitioners, the majority of these works are qualitative studies. In a perspective of implementation of such solutions, it is required to understand which is their impact on the execution of assembly activities in terms of task completion time, quality and mental workload. However, very few papers present quantitative studies, especially when dealing with PAR, despite the high interest that is recently gaining among companies. To fill this gap, in this paper, we presented a case study of a prototype of PAR solution, comparing its performances in terms of task completion time, quality, and mental workload with those of paper-based and computer-assisted instructions. The remainder of this paper is structured as follows. Section 2 provides a review of the existing literature on the AR solutions used to assist human workers. Section 3 introduces our case study, while Sect. 4 illustrates the results obtained from the case study. Finally, in Sect. 5 the results are discussed and the conclusions are drwan.

2 Literature Review

In this section the results of a literature review carried out using Scopus database as search engine and limiting the research from January 2005 to August 2020 and English as language. Due to the need and importance of understanding and quantifying the impact of AR solutions on assembly operations, we considered only the papers reporting quantitative results.

Värno et al. [15] used AR to present the instructions to the assembly workers through a tablet. The parameters studied during the tests are the assembly time and the errors commited during the execution of the assembly tasks. The presented prototype is compared with paper-based instructions and resulted in better performing with respect to both the parameters. Koning et al. [16] presented an AR assistance system, with smart glasses and gloves, intended to assist an inexperienced worker during a manual assembly. They validate their solution through a user test that proved that the system is suitable for assisting in the manual assembly, reducing the number of errors respect to the case where AR is not used. Moreover, it provided a learning effect to its users while also offering a positive user experience. Two experiments with 50 participants were conducted in [9] to compared an animated AR system and the paper-based manual system. They studied the task completion time, the number of errors and the cognitive workload. The results of the experiments revealed how the AR system yielded better performances than the paper-based manual with respect to all the three considered parameters. The same parameters were also considered by Hou, Wang and Truijens [17], where the authors investigated how much improvement in assembly productivity and performance can be achieved by lowering cognitive workload via AR. AR instructions are presented through a screen and they are confronted with isometric drawings. A prototype developed based on the Ocolus Rift platform is presented and compared to paper-based instructions in Syberfeldt et al. [14]. Contrarily to other works, paper-based instructions were characterized by better feedback from the human workers resulted in lower assembly time. The authors stated that this was due to the fact that the AR solution was perceived complex by the operators. A Cognition-based interactive Augmented Reality Assembly Guidance System (CARAGS) is bench marched against a LCD screen-based digital documentation and a traditional AR assembly guidance system in [18]. After the experiments, CARAGS has been shown to be the most intuitive, easy to use, and satisfactory guidance system among the three guidance systems based on the average values. It also gives the opportunities to complete the assembly tasks in less time respect to the other two solutions. The results in [19] demonstrated how the presented AR solution provides a more mental-relaxed solution to support the operators in an assembly task. This, even if the AR solution less performed in terms of assembly time with respect to the pape-based instructions, can bring an important advantage considering the highly customized products that are demanded now a day. Two different sets of visual features through AR, concrete AR (CAR) and abstract AR (AAR) are presented and compared with paper-based instructions in [20]. The experiments showed how AAR had the highest average error rates, as well as the longest average completion time, and that the paper-based instructions obtained the best results. However, both the AR solutions help operators in being more confident in performing assembly tasks. A system with AR together with data analytics is introduced by Lai et al. [21]. The experimental results showed how this system, compared to the paper-based instructions, can reduce the assembly completion time and the number of errors committed during the assembly activities. Performance, ease of use and acceptance of two AR-based methods (mobile and spatial AR), are compared in [22]. The results of the experiments demonstrated how participants were faster and made fewer error using the spatial AR solution. This solution gave the opportunity to project the assembly information of a puzzle directly on the workplace where the assembly activities were executed. The findings of Vanneste et al. [23] suggested that projection-based AR has the potential to cognitively support operators during assembly tasks and can hence contribute to better quality, a lower stress level, a higher degree of independence and a lower perceived complexity. A work with projection-based AR is presented in [24]. Their tests indicate that this system is perceived as more helpful and more engaging compared with a similar system using AR smart glasses or an assembly station without assistance. However, they do not show any numerical results that demonstrate their results. Two examples of projected AR solutions to help impaired workers are introduced in [25, 26]. In both, the authors compared different solutions and showed how AR is able to help the impaired workers during the executions of the assembly tasks.

From the literature it emerges two facts. First, that AR instructions can be beneficial for the performance of an assembly line, and, second, that PAR solutions are scarcely investigated with quantitative studies. PAR can overcome the other AR instructions performances for example giving the opportunity to the human workers to not wear, or grab, any kind of devices to perform the assembly activities. These devices, like the smart glasses for example, can be uncomfortable and can create blind spots even for people that wear glasses daily [7]. These reasons move us to create in the Logistic4.0 Lab the prototype of a smart workstation equipped with a Kinect-projector assistance system for manual assembly presented, with a case study, in the next chapter.

3 Case Study Description

To assess the potential of the assembly assistance system in terms of productivity and mental workload of the workers, the Logistics 4.0 Laboratory at the Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology developed a smart assembly workstation. The smart assembly workstation consists of a Kinect-camera, motion recognition software, work-instruction program and a projector. While the cameras of the Kinect and the motion recognition software track the movement and trigger action in the work-instruction program, the projector can visualize necessary information for the worker to pick and assemble a product (Fig. 1). This innovative, assistive work assembly process can be classified as Projected Augmented Reality (PAR). In most production environments paper-based manuals and workplace-mounted monitors provide work instructions. Therefore, the PAR was compared to paper-based and computer-assisted instruction method in times of productivity and mental workload.

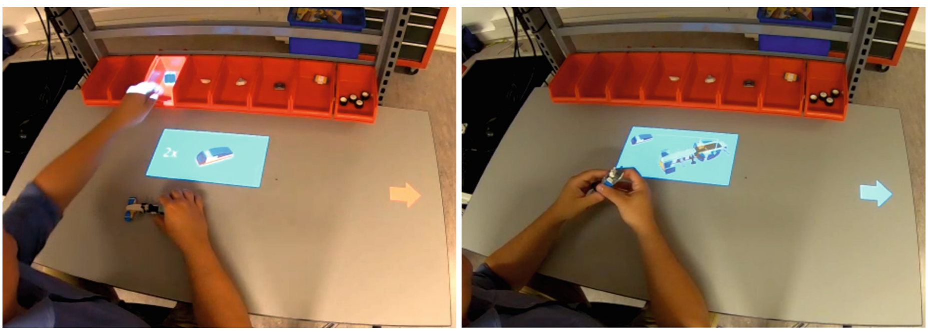

Fig. 1. The smart workstation with Projected Augmented Reality

The test population consisted of 15 participants, who carried out a series of assembly tests with different workstation configuration in the Logistics 4.0 Laboratory.

The participants must assemble a LEGO model following the provided assembly information.

In this paper, due to pages restriction, we are going to show only the results obtained from the assembly of two components (Front wing and Side pod, Fig. 2) of a LEGO product These two components are characterized by different degrees of complexity: the Front wing has a lower degree of complexity (3 different parts, 4 work steps), while the Side pod has a higher degree of complexity (8 different parts, 8 work steps).

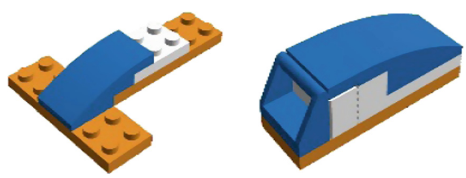

Fig. 2. The Front wing (on the left) and the Side pod (on the right)

4 Results

In the experiment, we the first measured the time for completing the assembly tasks and the number of errors performed during the assembly. The results allowed to assess the performance and accuracy of the assistance system prototype. In the second part, after completing the assembly tests at the smart workstation, were asked to the participants of the experiment to fill out an questionnaire.

The computer-assisted instructions achieved the best results in the Task Completion Times compared to the other alternatives (see Fig. 3, left). The "Front wing" was assembled in 29.98 s with SD = 5.35 s and the "Side pod" in 46.19 s with SD of 6.79 s.

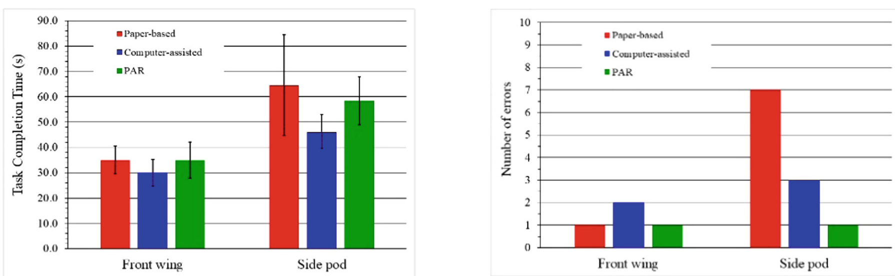

Fig. 3. Task Completion Time (left) and number of errors (right) of the two assembled components

The quality of the assembly activities were measured by counting the number of assembly and picking errors (see Fig. 3, right). The results show that the PAR system can reduce the possibility of committed errors during the especially for the more complex assembly task of the "Side pod".

The mental workload was measured thanks to the compilation of a simplified NASA-TLX questionnaire. The questionnaire asked the participants to give feedback on perceived enjoyment, frustration, perceived ease of use, effort, and mental demand for each work instruction method. The PAR system obtained the overall best results and scored especially high in perceived enjoinment (86.7%) and ease of use (86%).

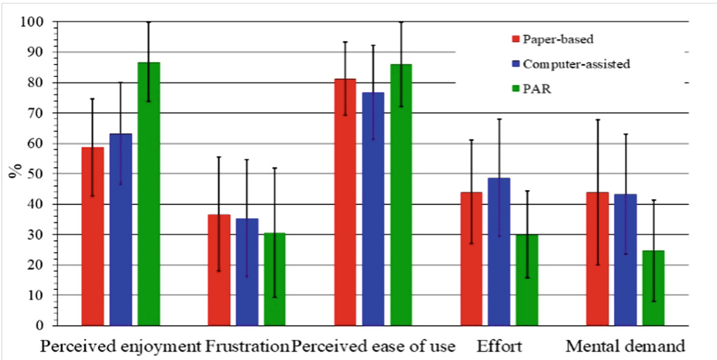

Fig. 4. Simplified NASA-TLX

5 Discussion and Conclusion

In this paper, a prototype of a PAR system has been developed in order to quantify the benefits that an assembly line can obtain from its implementation. The results of the case study suggest that a PAR assistance system has several advantages over the paper-based and computers-assisted methods. Although PAR did not lead to the lowest Tasks Completion Time, Fig. 3, the use of this solution can still be beneficial in situations where workers have to wear gloves or they have to use tools during the execution of the assembly tasks since with PAR they do not have to drag their finger on a touch screen or to move paper pages in order to move to the next assembly task. These operations can be problematic when workers have to wear gloves or they have to use tools during the execution of the assembly tasks. The PAR system can guarantee a higher quality of the final products since the numbers of mistakes made by the human workers are lower, Fig. 3. This means fewer products that need to be reassembled with a saving in time and money. Moreover, the results from the questionnaires showed how a PAR systems leads workers to do their work with less effort then the other two solutions, Fig. 4. In such a way, workers' health can be preserved resulting in a higher productivity thanks to the reduced absenteeism related to sickness leaves.

Despite the just mentioned advantages, our solution is limited by some limitations, such as the inability to detect the correctness of the assembly operations. Another limitation that hinders our PAR from being the fastest solution is the fact that each task after being executes need to be confirmed, since there is not a system that can detect the execution of the assembly process step by step and understand when a task is over and the next has to start.

However, despite the two mentioned limitations that need to be solved in the future development of the system, the benefits provided by the PAR system are several. In order to study in more detail these benefits, as possible future work, our solutions can be tested in a real industry case study. Another future work can be the study of our solution in a business case point of view, comparing, for example, the costs of its implementation and maintenance with the same costs of the other two studied solutions in the case study (paper-based and computer-assisted instructions).

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Paper 5

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A methodological framework to integrate motion capture system and virtual reality for assembly system 4.0 workplace design

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ABSTRACT

Nowadays new products are required more and more often. Since a certain product is assembled only on a specific Assembly System (AS), a new AS has to be designed every time a new product is developed. Similarly, since an AS is constituted by one or more workplaces, new workplaces need to be designed every time a new product is developed. However, this is not feasible considering the time- and resource-consuming AS workplace design procedures currently used (e.g., physical mock-ups and computer-aided systems). New solutions have thus emerged to accelerate the AS workplace design procedures, especially since the advent of Industry 4.0 (I4.0) technologies. Specifically, the combined use of motion capture (mocap) systems and Virtual Reality (VR) has been considered very promising, with many researchers showing its potential. However, to the best of the authors' knowledge, none of them suggests a clear methodology to follow when designing AS workplaces using the mocap system and VR. In this paper, we thus aim to fill this gap by developing a methodological framework that describes in detail the different steps to be followed. Moreover, the methodological framework has been developed in such a way that both productivity and Occupational Safety and Health (OSH) considerations are included. Furthermore, it encompasses the current ageing workforce scenario by explicitly including the ageing workforce's main characteristics (reduced flexibility and strength and greater experience of older operators). A simple but representative case study has then been carried out to demonstrate how to use the methodological framework and to prove its validity.

1. Introduction

Nowadays customers require new and customised products more and more often, and companies have hence to be able to easily follow these requirements in order to survive in today's competitive market. Companies thus have to be able to change their Assembly Systems (ASs) in a fast and economic way to cope with the short life-time of the products, i.e., Assembly Systems (ASs) are required to be flexible and reconfigurable (Battaïa et al., 2018). This, together with the optimisation of the AS workplaces (defined according to Cavatorta and Dipardo (2009) as (i) the workstation where the assembly tasks are executed, (ii) all the equipment that is necessary to execute the tasks, and (iii) all the systems necessary to store the components that are not convenient to store directly in the workstation), is fundamental to assemble new products at low costs, short time to market, and high reliability of deliveries (Battini et al., 2011; Holubek and Ružarovský, 2014; Porta et al., 2020, Arena et al., 2021). Moreover, due to the presence of human operators in AS workplaces, their optimisation has to be carried out with respect not only to productivity but also to Occupational Safety and Health (OSH). Human operators are, in fact, fundamental to guarantee the high flexibility required by ASs (Makris et al., 2016), and it is thus important to promote their comfort to improve their OSH, especially their wellbeing. This can be achieved by considering the right ergonomic interventions during the workplace design process. These interventions can involve some adjustments in the AS workplace (Kim and Junggi Hong, 2013) and it is crucial that they also consider the current ageing of the workforce (OECD, 2015). Indeed, the ageing of the operators could have a negative impact on the AS productivity (Strasser, 2018): assembly tasks require physical efforts to be executed, but ageing is known to reduce physical capabilities. For example, Peng and Chan (2019) reported that the musculoskeletal capacity decreases by 20% after the age of 60. Therefore, it is necessary to limit the drawbacks associated with the decreased physical capabilities of the ageing workforce, and this can be done with the proper design of the AS workplace (Truxillo et al., 2015;

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Calzavara et al., 2020). In fact, an effective workplace can lead to a decrease in the physical burden of the human operators, thus reducing the ergonomic risks and improving the OSH (Roper and Yeh, 2007). This, in turn, results in increased productivity, better working conditions, and operators' wellbeing in an AS (Eswaramoorthi et al., 2010).

The design of these workplaces can be facilitated by the advent of Industry 4.0 and its technologies (Burggräf et al., 2019). The term Industry 4.0 is used to indicate the fourth industrial revolution that the industrial environment is currently experiencing (Wang, 2016). This revolution is moving companies toward a gradual and constant automation of traditional manufacturing practices (Schwab, 2016) and ASs are involved in this revolution, introducing the concept of Assembly System 4.0 (AS4.0) (Bortolini et al., 2017; Cohen et al., 2019). In particular, in the AS4.0 the new technologies of Industry 4.0 can be used both to enable better performance (Battini et al., 2020; Fager et al., 2020; Peron et al., 2020; Simonetto et al., 2020; Arena et al., IN PRESS) and to design their workplaces (Dolgui et al., 2021). Indeed, regarding this last point, the combined use of the motion capture (mocap) system and Virtual Reality (VR) has been reported to improve the AS workplace design compared to the currently used AS workplace design procedures (e.g., physical mock-ups and computer-aided systems) with respect to both productivity and operators' wellbeing (Faccio et al., 2017; Battini et al., 2018). Specifically, a mocap system allows the creation of a digital copy of the operator in real time thanks to *"a virtual representation of the skeleton and its movements"* (Bortolini et al., 2020), and this facilitates and improves ergonomic assessments, since AS workplace designers have access to the exact evolution over time of the position and orientation of the operator's different limbs in a common reference system (Oyekan et al., 2017). VR, instead, gives the opportunity to create a three-dimensional environment where users can interact efficiently with three-dimensional objects in real time using their natural senses and skills (Riva, 2002). The adoption of a mocap system and VR during the design phase of an AS makes it possible to overcome the main limitations of the currently used AS workplace design procedures, i.e., subjective and time-consuming assembly time measurements and ergonomic assessments (Battini et al., 2011; Battini et al., 2014). The combined use of these two technologies, in fact, enables fast and reliable assembly time measurements and ergonomic assessments (see Section 2.1 for more details).

It is hence clear that the potentialities associated with the use of these technologies are enormous, but it is still unclear how to maximise the associated benefits. In fact, to the best of the authors' knowledge, a clear description of the methodology that needs to be followed when designing using the mocap system and VR is still missing, and this represents one of the main reasons why *"their adoption within real industrial environments is still very limited"* (Prabhu et al., 2016). In this work, to fill this gap, we developed a methodological framework that AS workplace designers can follow when using mocap and VR. Specifically, the methodological framework herein developed gives a central role to the operator. In more detail, the operator is included in the methodological framework by considering his/her main characteristics, i.e., (i) physical strength and joint mobility and (ii) experience. This is extremely important in consideration of the current ageing of the workforce. In fact, a reduction in physical strength and joint mobility and an increase in experience is known to be associated with the ageing workforce (Börsch-Supan and Weiss, 2016; Roda et al., 2019; Peng and Chan, 2020). Characteristic (i) is considered in the ergonomic assessments, where, referring to the work of Wolf and Ramsauer (2018), we modified the ergonomics index Rapid Entire Body Assessment (REBA). Dealing with (ii), then, the experience of the ageing workforce is considered in the design phase: thanks to the experience they gained over the years, they can provide advice that can simplify and speed up the design procedure (Di Pasquale et al., 2020). The methodological framework has then been successfully applied to a simple but representative case study to prove its validity and to demonstrate its use.

The rest of the paper is organised as follows. In Section 2 we present a narrative literature review dealing with the design of AS workplaces (Section 2.1) and thereafter the impact of the ageing workforce on productivity and OSH performance in AS workplaces (Section 2.2). Specifically, in this work we focus only on operators' wellbeing as OSH performance. Section 3 then presents the methodological framework developed herein. In Section 4 the case study is described and discussed. Finally, Section 5 concludes the work.

2. Literature review

In this section, a narrative literature review is conducted in order to have an overview of the evolution of the AS workplace design procedures (Section 2.1) and of the impact of the ageing workforce on productivity and OSH performance in these workplaces (Section 2.2). Specifically, as in the rest of the work, we focus only on operators' wellbeing as OSH performance.

2.1. Design of the assembly system workplace

AS workplace design, defined by Launis et al. (1996) as the "process and activity which leads to the birth of the workplace", has been subject to substantial changes over the last years. From what we will refer to as the "traditional AS workplace design procedure", i.e., the construction of the physical workplace mock-up proposed by Das and Sengupta (1996), in fact, new design procedures have been developed, especially thanks to the technological developments over the years, aiming to overcome the main limitations of the traditional AS workplace design procedure (i.e., time- and resource-consuming).

Based on the pioneering work of Warnecke and Haller (1982) and Bauer and Lorenz, (1985), Zha and Lim (2003) suggested overcoming these limitations using computer-aided systems. Specifically, they developed an algorithm that optimised the AS workplace design in a virtual environment, hence eliminating the need to create several physical mock-ups. Similarly, Udosen (2007) studied the possibility of optimising the AS workplace design thanks to a computerised heuristic. Through a case study, they demonstrated the possibility of optimising the AS workplace with respect to the cycle time in a faster and easier way compared to the traditional approach. However, the use of computer-aided systems became unsatisfactory when the urge to include also ergonomic considerations in the AS workplace design emerged.

The continuously increasing flexibility required by the market over the last years has in fact rendered the use of human operators in AS fundamental. The operators' capability to easily adapt to changes in production has in fact been considered essential in order to cope with the market's characteristics. Therefore, the concept of the human-centred AS workplace has started to arise (Giacomin, 2014; Caputo et al., 2019), pointing out the necessity to include ergonomic considerations in AS workplace design (Neubert et al., 2012; Šišková and Dlabač, 2013). Worthy of mention in this perspective is the work of Battini et al. (2011), who developed a methodological framework to optimise the AS with respect to both productivity and operators' wellbeing.

However, despite some improvements, the computer-aided systems have not been fully capable of adapting to these needs. In fact, although much has been done from the initial procedure where a physical mock-up was needed to evaluate the operators' wellbeing in the computer-aided designed AS workplace through photos and/or videos of the assembly operations, some limitations still exist (Naddeo et al., 2014). Specifically, although in their latest versions computer-aided systems make it possible to study both productivity and operators' wellbeing directly in the virtual environment (Feldmann and Junker, 2003), hence overcoming the limitations of using physical mock-ups and photos and/or videos of the assembly operations for the ergonomic assessments (Realyvásquez-Vargas et al., 2020), the results are not fully representative of the reality. In fact, the ergonomic assessments are carried out on a virtual operator which does not represent the reality, since its movements and anthropometrical data differ from those of the operator for whom the AS workplace is being designed.

Recently, the combined use of the mocap system and VR has emerged as a new AS workplace design procedure that can overcome these limitations (Jayaram et al., 2006; Di Pardo et al., 2008). Specifically, this AS workplace design procedure consists in creating first the virtual environment in which the operator is immersed through the use of VR. The operator is then equipped with a mocap system that allows the creation of the operator's digital twin, i.e., a digital copy of the operator that is a truthful representation of the reality. In this way, the operator can virtually perform all the activities that he would normally do during his job, but without the need for a physical mock-up. Moreover, the ergonomic assessments are carried out on the operator's digital twin, which has the same anthropometric data and makes the same movements. Furthermore, it is also possible to carry out the ergonomic assessments in real time (Vignais et al., 2013; Battini et al., 2014).

Some researchers have thus been attracted by the potentialities offered by the combined use of the mocap system and VR for AS workplace design, and they have started investigating these

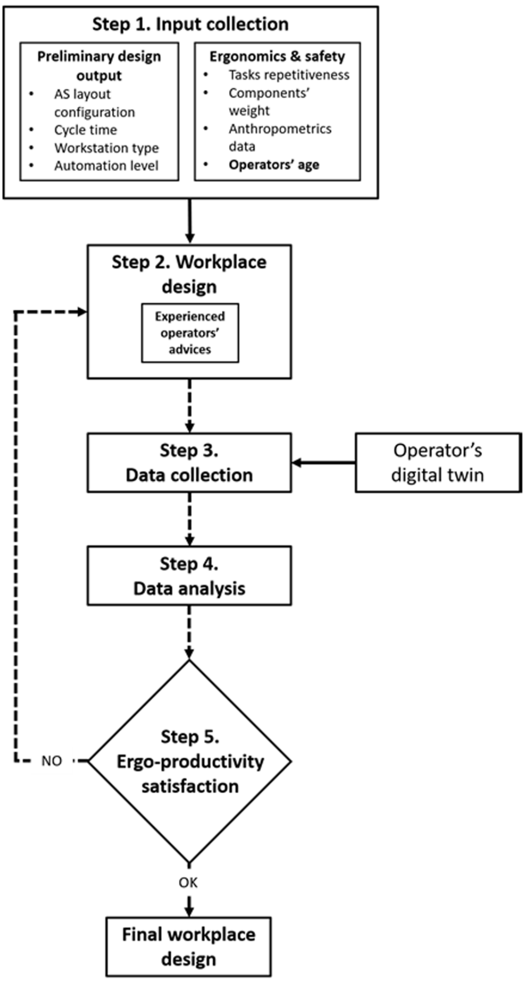


Fig. 1. Methodological framework. The dashed arrows indicate the steps subjected to possible changes during the iterative process.

potentialities in more detail (Peruzzini et al., 2017; Vosniakos et al., 2017; Michalos et al., 2018; Caputo et al., 2017; Battini et al., 2018). Peruzzini et al. (2017), for example, evaluated the AS workplace design procedure in a steel pipe manufacturer using either the mocap system and VR or a computer-aided system, and they reported that the outcomes of the AS workplace design procedure were substantially improved using the former thanks to the more accurate ergonomic assessments that could be obtained. Similar results were obtained also by Vosniakos et al. (2017) for the assembly of small to medium aircraft wings, and by Caputo et al. (2017) for assembly tasks in a lab environment. Michalos et al. (2018) then further proved the efficacy of this design procedure, focusing on the assembly of a robotic wrist. Specifically, they demonstrated that through the combined use of the mocap system and VR it was possible to easily redesign the robotic wrist AS workplace and to improve its performance in terms of the distance walked and task execution times. Finally, Battini et al. (2018) further investigated the potentialities of this design procedure, suggesting the possibility of coupling the mocap system and VR with a heart rate monitoring system in order to include also fatigue considerations in the AS workplace design.

However, despite the increasing interest in the use of the mocap system and VR for AS workplace design, to the best of the authors' knowledge a clear and detailed procedure to follow when designing the use of these technologies is still missing. In this work, we thus aim to fill this gap by developing a methodological framework that the AS workplace designer can follow, allowing full exploitation of the potentialities associated with the combined use of the mocap system and VR. Moreover, with the methodological framework we aim to overcome another limitation of the current design procedures, which, in fact, give only limited consideration to the operators. The different physical strength and joint mobility that can characterise the operators (due to their different ages, for example) are not considered in the ergonomic assessments, and their different levels of experience are not considered in any way in the current design procedures either. In the methodological framework herein developed we overcome these limitations. Specifically, the operators' physical strength and joint mobility are included in the ergonomic assessments, while their experience is used for useful advice concerning the AS workplace layout (e.g., the position of components and/or tools).

2.2. Ageing in the assembly system workplace

It is widely known that the world population is ageing, with the most developed countries having the highest share of older people (United Nations, 2018). This has great repercussions on the labour market, which is naturally experiencing an ageing workforce due to the necessity of increasing the retirement age (Hanson and Lindgren, 2020). This represents a key issue in some industrial sectors, especially in manufacturing. In fact, in a sector such as manufacturing where repetitive movements are often required, the decline of the operators' physical functions as the years go by (e.g., reduced musculoskeletal force, flexibility and motion capability) certainly represents a threat (Shephard, 2000; Ilmarinen, 2001; Bouma, 2013; Cote et al., 2014; Bures and Simon, 2015; Truxillo et al., 2015; Peng and Chan 2019; Orrù et al., 2020; Peng and Chan, 2020). For example, Roper and Yeh (2007) reported that, as a consequence of the decline of the operators' physical functions, musculoskeletal disorders (MSDs) are one of the most commonly found health risks among ageing workers. Similar observations can be found also in Jones et al. (2013). Specifically, Landau et al. (2008), analysing the assembly operations in the automotive industry, reported that lumbar spine and head-neck-shoulder symptoms are the most frequent MSDs that ageing workers suffer from, in agreement with Qin et al. (2014). It is hence clear that, to reduce the occurrence of MSDs, the ergonomic risks need to be reduced. To do so, Balderrama et al. (2015), for example, suggested assigning ageing workers to appropriate job positions, where the work demands match their physical abilities. Similarly, Kovalski-Trakofler et al. (2005) suggested that ageing workers should avoid activities involving extreme joint movements, excessive force and highly repetitive movements since they involve high ergonomic risks.

Moreover, Varianou-Mikellidou et al. (2020), confirming the results of Roper and Yeh (2007) and Pennathur et al. (2003), reported that the decline of the operators' physical functions with increasing age affects also their efficiency. Compared to their younger colleagues, in fact, ageing workers are reported to be slower in their reactions and movements, as well as to require longer resting times after physical efforts (Zieschang and Freiberg, 2011). This, in turn, decreases their productivity. Göbel and Zwick (2009), in fact, reported that the productivity decreases after the age of 40. Similar results were also obtained by Alessandri et al. (2020) and by Abubakar and Wang (2019). Specifically, the latter reported that the decrease in productivity starts already at the age of 38, with an increase of 1% in the average task execution time every year after that age. However, Börsch-Supan and Weiss (2016) reported the opposite findings. In fact, evaluating truck assembly, they reported that the productivity profile of individual workers was increasing until the age of 65, and they explained their results by observing that older workers were able to compensate for the decline of their physical functions thanks to the experienced gained over the years. In fact, although ageing workers were found to make slightly more errors than their younger colleagues, they made hardly any severe errors due to their increased experience. Similar results were found also by Roosaar et al. (2019) and Kim (2019), who showed that ageing workers remained at least as productive as their younger colleagues thanks to their experience.

From what is reported above, there clearly emerges a need to consider explicitly the age of the operators in ergonomic and productivity-related considerations, especially when designing the AS workplace. For example, acting on the components location, extreme joint movements could be avoided, as well as limiting the negative impact of the ageing workers' slower movements. In this work, we developed a methodological framework for the workplace design that explicitly considers the age of the operator, including both the negative and positive aspects (reduced physical functions and increased experience, respectively), as better described in the previous section.

3. Methodological framework

In this section the methodological framework developed to guide an AS workplace design that includes both ergonomic and productivity-related considerations is reported (Fig. 1) and explained in detail. Specifically, the AS workplace design procedure considered deals with the combined use of the mocap system and VR. Before moving forward, it is worth mentioning that the methodological framework is meant to be used during the detailed design phase, and it has been developed in such a way that it can be combined with already existing frameworks for AS design. For example, the framework developed herein can be used for carrying out steps 5 to 8 of Battini's framework (Battini et al., 2011).

3.1. Step 1 – Input collection

The first step is the collection of the input parameters. Since, as mentioned earlier, the methodological framework developed herein is meant to be used in the detailed design phase, we consider the known outputs of the preliminary design phase, and therefore the (i) AS layout configuration, (ii) cycle time (paced/un-paced), (iii) workstation type (i.e., open/closed, parallel/serial, two-sided, …), and (iv) automation level (i.e., percentage of automation, type of equipment, …) are known. Moreover, the product characteristics that influence ergonomics and safety (e.g., component weights) are also known in this design phase. Furthermore, the operators who will work on the AS workplace under development are generally known, and thus also their anthropometric data and age.

3.2. Step 2 – Workplace design

Once the inputs have been collected, the AS workplace design can be carried out. In this step, contrary to the traditional AS workplace design approach where physical mock-ups are needed, the workplace is designed virtually, using a 3D modelled environment. Many different alternatives can hence be easily developed and assessed, without the need to build a physical mock-up for each alternative. This, as already stated before, brings great benefits in terms of time and cost reduction.

During this phase, it is fundamental that the AS workplace designers are assisted by experienced operators. In fact, as we saw from the literature review, operators are affected by a gradual decrease of both physical and cognitive abilities with increasing age (Shepard, 2000; Bouma, 2013; Bures and Simon, 2015), and experienced operators, thanks to the experience gained over the years, can provide useful advice to the AS workplace designers to take these aspects into consideration. For example, to ensure their wellbeing, older operators might be required to make fewer movements, move fewer heavy objects, and do fewer complex activities during their daily assembly activities. Experienced operators, then, based on their knowledge, can advise the AS workplace designers on the proper position of, e.g., components and equipment to avoid poor work postures and unnecessary movements. Moreover, experienced operators can suggest to the AS workplace designers whether (i) the operators need to be supported by new equipment (e.g., lifter, automatic screwdrivers, collaborative robots, etc.) and (ii) the environmental conditions (e.g., lighting) need to be adapted or not, based also on their age. Moreover, in this phase, it is crucial that the AS workplace designers and the experienced operators adopt a holistic approach, where they consider productivity and operators' wellbeing as two complementary aspects, not as two separate entities. The AS workplace layout influences, in fact, both the productivity and operators' wellbeing through the whole assembly process: for example, the positioning of a component (or tool) in a certain location with the aim of making the assembly tasks faster might have a negative impact on the operators' wellbeing, and vice versa. Moreover, it is equally important that the AS workplace designers and the experienced operators do not consider each task as single, separate entities, but as a part of a wider aspect. Sometimes, in practice, some trade-offs are necessary to reach the overall objectives: the productivity and/or safety of an assembly task might need to be penalised to reach the desired goals in terms of productivity and operators' wellbeing for the whole assembly process.

It is worth noting that in this step, although many software tools are available to model a 3D environment, only those software tools that can interact with the mocap system and with VR can be used (e.g., Siemens Jack™). The interaction with the mocap system is, in fact, a crucial aspect since it makes it possible to obtain the real movements of the operator and to accurately replicate them in the 3D modelled environment.

3.3. Step 3 – Data collection

Once the virtual workplace is built, the collection of the data can take place. In this step, an operator needs to be equipped with the mocap system and with VR. Thanks to the combined use of the mocap system and VR, he will be immersed in the 3D modelled environment, being able to move and to interact with it. In this way he can carry out the assembly process virtually, without the need for any physical mock-up. While the virtual assembly process is being carried out, the mocap system allows the recording of the assembly operations (from now on we will refer to this as "mocap-based recording"), as well as the physical data (e.g., body joint angles, body segment orientation and positions) that will be used in Step 4 to evaluate the ergonomics. For the sake of clarity, from now on we will refer to these physical data as "ergonomics-relevant data", and they are available for each frame of the mocap-based recording (the frame rate can usually be decided beforehand). It will be clear in the description of Steps 4 and 5 that this represents a very important aspect.

Before moving to the description of Step 4, it is worth mentioning that at the beginning of Step 3 a crucial activity is needed to be able to collect useful and reliable data. A digital twin of the operator carrying out the virtual assembly process needs to be created before carrying out the virtual assembly process. In this way, we ensure that the anthropometric data of the operator's digital twin corresponds to those of the operator who will perform the virtual assembly process. This is fundamental for obtaining accurate and reliable ergonomic assessments. In this step, we recommend that the operator chosen to carry out the virtual assembly process is representative in terms of the anthropometric data of the operators who will work on the AS workplace under development. Considerations about the age of the operator chosen to carry out the virtual assembly are reported in Step 4.

3.4. Step 4 – Data analysis

Once the data are collected, they need to be analysed with respect to productivity and ergonomics. The productivity can be evaluated by means of time-related parameters (e.g., task execution times), which in the following we will refer to as "productivity KPIs", while the ergonomics can be evaluated using ergonomic indexes (RULA, REBA, NIOSH, OWAS, etc.). During the data analysis step, in order to optimise the outcomes, the AS workplace designers are required to divide the whole assembly process into the different assembly tasks that constitute it. Thus, each assembly task has to be associated with its own data (mocap-based recording and ergonomics-relevant data). In this way, the AS workplace designers can evaluate the productivity KPIs and the ergonomics index scores for each assembly task. The former can be evaluated through the mocap-based recording of the assembly: the task execution time, for example, can be evaluated based on the length of the mocap-based recording of the task under consideration. For the ergonomic scores, instead, the AS workplace designers have to consider the ergonomics-relevant data of each frame that constitutes the assembly task under consideration. Through simple formulas, these data can be converted into the ergonomic scores in a fast way (the process can be automated by using EXCEL, MATLAB or any other similar tool). For example, considering the REBA index, the relative angle between the neck and the trunk corresponds to the "neck score" in the REBA index. By doing so, it is hence possible to evaluate for each task the average and the distribution of the ergonomic scores (i.e., considering again the REBA index, how frequently is the REBA score equal to 1, to 2 and so on). Moreover, by analysing jointly the mocap-based recording of each task and the REBA scores of each frame constituting that specific task, it is possible to determine the subtasks that involve high ergonomic risks and to link them to the AS workplace layout, hence facilitating the AS workplace design improvement procedures. While doing this, the AS workplace designers can also note, for each task, what we will refer to as a value-added ratio, i.e., the ratio between the time spent on necessary activities and the total task execution time. In this way, it is easier to identify which tasks are characterised by highly unproductive activities (i.e., activities that do not add value for the assembly operations, e.g., moving, travelling, etc.), hence having a negative impact on the productivity KPIs, and to link them to the AS workplace layout.

During the ergonomic assessments, it is crucial that the age of the operator is explicitly considered. However, this is still overlooked in the literature, and, to the best of the authors' knowledge, only Wolf and Ramsauer (2018) proposed a solution for this. In detail, they proposed to modify the ergonomic scores by means of age-based multipliers, and they suggested evaluating these age-based multipliers by means of mathematical formulas. Specifically, they suggested obtaining these mathematical formulas by interpolating literature data about the decline in the ability under consideration (muscular strength, aerobic capacity, etc.) with respect to age. For example, they were interested in an age-based multiplier for strength reduction in order to include age considerations in the KIM ergonomics index. To evaluate this age-based multiplier ($f_{strength}$), they developed the mathematical formula reported in Equation (1) by fitting the data available from the literature regarding the changes in the muscular strength with respect to age.

$$f_{strength}(\%) = 0.00058 \cdot age^3 - 0.08478 \cdot age^2 + 3.24439 \cdot age + 62.92006 \quad (1)$$

It is worth noting that the values of $f_{strength}$ provided by Equation (1) are in line with the age-based multipliers of the REFA method and with those provided by ISO 11228 and EN 1005.

Building on this approach, we suggest in Equation (2) the age-based multiplier for joints flexibility reduction ($f_{flexibility}$), which is needed when the ergonomic indexes contain assessments on joint flexibility (e.g., allowable joint angle limits in the REBA index). To obtain the mathematical formula reported in Equation (2), we fitted the joints flexibility reduction data reported in Table 1 of Wolf and Ramsauer's work (2018).

$$f_{flexibility}(\%) = -0.00019 \cdot age^3 + 0.034286 \cdot age^2 - 2.538095 \cdot age + 145 \quad (2)$$

By considering these age-based multipliers in the ergonomic assessments, we can ensure that the age of the operator is explicitly considered (see Appendix A for more details on how to include the age-based multipliers in the REBA index). Specifically, we strongly recommend following a precautionary approach, where the age of the oldest operator who will work on the AS workplace under development is used in these formulas.

It is not strictly necessary that the operator used for the virtual assembly is the oldest operator who will work on the AS workplace under development, and it can also be a younger colleague. The choice depends on the following considerations and a trade-off decision might be needed. On the one hand, if the oldest operator is used as the operator for the virtual assembly, any potential decrease in productivity associated with the increase of age is included. However, if the technological skills of the oldest operator are limited, it might take too much time to train him sufficiently to carry out a virtual assembly process that is representative of the reality. On the other hand, if a younger colleague is used for the virtual assembly, the chances of low technological skills are limited, but any potential decrease in productivity associated with the increase of age will get lost. The choice depends therefore on the workforce characteristics (in terms of technological skills) and on the assembly process under consideration (i.e., whether the assembly process is affected timewise by the age of the operator or not). However, whatever the choice is, the ergonomic assessments have to be modified with the age-based multipliers calculated with the age of the oldest

Table 1
Execution time, average REBA score and value-added ratio for each task in the as-is configuration.

Task	Task execution time (s)	Average REBA score		Value-added ratio (%)
		Age = 27	Age = 60	
1	19.0	3.40	3.82	62.2
2	7.2	2.30	3.51	60.3
3	14.5	3.51	3.88	62.0
4	72.6	4.63	5.23	54.5
5	87.5	4.47	6.65	37.8
6	62.0	4.50	5.40	67.6
7	6.3	3.42	4.42	77.1
8	18.0	4.36	4.96	41.5
9	19.4	3.91	5.33	29.3
10	75.8	4.29	4.84	60.4
11	62.5	5.03	5.96	69.3
12	22.2	2.60	3.12	40.6
13	16.2	1.76	2.14	73.2
14	56.1	4.51	5.25	48.0
15	59.1	3.49	4.36	43.4
16	132.1	3.94	4.78	43.0
17	28.1	3.90	4.32	41.7
Total	**758.6**	**4.12**	**4.97**	**51.2**

Fig. 2. Pump assembled in the case study.

operator.

3.5. Step 5 – Ergo-productivity satisfaction

The productivity KPIs and the ergonomic scores obtained from the previous step serve as input in this step, the ergo-productivity satisfaction. This is a decision step, where the AS workplace designers have to decide whether the productivity KPIs and ergonomic scores are satisfactory or not (with respect to the company's requirements, legal requirements, etc.). If they are, this represents the final AS workplace design, if not, then the user has to go back to step 2.

In the latter case, the workplace designers and the experienced operators can draw on the results of step 4 to improve the AS workplace design by modifying its layout. Thanks to those results, in fact, the workplace designers and the experienced operators know which are the tasks that decrease productivity and operators' wellbeing (i.e., the tasks characterised by low value-added ratios and high ergonomic scores, respectively). Moreover, they also know which subtasks are responsible for these criticalities and how they are linked to the AS workplace layout. Again, it is important that, when redesigning the AS workplace, the AS workplace designers and the experienced operators adopt a holistic approach, i.e., they (i) do not focus only on the critical tasks and (ii) do not consider productivity and operators' wellbeing as two separate entities, but as two complementary aspects. This is fundamental, since focusing the AS workplace improvements only on one single task and on one single aspect (i.e., productivity or ergonomics) per time would not lead to the best results achievable, since the modification of one task has impacts also on other tasks, sometimes worsening them. Once an improved design has been identified, the workplace designers can move again through steps 3–5. It should be noted that the operator's digital twin does not need to be created (or modified) every time the iteration takes place, unless the operator carrying out the virtual assembly operation changes.

4. Case study and discussion

To demonstrate how to use the methodological framework developed herein and to prove its validity, we used a simple but representative case study carried out at the Logistic 4.0 Lab at NTNU. Specifically, in the case study we applied the methodological framework for the redesign of the AS workplace of a medium/big size pump (Fig. 2), which is constituted of 25 components assembled through 17 main tasks (information about the components and the different tasks can be found in Appendix B).

The case study was carried out as follows. First, a second-year Ph.D. student working on AS4.0 designed the initial workplace, which from now on we will refer to as the "as-is configuration". In this phase, the AS workplace was built physically in approx. 10 h, and the Ph.D. student decided the AS workplace layout, e.g., the location of components and tools (wrenches and manual and automatic screwdriver), sub-assemblies' feedings, etc., by himself, i.e., without any support from more experienced personnel. It is worth noting that since the focus of the case study is only on the methodological framework, we considered the pump to be assembled in a single workplace. Although this does not faithfully reproduce the real industrial scenario where the assembly process is carried out among several AS workplaces (i.e., in an assembly line), we decided to consider a single workplace to facilitate the understanding of how to apply the methodological framework.

Then, we gathered all the information necessary to carry out the redesign of the AS workplace according to the methodological framework, i.e., (i) which are the tasks that negatively affect the productivity and the operators' wellbeing, and (ii) which are the subtasks that are responsible for these criticalities and their link to the AS workplace layout. The redesign of a current workplace can, in fact, be considered equivalent to the case where the first virtual design does not satisfy the ergo-productivity requirements and a second iteration is needed: as during the second iteration the methodological framework requires that information, in the same way they are needed in the case of a redesign.

To obtain that information it was hence necessary to carry out the assembly process and to collect and analyse the data according to Step 3 and Step 4 of the methodological framework, respectively. The assembly process was carried out by the Ph.D. student mentioned above (to whom we will refer as the "case-study operator" in the following), who was trained for two hours the day before the *Data Collection Step* in order to increase his assembly skills. During the *Data Collection Step*, the case-study operator was equipped with a mocap system to obtain the mocap-based recording and the ergonomics-relevant data. The mocap system used was the inertial motion capture system developed by Synertial, which consisted of 29 inertial measurement units (IMUs) that, thanks to an advanced compensation system, guaranteed to obtain very accurate ergonomics-relevant data. Specifically, the IMUs being placed on a full body suit, these data covered the full body, including also the hands (15 IMUs on the body and 7 on each hand). The mocap system was connected to a personal computer via a WIFI connection (this was possible because all the sensors communicate with a small portable multi-processing unit that in turn communicated with the personal computer), and the required data were obtained by using the Synertial SynDash software. It should be noted that to obtain reliable ergonomics-relevant data the case-study operator's digital twin was needed (see the previous section for more details), and to do so we used Synertial AutoCal.

The outcome of the *Data Collection Step* consisted of a 758.6-seconds mocap-based recording of the assembly process constituted by 45,519 recording frames (and hence ergonomics-relevant data). These data were then analysed according to the *Data Analysis Step* of the methodological framework. Following the procedure of the *Data Analysis Step*, we divided the mocap-based recording of the whole assembly process into the 17 different assembly tasks. In this way, we were able to evaluate the productivity KPIs and the ergonomics index scores for each assembly task. Specifically, we considered the tasks execution times and the REBA index as the productivity KPI and ergonomics index, respectively. The execution time and the average REBA score of each task are reported in Table 1. It is worth noting that the age of the case-study operator (27 years) was explicitly considered in the ergonomics assessment by means of the age-based multipliers $f_{strength}$ and $f_{flexibility}$, which assumed a value of 1 and 0.98, respectively. Moreover, for the purpose of showing the importance of considering the age of the operators in the ergonomic assessments, in Table 1 we report also the (fictitious) case where the age of the case-study operator was 60 years ($f_{strength}$ and $f_{flexibility}$ equal to 0.77 and 0.75, respectively). As can be seen, this has a marked impact on the ergonomic assessments, and this can be clarified even better if the distribution of the ergonomic scores is considered (see

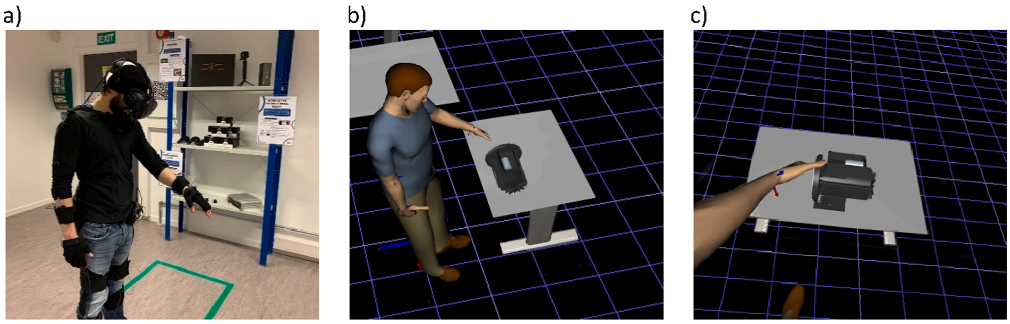


Fig. 3. Detail of the virtual assembly: operator equipped with the mocap system and VR (a), (b) virtual operator (c) view of the assembly operation in VR.

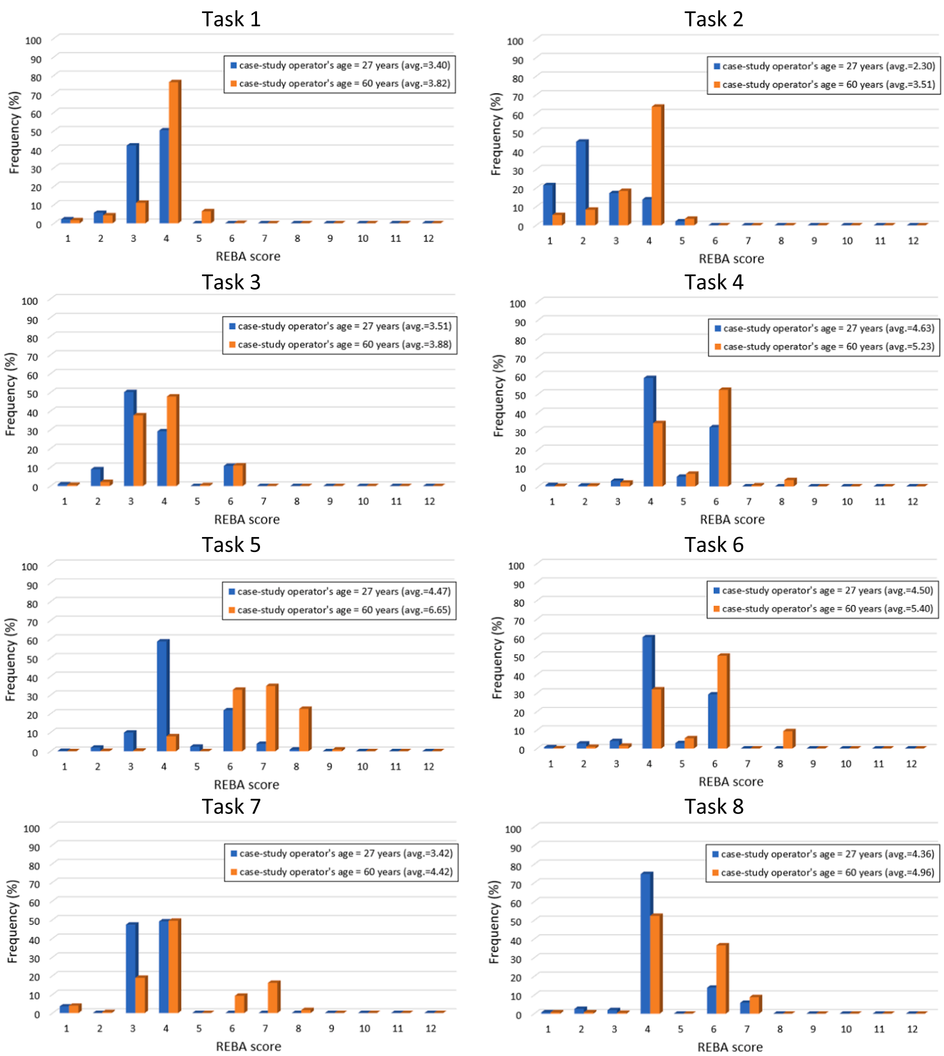


Fig. C1. REBA scores (average and distribution) for each task considering the real age (blue histograms) or a higher fictitious age (orange histograms) of the case-study operator in the ergonomic assessments of the as-is configuration.

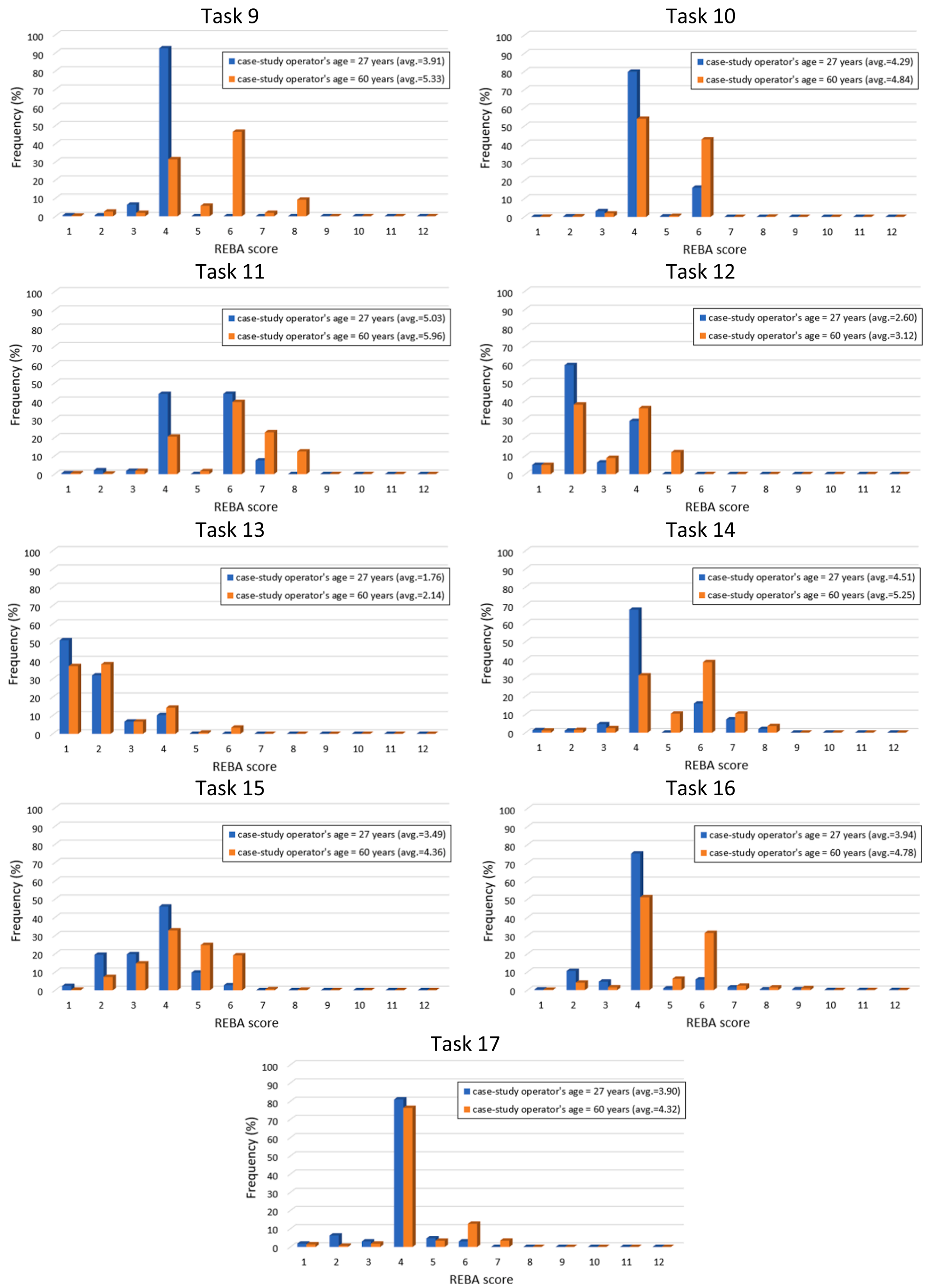


Fig. C1. (*continued*).

Fig. C.1 in Appendix C). Therefore, as suggested in the methodological framework, in the following, we will consider the age of the case-study operator equal to 60 years when dealing with any ergonomic consideration. Moreover, as reported in the *Data Analysis Step*, we analysed jointly the mocap-based recording of each task and the REBA scores of each frame constituting that specific task to identify the subtasks that present a high ergonomic risk (i.e., REBA score equal to or higher than 8) and how these are linked to the AS workplace layout. Furthermore, while doing so, we evaluated the value-added ratio for each task (which are also reported in Table 1) and we determined the unproductive activities responsible for low value-added ratios, as well as their link to the AS workplace layout.

It was hence possible to identify the tasks that reduced the productivity (i.e., tasks with low value-added ratios) and the operators' wellbeing (i.e., tasks with high ergonomic risks), which are:

- For productivity: tasks 5, 8, 9, 12, 14, 15, 16 and 17
- For operators' wellbeing: tasks 4, 5, 6, 7, 9, 11, 14 and 16

Moreover, we identified also the subtasks responsible for these criticalities and we linked them to the AS workplace layout, finding that they were mainly due to the location of the components.

After collecting this information, we were then able to proceed with the redesign of the AS workplace according to the methodological framework developed herein. In the following, we will describe in detail the procedures carried out in the different steps of the methodological framework. Specifically, since we applied the methodological framework for a redesign (that we said before to be equivalent to a second iteration) we will discuss only Steps 2–5.

4.1. Step 2 – Workplace design

In this Step, the AS workplace was redesigned virtually using Siemens Jack™. Specifically, we adopted Siemens Jack™ to model the 3D environment because it can interact with the mocap system and with the VR available in the Logistic 4.0 Lab (Synertial mocap and HTC VIVE™, respectively). The redesign procedures were carried out by a postdoctoral fellow in digital production and logistics systems, together with a full professor in industrial logistics. The former assumed the role of the AS workplace designer, modelling the 3D environment, while the latter assumed the role of the experienced operator, providing advice to the AS workplace designer concerning the AS workplace layout. Specifically, to provide meaningful advice, the information obtained from the analysis of the as-is configuration, in which there were tasks decreasing the productivity and the operators' wellbeing, as well as subtasks that were responsible for these criticalities and their link to the AS workplace layout, was crucial. Having ascertained that the inadequate location of certain components was the main cause of the low value-added ratios and high ergonomic risks of the activities reported above, the full professor was able to identify some improvement actions. Specifically, when providing his advice, the full professor adopted the holistic approach mentioned in the methodological framework, considering the repercussions that repositioning components and tools (and modifying the AS workplace layout in general) to increase the value-added ratio of a certain task could have on the ergonomic risk level of that task (and vice versa) and on the productivity and operators' wellbeing of the whole assembly process. Some examples of advice were that:

- adjusting the height of the workstation could reduce the ergonomic risks in tasks 4 and 14, with no impact on the productivity (or on that task or the whole assembly process);

- the relocation of the components necessary to reduce the ergonomic risks in tasks 6, 7 and 11 could slightly affect the productivity (slightly higher task execution time); however, relocating these components allows an increase in the overall productivity of the assembly process since the repositioning of other components is then possible.

Based on these and other suggestions from the full professor, the workplace was then virtually designed in approx. 5 h.

4.2. Step 3 – Data collection

This step was already described in detail when dealing with the as-is configuration, but its main parts will now be summarised.

The assembly process was carried out virtually by the case-study operator equipped with the mocap system and with the VR available in the Logistic 4.0 Lab (i.e., Synertial mocap and HTC VIVE™, respectively) (Fig. 3). It is worth recalling that the case-study operator was trained for 2 h the day before collecting the data in order to familiarise himself or herself with the VR and to learn how to interact with the 3D modelled environment.

Table 2
Execution time, average REBA score and value-added ratio for each task in the redesigned configuration.

Task	Task execution time (s)	Average REBA score		Value-added ratio (%)
		Age = 27	Age = 60	
1	20.9	3.48	3.92	56.7
2	8.3	3.62	3.84	52.4
3	12.9	4.37	4.67	70.0
4	70.7	4.22	4.78	56.0
5	52.3	4.27	5.12	63.3
6	69.5	3.88	3.97	60.3
7	6.9	3.35	3.84	70.6
8	13.5	2.79	2.97	55.3
9	9.3	3.10	4.17	61.0
10	78.1	3.19	3.87	58.6
11	64.3	4.06	4.13	67.4
12	13.1	3.35	3.75	68.9
13	17.3	3.54	3.91	68.6
14	38.2	3.58	3.87	70.5
15	49.3	3.48	4.17	52.1
16	98.0	3.57	4.10	57.9
17	19.0	3.74	3.80	61.5
Total	**641.6**	**3.74**	**4.24**	**60.6**

The assembly process was recorded through the mocap system, which allows recording of the assembly operations and the ergonomics-relevant data. Specifically, the mocap-based recording was 641.6 s long and consisted of 38,493 recording frames (and hence ergonomics-relevant data).

It is worth noting that to collect useful and reliable data it is necessary to have the digital twin of the case-study operator in order to ensure that the anthropometric data of the physical and virtual operator correspond. However, this time it was not necessary to develop it again since it was already available from the assessment of the as-is configuration.

4.3. Step 4 – Data analysis

The outcome of Step 3 (a 641.6-seconds mocap-based recording of the assembly process constituted by 38,493 recording frames and as many sets of ergonomics-relevant data) was then divided into the 17 different assembly tasks and analysed in terms of task execution times and the REBA index (the chosen productivity KPI and the ergonomics index, respectively) (Table 2), lasting approx. 2 h. Again, to further emphasise the importance of considering the age of the operators in the ergonomic assessments through the age-based multipliers, we report in Table 2 the average REBA score for each activity considering two ages of the case-study operator, i.e., the real one (27) and the fictitious one (60). More details of the ergonomic assessments can be found in Fig. C.2 in Appendix C.

4.4. Step 5 – Ergo-productivity satisfaction

In this step, according to the methodological framework, the productivity KPI and the ergonomic scores have to be compared with the company's requirements (or any other requirement) to evaluate whether the AS workplace design is satisfactory or not. However, since our case study was not carried out in collaboration with any company but in the Logistic 4.0 Lab in order to illustrate the use of the methodological framework and to prove its validity, we did not have any benchmark values. Therefore, we simply evaluated whether the

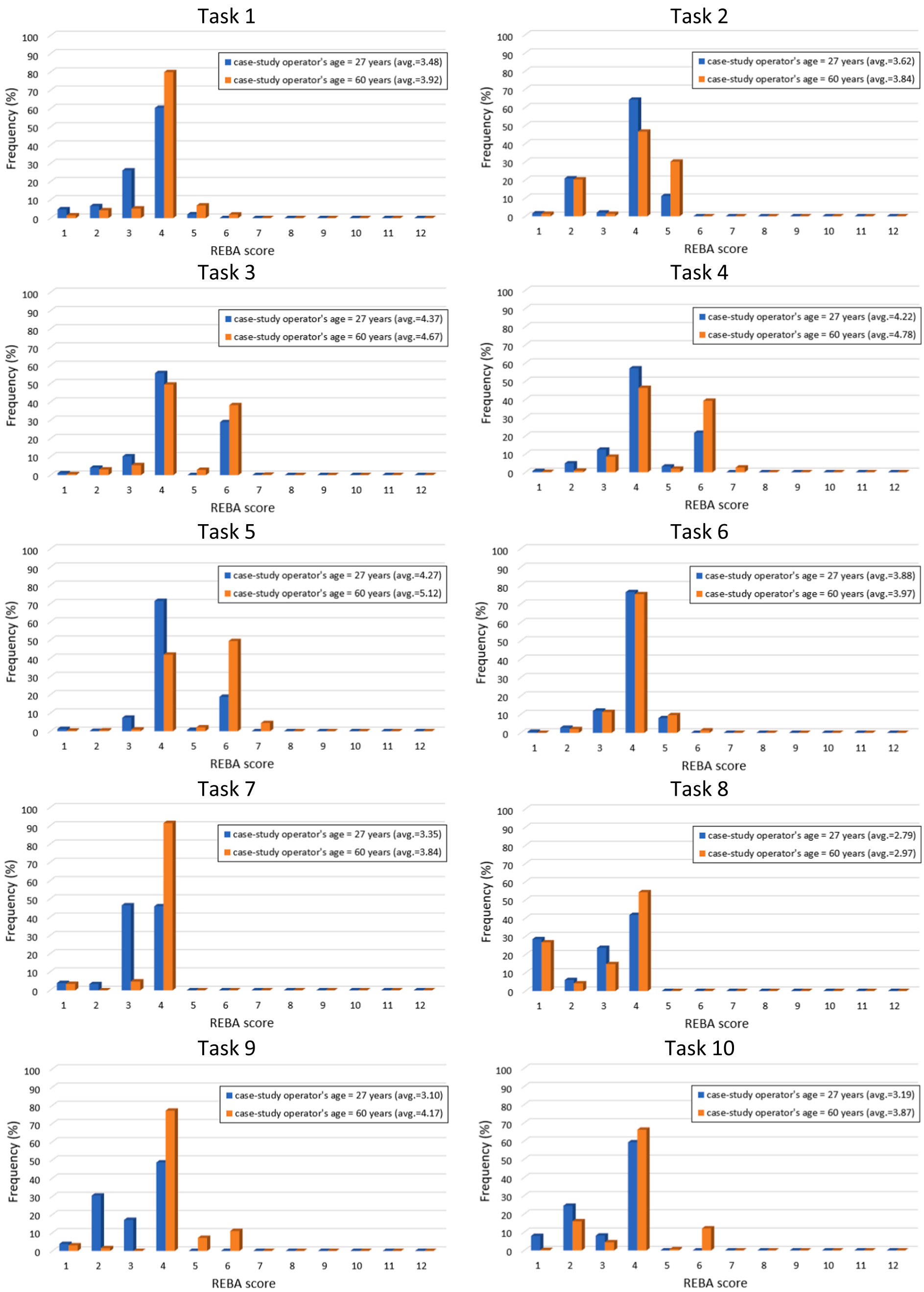


Fig. C2. REBA scores (average and distribution) for each task considering the real age (blue histograms) or a higher fictitious age (orange histograms) of the case-study operator in the ergonomic assessments of the redesigned configuration.

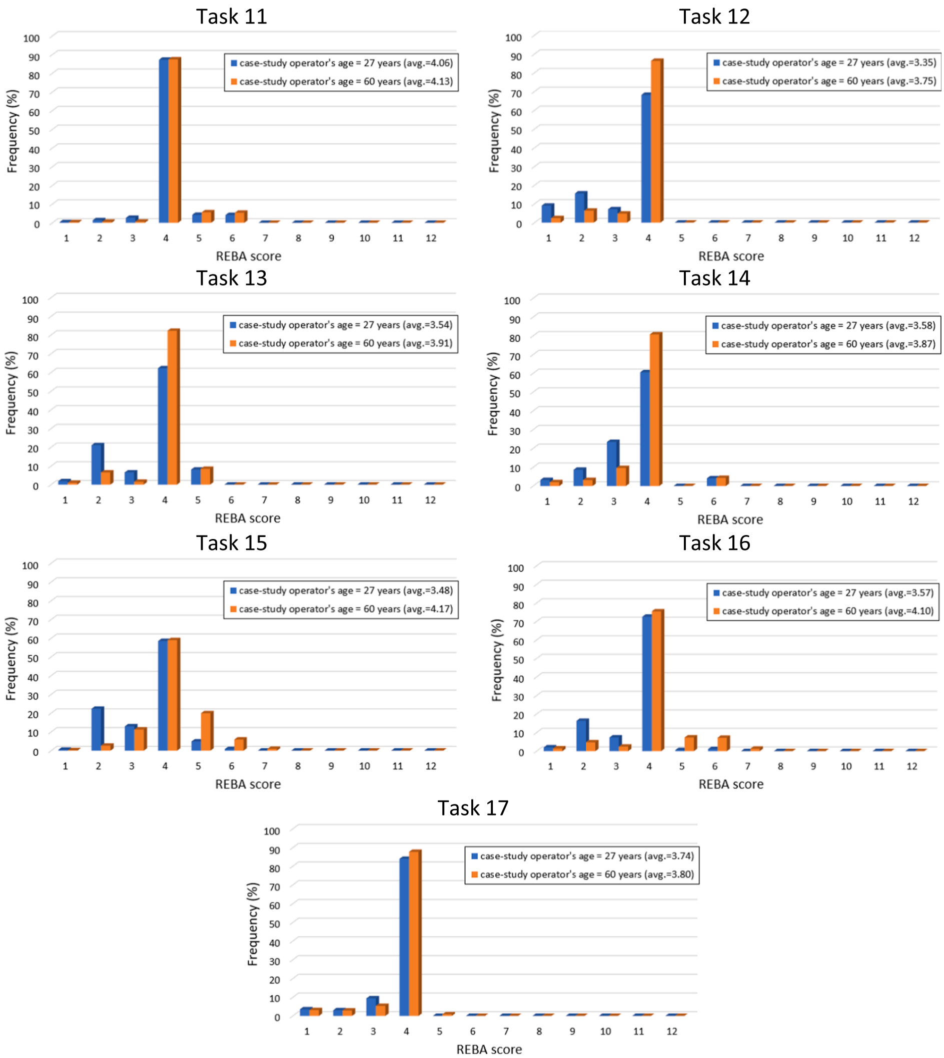


Fig. C2. (*continued*).

redesigned AS workplace performed better than the as-is configuration with respect to both productivity and operators' wellbeing (a comparison of the as-is and redesigned configuration is reported in Table 3). From the analysis of the task execution times it emerges that, although some tasks are characterised by higher execution times (tasks 1, 2, 6, 7, 10, 11 and 13), the total assembly time in the redesigned configuration is lower than in the as-is configuration (758.6 vs 641.6 s). The methodological framework developed herein, in fact, allowed us to identify the unproductive activities (e.g., travelling to pick the right tool, moving to pick the right component, etc.) and their causes (i.e., many components and tools were stored in locations which were not optimal). This information was then used by the experienced operator (i.e., the full professor in industrial logistics in our case study) to provide advice on how to eliminate and/or reduce some of these unproductive activities (hence the higher value-added ratios in the redesigned configuration). However, while giving this advice, the experienced operator had to make some trade-off decisions, penalising the execution times of some tasks to favour the total assembly time. This is part of the holistic approach mentioned in the methodological framework, where each task is not considered as a single entity, but as a part of a wider context.

Moreover, since the holistic approach jointly considers productivity and ergonomics, the overall operators' wellbeing was also increased. In fact, although some tasks are characterised by a higher average REBA score in the redesigned configuration (tasks 1, 2, 3, 12 and 13), the overall average REBA score decreased. Furthermore, no tasks with high ergonomic risks (i.e., REBA score equal to 8 or higher) were present in the redesigned configuration (Figs. C.1 and C.2 in Appendix C).

It is worth reiterating the importance of considering the age of the operator in the ergonomic considerations. As can be seen from Tables 1-3, considering different ages of the case-study operator through the age-based multipliers had a marked impact on the REBA scores: for example, the average REBA score of task 5 in the as-is configuration moved from 4.47 to 6.65 by considering the age of the case-study operator equal to 60 instead of 27 years. The effects of considering the case-study

Table 3
Tasks execution times, REBA average scores (both considering the age of the case-study operator equal to 27 years and 60 years) and value-added ratios in the as-is and redesigned configuration.

Task	Task execution time (s)		Average REBA score				Value-added ratio (%)	
			Age = 27		Age = 60			
	As-is	Redesigned	As-is	Redesigned	As-is	Redesigned	As-is	Redesigned
1	19.0	20.9	3.40	3.48	3.82	3.92	62.2	56.7
2	7.2	8.3	2.30	3.62	3.51	3.84	60.3	52.4
3	14.5	12.9	3.51	4.37	3.88	4.67	62.0	70.0
4	72.6	70.7	4.63	4.22	5.23	4.78	54.5	56.0
5	87.5	52.3	4.47	4.27	6.65	5.12	37.8	63.3
6	62.0	69.5	4.50	3.88	5.40	3.97	67.6	60.3
7	6.3	6.9	3.42	3.35	4.42	3.84	77.1	70.6
8	18.0	13.5	4.36	2.79	4.96	2.97	41.5	55.3
9	19.4	9.3	3.91	3.10	5.33	4.17	29.3	61.0
10	75.8	78.1	4.29	3.19	4.84	3.87	60.4	58.6
11	62.5	64.3	5.03	4.06	5.96	4.13	69.3	67.4
12	22.2	13.1	2.60	3.35	3.12	3.75	40.6	68.9
13	16.2	17.3	1.76	3.54	2.14	3.91	73.2	68.6
14	56.1	38.2	4.51	3.58	5.25	3.87	48.0	70.5
15	59.1	49.3	3.49	3.48	4.36	4.17	43.4	52.1
16	132.1	98.0	3.94	3.57	4.78	4.10	43.0	57.9
17	28.1	19.0	3.90	3.74	4.32	3.80	41.7	61.5
Total	**758.6**	**641.6**	**4.12**	**3.74**	**4.97**	**4.24**	**51.2**	**60.6**

operator's age are even more evident if Fig. C1–C2 in Appendix C are considered: many tasks that did not involve high ergonomic risk when the case-study operator was considered young (age = 27 years) became high-risk when he was considered old (age = 60 years). Therefore, as reported in the methodological framework, the ergonomics assessment should always include the age of the operator. But the highest age should be considered when designing an AS workplace not only because it allows consideration of the fact that some activities might not be of high ergonomic risk for young operators, but because they might become so when the age increases.

5. Conclusion

In this paper, we answered the need for a clear description of the methodology that needs to be followed when designing an AS workplace using the mocap system and VR. The combined use of the mocap system and VR has, in fact, emerged as a breakthrough in AS workplace design, since it makes it possible to overcome the main limitations of the currently used AS workplace design procedures. For example, the combined use of the mocap system and VR does not require the large amount of time and resources needed by the traditional AS workplace design procedure (i.e. the construction of a physical workplace mock-up) to optimise the AS workplace design, since several AS workplace designs can be easily and rapidly created and tested digitally. Moreover, the use of the mocap system and VR can also overcome the main limitation of computer-aided systems (i.e. ergonomic assessments not fully representative of the reality) since the mocap system allows the creation of a digital copy of the operator that is a truthful representation of the reality. However, prior to our work, it was still unclear how best to use them for AS workplace design in order to fully exploit their enormous potentialities, especially when aiming to maximise the AS workplace design considering both the productivity and the operators' wellbeing. The methodological framework developed herein solved this issue, providing five simple steps that can be followed when designing an AS workplace with the mocap system and VR. Moreover, the methodological framework makes it possible to consider the current labour market, since it provides the possibility to include ageing workers and their associated benefits and drawbacks in the AS workplace design procedure. Furthermore, the methodological framework allows both the productivity and operators' wellbeing to be maximised considering a holistic approach.

The validity of the methodological framework has been proved by means of a simple but representative case study. The methodological framework was successfully applied to the redesign of the AS workplace of a medium/high size pump. Specifically, the task assembly times were reduced by around 15%, and the ergonomic risks were also reduced from high to medium. Fundamental for these achievements was the detailed data analysis step described in the methodological framework, which made it possible to easily identify the tasks that were critical for the productivity and for the operators' wellbeing. Moreover, the possibility to design the workplace virtually halves the time spent on building the AS workplace (the digital AS workplace was built in approx. 5 h, while the physical one in approx. 10 h).

However, to prove its validity further, the methodological framework needs to be applied in other case studies, where real industrial applications, bigger sample sizes (meaning the number of operators considered) and the repetitiveness of the data are considered. Nevertheless, the potentialities of the methodological framework have been shown to be considerable, and they will be further investigated in the future in order to overcome the main limitations just described.

CRediT authorship contribution statement

Marco Simonetto: Investigation, Conceptualization, Writing – original draft, Software, Methodology. **Simone Arena:** Methodology, Conceptualization, Writing – review & editing. **Mirco Peron:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft.

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.

Appendix A

Here we will show how to include the age-based multipliers $f_{strength}$ and $f_{flexibility}$ in the ergonomic assessment. We will limit our demonstration to the REBA index, but the same procedure can be applied to any other ergonomic index containing allowable joint angle limits.

REBA is an ergonomic index used to evaluate the ergonomic risks of the whole body, assigning a score to the following body regions: neck, trunk, legs, upper and lower arms, and wrists. The former three are evaluated in the so-called body segment section A, while the latter three in the so-called body segment section B. The scores of the two body segments are modified considering additional adjustments and then combined to obtain the ergonomic risk. Specifically, the assessment of the body segment section A consists of six steps:

1. Locate neck position,
2. Locate trunk position,
3. Locate legs position,
4. Look-up posture score in Table A,
5. Add force/load score,
6. Score A,

similarly to the body segment section B:

7. Locate upper arm position,
8. Locate lower arm position,
9. Locate wrists position,
10. Look-up posture score in Table B,
11. Add coupling score,
12. Score B

The age-based multipliers need to be considered in Steps 1–3, 5, 7–9, specifically $f_{strength}$ in Step 5, while $f_{flexibility}$ in the others. Considering first $f_{strength}$, Step 5 in the traditional REBA corresponds to the following:

$$\begin{cases} ifload < 11lbs. = +0 \\ ifload11to22lbs. = +1 \\ ifload > 22lbs. = +2 \end{cases}$$

Step 5 in the REBA, modified to include age considerations by introducing the age-based multiplier $f_{strength}$, corresponds to:

$$\begin{cases} load < (11\bullet f_{strength})lbs. = +0 \\ load(11\bullet f_{strength})to(22\bullet f_{strength})lbs. = +1 \\ load > (22\bullet f_{strength})lbs. = +2 \end{cases}$$

Similarly for $f_{flexibility}$. Considering as an example Step 1, the traditional REBA is:

$$\begin{cases} load < (11\bullet f_{strength})lbs. = +0 \\ load(11\bullet f_{strength})to(22\bullet f_{strength})lbs. = +1 \\ load > (22\bullet f_{strength})lbs. = +2 \end{cases}$$

Modifying Step 1 to include age considerations through the age-based multiplier $f_{flexibility}$ leads to:

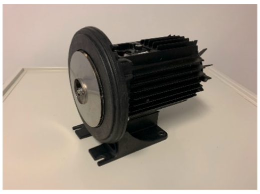
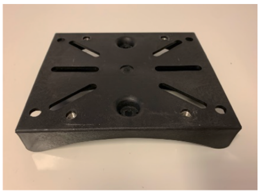
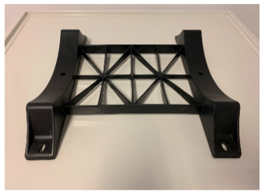
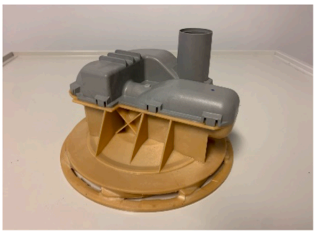
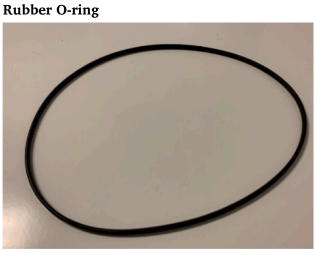
$$\begin{cases} neckangle < 0^{\circ} = +2 \\ 0^{\circ} \leq neckangle \leq 10^{\circ}\bullet f_{flexibility} = +0 \\ 10^{\circ}\bullet f_{flexibility} < neckangle \leq 20^{\circ}\bullet f_{flexibility} = +1 \\ neckangle > 20^{\circ}\bullet f_{flexibility} = +2 \end{cases}$$

Similarly for Steps 2, 3 and 7–9.

Appendix B

In Table B1, the 25 different components constituting the pump used in the case study are gathered, while in Table B2 the different tasks are described.

Table B1
Components constituting the pump.

Tank	Square nuts	Caps
		
Engine	**Pump base**	**Tank support**
		
Valve	**Fan cover**	**Small screws**
		
Hydraulic cover	**Rubber O-ring**	**Hoop**
		
Long circular screw	**Nut type 2**	**Metallic tube**
		
Pressure gauge	**Electrical housing cover**	**Long shank screws**
		

(*continued on next page*)

Table B1 (*continued*)

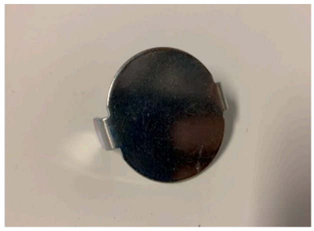
Tank	Square nuts	Caps
Electrical components 	**Phillips head screws** 	**Internal grey ring** 
Square screws 	**Long shank Phillips screws** 	**Metallic disc** 
Square gasket 		

Table B2
Tasks description.

Task number	Task description
1	Assembly of the *pressure gauge* on the *metal tube*
2	Assembly of the *metallic disc* on the *electrical components*
3	Assembly of the *square gasket* on the *electrical components*
4	Assembly of the *metallic tube* on the *electrical components* (using *Long shank Phillips screws*)
5	Assembly of the *electrical components* on the *engine* (using *Phillips head screws*)
6	Assembly of the *electrical housing cover* on the *electrical components* (*using long shank screws*)
7	Assembly of the *internal grey ring* on the *engine*
8	Assembly of the *valve* on the *hydraulic cover*
9	Assembly of the *rubber O-ring* on the engine
10	Assembly of the *hydraulic cover* (with the *valve* in it) on the *engine*, using the *hoop* (and the *long circular screw* and *nut type 2*)
11	Assembly of the *fan cover* on the *engine* (with *small screws*)
12	Assembly of the *metallic tube* on the *hydraulic cover*
13	Assembly of the *caps* on the *metallic tube* and on the *hydraulic cover*
14	Assembly of the *tank* on the *tank support* (with two of the *square nuts*)
15	Assembly of the *pump base* on the *tank* (with two of the *square nuts*)
16	Assembly of the *engine* on the *pump base* (with *square screws*)
17	Assembly of the *metallic tube* on the *tank*

Appendix C

Fig. C1 reports the REBA scores (average and distribution) for each task. To show the importance of considering the age of the operators in the ergonomic assessments, we carried out these assessments considering both the real age of the case-study operator (27 years, blue histograms) and a higher, fictitious age (60 years, orange histograms).

Fig. C2 reports the REBA scores (average and distribution) for each task considering both the real age of the case-study operator (27 years, blue histograms) and a higher, fictitious age (60 years, orange histograms).

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