UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL

ESCOLA DE ENGENHARIA

PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA DE PRODUÇÃO

Jéssica de Assis Dornelles

Smart Working Technologies in Industry 4.0: Contributions to different manufacturing activities and workers' skills

Porto Alegre

2022

Jéssica de Assis Dornelles

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Dissertação submetida ao Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul como requisito parcial à obtenção do título de Mestre em Engenharia de Produção, modalidade Acadêmica, na área de concentração em Sistemas de Qualidade.
Orientador: Professor Alejandro Germán Frank, Dr.

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Esta dissertação foi julgada adequada para a obtenção do título de Mestre em Engenharia de Produção na modalidade Acadêmica e aprovada em sua forma final pelo Orientador e pela Banca Examinadora designada pelo Programa de Pós-Graduação em Engenharia de Produção da Universidade Federal do Rio Grande do Sul (PPGEP/UFRGS).

____

Prof. Alejandro Germán Frank, Dr.

Orientador PPGEP/UFRGS

____

Prof. Alejandro Germán Frank, Dr.

Coordenador PPGEP/UFRGS

Banca Examinadora:

Prof. Dr. Eduardo de Senzi Zancul (Universidade de São Paulo)

Prof. Dr. Moacir Godinho Filho (Universidade Federal de São Carlos)

Prof. Dr. Tarcísio Abreu Saurin (Universidade Federal do Rio Grande do Sul)

"Each person must work for their improvement and, at the same time, share in the collective responsibility for all humanity."

— Marie Curie, first woman to win two Nobel Prizes

AGRADECIMENTOS

Primeiramente, agradeço a Deus por todas as bênçãos que recebo todos os dias e por me manter firme em meus objetivos.

Agradeço também aos meus pais e irmãos, que me apoiaram nessa empreitada rumo ao meu desenvolvimento profissional e pessoal.

Também sou grata a minha rede de apoio em Porto Alegre composta pelos meus cachorrinhos e companheiros e, também, aos meus amigos e amigas de anos.

Agradeço especialmente aos meus professores e parceiros, Prof. Alejandro Frank e Prof. Néstor Ayala, pela credibilidade, paciência e dedicação.

Sou grata a toda equipe do Núcleo de Engenharia Organizacional (NEO-UFRGS), que são motivo de inspiração e motivação para mim.

Também agradeço a todos os colegas e amigos que fiz durante a jornada do mestrado, que mesmo diante do distanciamento, conseguimos criar uma ótima relação.

Por fim, também agradeço à banca examinadora pela disposição e contribuição para a avaliação dessa dissertação.

CRÉDITOS

A pesquisa apresentada foi desenvolvida no Núcleo de Engenharia Organizacional da Universidade Federal do Rio Grande do Sul (NEO/UFRGS), como parte integrante do Programa de Pós-graduação em Engenharia de Produção da mesma universidade (PPGEP/UFRGS). O desenvolvimento desta dissertação foi possível graças à bolsa de mestrado outorgada à candidata pela Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) do Ministério da Educação, do Governo Federal do Brasil.

RESUMO

A Indústria 4.0 é considerada a quarta revolução industrial porque utiliza uma ampla integração de tecnologias de informação e de operação na fabricação industrial. Apesar dessa perspectiva tecnológica, diversos estudos vêm evidenciando a importância de considerar o fator humano para o desenvolvimento de um sistema de manufatura inteligente. Nesse sentido, a dimensão denominada como Smart Working precisa ser melhor investigada, uma vez que entender como as tecnologias afetam os trabalhadores e as habilidades desses são cruciais para o bom desempenho das fábricas. Em razão disso, o objetivo desta dissertação foi entender como as Smart Working Technologies (SWT) podem contribuir para as atividades e as habilidades dos trabalhadores da manufatura. Para tanto, primeiramente foi realizada uma análise abrangente da literatura para identificar as SWT e seus impactos nas capacidades dos trabalhadores em suas atividades de manufatura. Deste modo, foram analisados 80 artigos que relacionam as SWT em oito atividades de manufatura. Posteriormente, foi selecionada uma das SWT mais relevantes conforme a literatura, os robôs colaborativos, para identificar os efeitos das tecnologias nas habilidades dos trabalhadores. Deste modo, foram analisados 138 casos de aplicação reportados por uma das empresas fornecedoras líderes mundiais, bem como três entrevistas com empresas adotantes da tecnologia. Os resultados apontam que existem 15 SWT que podem ser implementadas nas atividades de manufatura e relacionadas às capacidades dos trabalhadores. Além disso, os resultados também apontam que podem existir quatro efeitos das SWT nas habilidades dos trabalhadores. Estes achados demonstram que de acordo com a estratégia da empresa uma SWT pode impactar de diferentes formas os trabalhadores.

Palavras-chave: Tecnologias do Trabalho inteligente; Indústria 4.0; Manufatura; Trabalhadores; Habilidades.

ABSTRACT

Industry 4.0 is considered the fourth industrial revolution because it uses a broad integration of information and operating technologies in industrial manufacturing. Despite this technological perspective, several studies have highlighted the importance of considering the human factor to develop a smart manufacturing system. In this sense, the Smart Working dimension needs to be further investigated since understanding how technologies affect workers and their skills are crucial for factories' good performance. Therefore, the objective of this dissertation was to understand how Smart Working Technologies (SWT) can contribute to the activities and skills of manufacturing workers. To this end, firstly a systematic literature review was carried out to identify SWTs and their impacts on workers' capabilities in their manufacturing activities. Thus, 80 articles relating to SWT in eight manufacturing activities were analyzed. Subsequently, one of the most relevant SWTs according to the literature, collaborative robots, was selected to identify the effects of technologies on workers' skills. In this way, 138 application cases reported by one of the world's leading supplier companies were analyzed, as well as three interviews with companies that adopted the technology. The results show that there are 15 SWT that can be implemented in manufacturing activities and related to workers' capabilities. In addition, the results also point out that there may be four effects of SWT on workers' skills. According to the company's strategy, these findings demonstrate that an SWT can impact workers in different ways.

Keywords: Smart working technologies; Industry 4.0; Manufacturing; Workers; Skills.

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SUMMARY

1 INTRODUCTION

Industry 4.0 (I4.0) can be defined as the new industrial stage in which integrating emerging technologies with organizational concepts and principles is used to create industrial value (Frank et al., 2019; Ivanov et al., 2021). In many situations, the technological nature of I4.0 presents conflicts concerning manufacturing workers, being presented as a threat to the future of jobs (Autor et al., 2020; Schuh et al., 2020). However, many studies suggest that this is not necessarily the way to go for most companies, as workers remain necessary and valuable for flexible operations (Fantini et al., 2020; Peruzzini et al., 2020). Therefore, although I4.0 is a trend in practice and research, the dimension of Smart Working, the impacts of I4.0 technologies on workers, and the effects on workers' skills due to I4.0 technologies are still points that deserve further discussion (Ivanov et al., 2021; Meindl et al., 2021).

Given this context, it becomes relevant to investigate which technologies have the potential to support manufacturing workers and in which manufacturing activities these technologies can help workers. This is because, through the Human-Technology symbiosis, workers' capabilities can be leveraged, benefiting them in the various activities they need to perform (Romero et al., 2020). With this, smart factories will act as socio-technical systems that, based on digital technologies, will help people perform their activities even better (Marcon et al., 2021; Romero et al., 2020).

In addition to identifying technologies and potential activities in which they can help workers, it is also essential to understand the effects of technologies on workers when they are implemented. That is, considering that with the implementation of technologies, manufacturing activities can be modified, workers need to align their skills according to the new context (Perini et al., 2017). Generally speaking, the implementation of technologies can positively or negatively affect workers (Parker et al., 2017). Substitution, deskilling, and upskilling of workers' activities may occur among these effects (Dworschak & Zaiser, 2014; Hirsch-Kreinsen, 2016). In addition, it is also possible to identify the stage of reskilling in which, due to the implementation of the technology, the worker needs to develop new skills to operate it (Rangraz & Pareto, 2021).

In this sense, we first sought to carry out a comprehensive review of Smart Working Technologies (SWT), showing how each of them can impact the capabilities of workers according to the typology by Romero et al. (2016) and for which manufacturing activities they are implemented (Bueno et al., 2020; Hinckeldeyn et al., 2014; Á Segura et al., 2020). Then, we sought to select one of the most relevant SWTs according to the literature, collaborative robots (Dornelles et al., 2022), to identify the effects of technologies on the activities of manufacturing workers considering the human-robot collaboration level (Bauer et al., 2016; Wang et al., 2019) and the manufacturing workers' activities (Bueno et al., 2020; Hinckeldeyn et al., 2014; Á Segura et al., 2020).

1.1 OBJECTIVES

This dissertation aims to *understand how SWTs can contribute to manufacturing activities and affect workers' skills in the context of Industry 4.0 in manufacturing companies*.

This general objective is built based through *two* specific objectives:

1) *To identify SWTs and define in which manufacturing activities they are implemented, highlighting the capabilities of workers that can be impacted.* In this sense, we seek to answer the following questions: How can Industry 4.0 technologies contribute to workers' activities for a Smart Working-based manufacturing system? What are the contributions and limits of the use of such technologies? We used the typology by Romero et al. (2016) to classify the SWTs and the manufacturing activities related to the workers' capabilities.

2) *To define the SWT effects on workers in their manufacturing activities.* For this, we selected the collaborative robots (a relevant SWT according to the literature) to define the final structure of the dissertation (Figure 6). So, we sought to answer: How can the implementation of collaborative robots affect manufacturing workers in their activities? We performed a conceptualization about the effects of technologies on workers activities based on the types of human-robot collaboration according to Bauer et al. (2016) and Wang et al. (2019) considering observations, application cases of a supplier company, and interviews with provider managers, adopters and competitors of collaborative robots global Market.

These two specific objectives were developed in two independent and complementary articles articulated around a previous study carried out by Frank et al. (2019) that present the Smart dimensions of Industry 4.0. In this way, we deepened our analysis in the Smart Working dimension and its technologies aiming at the context of manufacturing companies and workers.

1.2 RESEARCH METHODS

We adopted a qualitative approach to achieve the two specific objectives of this dissertation. In the first article, linked to the achievement of specific objective one, we carried out a Systematic Literature Review (SLR) based on the five-step method of Denyer & Tranfield (2009), which is appropriate for research related to the area of operations management. In the second article, we carried out a case study with an inductive approach to conceptualize the effects of SWTs on the activities of manufacturing workers through document analysis, interviews and observations. To carry out this study, we deepened our analysis around collaborative robots, a prominent technology among SWTs in I4.0. Figure 1 summarizes the objectives of each article and the method.

The first article, *"Smart Working in Industry 4.0: How digital technologies enhance manufacturing workers' activities"*, comprises an SLR considering the full reading of 80 scientific articles that contained I4.0 technologies applied in manufacturing activities. Through the SLR steps proposed by Denyer & Tranfield (2009), it was possible to identify 15 SWTs applied in eight manufacturing activities. Thus, we relate these findings to the capabilities typology by Romero et al. (2016), showing that different technologies can be implemented in manufacturing activities to improve workers.

The second article, *"Using collaborative robots to create Industry 4.0 smart working environments: impacts on manufacturing workers' skills"*, search through a case study inductive approach based in documental review, interviews, and technology observation conceptualized the SWTs' effects in manufacturing workers' activities. To realize this conceptualization, we used collaborative robots case applications and human-robot collaboration classification by Bauer et al. (2016) and Wang et al. (2019) to validate the concepts.

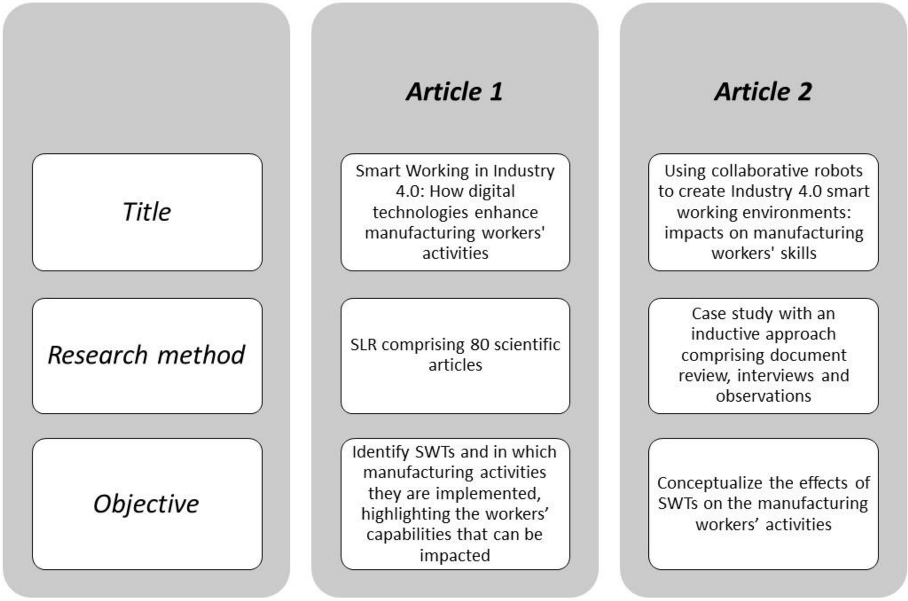

Figure 1 - Methodological structure of the dissertation

1.3 PRACTICAL AND THEORETICAL CONTRIBUTIONS

This dissertation presents practical and theoretical contributions. Among the theoretical contributions, through Article 1, we show the Smart Working Technologies (SWT), we expand the concept of Operator 4.0 to other occupational categories, such as technicians and engineers, supporting the concept of Worker 4.0. In addition to these, from Article 2, we also determine the types of effects cobots have on worker skills and how they relate to levels of human-robot interaction. As practical contributions, in Article 1, we demonstrate the technologies that can contribute to workers and their benefits and limitations. Furthermore, we also clarified which manufacturing activities can be supported by these technologies helping in the design of Smart Working environments. Through Article 2, we built a framework that can help in the decision-making process of implementing cobots for different activities. In addition, we clarified the kind of effect workers suffer from cobots.

1.4 STUDY LIMITATIONS

The main limitation of this study is to consider only one of the SWTs to validate the types of SWT effects on workers. Although we used collaborative robots in the analysis, a prominent technology in I4.0 and also relevant to supporting manufacturing workers (Dornelles et al., 2022; Østergaard, 2017), other studies could test with other SWT if these effects can also be related to them.

Another relevant limitation is the specific analysis of traditional manufacturing activities, which, as suggested (Frank et al., 2021), can be modified or even extinguished as industries implement digital age technologies. Thus, due to the speed in the advancement of technology implementation, new manufacturing activities may arise and require new studies to evaluate the concepts proposed in this dissertation.

In addition, other limitations are described in the body of each of the articles in more detail and other suggestions for future studies.

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2. ARTICLE 1 - SMART WORKING IN INDUSTRY 4.0: HOW DIGITAL TECHNOLOGIES ENHANCE MANUFACTURING WORKERS' ACTIVITIES

Jéssica de Assis Dornelles[+]

Néstor Fabián Ayala[+]

Alejandro G. Frank[+]

[+] Organizational Engineering Group (*Núcleo de Engenharia Organizacional – NEO*), Department of Industrial Engineering, Universidade Federal do Rio Grande do Sul, Brazil.

***This paper was published in Computers & Industrial Engineering (Elsevier, IF = 5.431).**

ABSTRACT

Prior studies have investigated the relationship between Industry 4.0 technologies and work. This paper acknowledges the contributions of such studies and builds on their perspective to broaden the understanding of the contribution of Industry 4.0 technologies to specific worker capabilities and manufacturing activities. The aim is to build a conceptual framework to consolidate a common view on this growing yet fragmented issue by integrating a wide range of findings from the literature. The study adopts a systematic literature review approach to systematize such knowledge in a singular and consolidated perspective on Industry 4.0 technologies and work. The study analyzes 80 papers in this field and investigates how different Industry 4.0 technologies are related to workers' manufacturing activities. Eight main manufacturing activities were considered to frame the analysis: assembly, maintenance, training, quality control, movement, machine operation, product and process design, and production planning and control. Eight worker capabilities that Industry 4.0 technologies can enhance were also considered: super-strength capability, augmented capability, virtual capability, healthy capability, smart capability, collaborative, social capability, analytical capability. Based on these 80 papers, this paper conceptualizes Smart Working-related technologies for Operators 4.0 and shows their benefits and limitations as described in the literature. The study shows how these manufacturing activities and worker capabilities can be supported by Industry 4.0 technologies, which is useful for future research and the design of operational processes in the Industry 4.0 context.

Keywords: Industry 4.0; Digital technologies; Smart Working; Operator 4.0; Workforce; Manufacturing.

1. INTRODUCTION

Industry 4.0 has been proposed as a new maturity stage of industrial activities driven by four base technologies: Internet of Things (IoT), Cloud Computing, Big Data, and Analytics (Frank et al., 2019). These technologies support other front-end Industry 4.0-related technologies such as robotics, virtual reality, and 3D printing to configure a cyber-physical system (Dalenogare et al., 2018). The technological nature of Industry 4.0 has sometimes put this concept at odds with the workforce and jobs (Autor et al., 2020, Schuh et al., 2020). For some scholars, an advanced level of Industry 4.0 means high automation and independence from operational workers, using workers only for cognitive tasks on the shopfloor (Dinlersoz and Wolf, 2018, Fallaha et al., 2020, Weichhart et al., 2019). Perhaps unintentionally reflecting this perspective, the highest level of the German Academy of Science and Technology (ACATECH) Industry 4.0 maturity index is represented by autonomous production systems, which considers machines able to make decisions and adjust operations without workers' intervention (Schuh et al., 2020). However, a growing stream of the literature has suggested that this is not necessarily the path for most companies to follow, as workers are still necessary and valuable for operations (e.g., Fantini et al., 2020, Peruzzini et al., 2020). In the Industry 4.0 context, Romero et al. (2016) dubbed these workers "Operators 4.0", referring to the fact that they are enabled by smart technologies to perform their work. Moreover, Frank et al., 2019 called attention to the Smart Working dimension of Industry 4.0, suggesting that work processes can be part of the Industry 4.0 concept and, in such a case, rather than replacing workers, Industry 4.0 should play a role in enabling workers for improved productivity. In the same vein, the European Commission has acknowledged the relevance of creating human-centered manufacturing to be more resilient and sustainable, which has been named Industry 5.0 and is considered a complementary and expanded view to Industry 4.0 (Breque et al., 2021). All these perspectives provide a similar argument: that workers need to be enhanced by digital technologies in this new industrial age.

However, as recently evidenced by Meindl et al. (2021) in an extensive literature review (examining over 5000 papers) on the ten years of research in the Industry 4.0 field, the Smart Working dimension is still the least investigated one in the Industry 4.0 domain, representing the main gap for future research to fill in this area. Meindl et al. (2021) showed that the interface between Operators 4.0, the technologies used, and the several operations processes that need to be executed to obtain a Smart Working approach is still unclear. Other studies like those sponsored by the MIT Work of the Future Initiative (Autor et al., 2020) have stressed that it is still uncertain how advanced and digital technologies may impact or enable workers in the new digital transformation domain. The Initiative has empirically investigated this relationship showing that its effects can be twofold: jobs may be affected by technologies, but technologies can also enhance workers' capabilities to achieve higher productivity levels (Autor et al., 2020). Recent studies in the Operations Management field have been proposed to consider aspects of the dynamics between Industry 4.0 digital technologies and work, shedding some light on themes such as human-system interfaces (Grandi et al., 2020, Longo et al., 2017, Peruzzini et al., 2020), the different ways how humans can use wearables in the industrial context (Khakurel et al., 2017), and the impact of digital technologies on work design (Cagliano et al., 2019). Complementary studies have pointed to the contributions of technologies for cognitive aspects such as design (Peruzzini et al., 2018), production planning and control (Bueno et al., 2020), and shopfloor decision-making activities (Soban et al., 2016). These make up an incipient body of evidence starting to fill the gap referred by Meindl et al. (2021).

Indeed, research on human-centered Industry 4.0 has recently grown, and some contributions of Industry 4.0 technologies to manufacturing work are becoming clearer (Cagliano et al., 2019). Nevertheless, a broader view of the relationship between these technologies and workers' activities is still to be consolidated (Ghobakhloo et al., 2021, Meindl et al., 2021). Because workers' activities need to adapt as new technologies are implemented (Trstenjak & Cosic, 2017), it is now crucial to understand how this happens. Moreover, since the nature of work is complex (Longo et al., 2017), scholars should not treat operational work processes as a black box. Manufacturing may involve several types of activities; likewise, Industry 4.0 technologies can make different contributions for each of them (Frank et al., 2019). While extant studies only focus on the direct relationship between Industry 4.0 technologies and workers (Romero et al., 2016, Ruppert et al., 2018), a deeper understanding demands to consider the context where it happens, i.e., the type of manufacturing activities (Kirikova et al., 2012). Meindl et al. (2021) showed that the literature responding to these challenges is growing but still fragmented in several unconnected streams of research. Therefore, the following research questions are proposed: How can Industry 4.0 technologies contribute to workers' activities for a Smart Working-based manufacturing system? What are the contributions and limits of the use of such technologies?

Rather than following the trend of an empirical investigation on Industry 4.0 technologies and work (e.g., Fantini et al., 2020, Peruzzini et al., 2020), this study acknowledges the contributions of previous studies taking such a perspective to broaden the understanding of the contribution of Industry 4.0 technologies to work activities, but also remark that a better framework is needed to build a common view on this issue. Therefore, this study adopts a systematic literature review approach to answer the research question, aiming to systematize such knowledge in a singular and consolidated perspective on Industry 4.0 technologies and work. The study analyzes 80 papers in this field and investigates how different Industry 4.0

technologies are related to workers' manufacturing activities. Eight main manufacturing activities were considered to frame the analysis, namely (Bueno et al., 2020, Hinckeldeyn et al., 2014, Segura et al., 2020): assembly, maintenance, training, quality control, movement, machine operation, process, and product design, and production planning and control. By analyzing these 80 papers, the study conceptualizes Smart Working technologies for Operators 4.0 and shows their benefits and limitations as described in the literature. The results show how these manufacturing activities can be supported by Industry 4.0 technologies, which is useful for future research and the design of operational processes in the Industry 4.0 context.

2. THEORETICAL BACKGROUND

2.1. INDUSTRY 4.0 AND SMART WORKING

According to Frank et al. (2019), Industry 4.0 technologies can be divided into base and front-end technologies. Base technologies are general-purpose technologies that provide connectivity and intelligence for front-end technologies. Base technologies can be summarized as four: Internet of Things, Cloud Computing, Big Data, and Analytics (which include passive analytics and artificial intelligence) (Frank et al., 2019). Base technologies allow front-end technologies (technology applications) to be connected to a fully integrated manufacturing system (Tao et al., 2018, Wang et al., 2016). The front-end technologies supported by base technologies consider four ‘smart dimensions’ – Smart Manufacturing, Smart Products and Services, Smart Supply Chain, and Smart Working – which become the focus of Industry 4.0 technology application (Meindl et al., 2021). Smart Manufacturing considers the application of technologies to make the production system more ‘intelligent’; Smart Product-Service System considers the provision of connected products and services that integrate the customer with the manufacturing activity (Frank et al., 2019), and Smart Supply Chain considers how to integrate the supply chain with manufacturing activities (Benitez et al., 2021). A final but equally important dimension is Smart Working, which is expected to support the other ‘smart’ dimensions (Meindl et al., 2021). The study focuses the attention on this dimension because it acknowledges that, as well as the other smart dimensions, workers may also be the focus of technology application (Frank et al., 2019). While the other three smarts focus technology applications on creating intelligent and automated systems, Smart Working enhances workers with technology-enabled capabilities (Romero et al., 2016, Ruppert et al., 2018).

The Smart Working dimension is especially important when companies aim to increase their manufacturing system's flexibility because it considers the workers the most adaptable and resilient element in the manufacturing socio-technical system (Marcon et al., 2021). Smart

Working can be considered an expansion of the Operator 4.0 concept proposed by Romero et al. (2016) and is in line with the human-centered manufacturing proposed by those that suggested a new emergent Industry 5.0 concept (Breque et al., 2021). While the Operator 4.0 perspective is centered on workforce capacity, the Smart Working dimension takes a broader outlook on the work processes and the way tasks are executed in the manufacturing field (Frank et al., 2019, Meindl et al., 2021). It borrows the concept from the organizational management literature, in which Smart Working focuses on 'doing the work differently' and is enabled by digital tools (Bednar & Welch, 2020). The study follows this view because it considers operational and managerial manufacturing activities in the Industry 4.0 context, involving cognitive and routine processes demanded by workers. In this sense, the Smart Working dimension can reach a broader understanding that considers the activities of operators, managers, and engineers in the manufacturing field. Additionally, while the Industry 5.0 concept has embraced society development together with the human role in manufacturing systems (Breque et al., 2021), the Smart Working concept preserves the Industry 4.0 concept, but it enhances the worker role into this concept, which is still emerging (Meindl et al., 2021).

The Smart Working dimension of Industry 4.0 considers a set of technologies that can support workers to increase their productivity and flexibility to meet the manufacturing system's requirements (Kagermann et al., 2013, Stock et al., 2018). For instance, augmented reality may be used in design projects (Bruno et al., 2019), assembly operations (Lai et al., 2020), training (Tao et al., 2019, Tao et al., 2019), and quality control (Tarallo et al., 2018). Similarly, virtual reality may be used for training and assembly (Gorecky et al., 2017, Roldán et al., 2019). Collaborative robots, in turn, have diverse applications, including movement, operation, assembly (Calzavara et al., 2020, Cherubini et al., 2019, Weckenborg et al., 2020), and maintenance (Koch et al., 2017). These are just a few examples of technologies that support the worker and are part of the Smart Working dimension. The concept of 'Operator 4.0’ by Romero et al. (2016) describes typologies of operators that use different advanced technologies to improve physical, sensory, and cognitive capabilities in integration with the human cyber-physical system. The interactions between operators and machines, wearable technologies, sensors, or other technologies increase operator capabilities, enabling a better adaptation to the new work environment recreated by Industry 4.0 (Fallaha et al., 2020). However, although digital technologies are presented as useful for Smart Working, the literature has also suggested some limitations. For instance, it has been observed that the effects of smart glasses may be either positive or negative depending on the type of activity and each worker's profile (Dalenogare et al., 2019). Studies on other wearables also reported similar constraints (e.g., Longo et al., 2020, Simões et al., 2019). Therefore, the Smart Working literature also presents challenges that should be investigated before assuming this as an always positive approach for workers (Meindl et al., 2021). Therefore, this study collects evidence from both positive and negative perspectives to pursue a better understanding of the relationships between emerging technologies in Industry 4.0 and particular work settings.

2.2. SMART WORKING AND MANUFACTURING ACTIVITIES

Industry 4.0 has been related to operational or manufacturing activities in prior studies (Romero et al., 2016, Ruppert et al., 2018). Romero et al. (2016) considered different workers' capabilities that can be enabled by Industry 4.0 technologies: (i) the super-strength operator considers technologies such as exoskeleton to support physical-dependent activities, increasing strength and resistance; (ii) the augmented operator uses augmented reality to enrich workers' interaction with their real manufacturing environment; (iii) the virtual operator, considers the use virtual reality tools to create an immersive interaction and simulate the manufacturing environment virtually; (iv) the healthy operator uses wearable devices to measure health-related conditions, location, and personal data; (v) the smarter operator is supported by an intelligent personal assistant to improve the human–machine interface; (vi) the collaborative operator uses collaborative robots to perform joint activities; (vii) the social operator is supported by social networks to quickly address any challenges arising in the activities; and (viii) the analytical operator uses tools like big data and artificial intelligence to support decision-making processes.

Complementarily to this view from Romero et al. (2016), this present paper analyzes Smart Working in the Industry 4.0 context from another point of view by including the main manufacturing activities. Segura et al. (2020) described the manufacturing activities of the Operators 4.0 in six main types: assembly, maintenance, quality control, training, inventory (or material movement), and machine operation. In order to detail these six manufacturing activities, the assembly activity can be defined as the set of operations (actions) performed on a series of components (resources) that must follow a particular order and certain conditions (Tarallo et al., 2018). Maintenance comprises planned and unplanned actions taken to keep the equipment in acceptable operating conditions (Wang et al., 2007). Quality control is an activity to ensure the stability of process parameters by evaluating the actual performance and comparing it with specifications (Juran & De Feo, 2010). Training is a necessary activity to transfer knowledge and skills to new workers, which in the manufacturing field has a strong learning-by-doing component (Marchi et al., 2019; Peniche et al., 2012). Material movement activities consider handling materials, components, and products on the shop floor to keep the inventory organized (Hicks, 2007). Machine operations consider one of the operators' main activities: using their skills and knowledge to handle the production equipment to execute operational processes (Seider et al., 2019).

In addition to the routine (and sometimes non-cognitive) activities described above, work can also involve cognitive and non-routine activities (Autor and Handel, 2013, Frey and Osborne, 2017). Therefore, the study extends these manufacturing activities to two additional aspects considered in the operations management literature: production planning and control (Bueno et al., 2020) and product and process design (Hinckeldeyn et al., 2014), which are also considered fundamental activities for smart manufacturing systems and can be supported by digital tools. Production planning and control activities involve cognitive activities necessary to define how, when, and how much to produce in the manufacturing activities. Then, the production execution follows up to verify any differences from the initial plan (Stevenson et al., 2005). Bueno et al. (2020) have shown that smart production planning and control is also a key activity in the Industry 4.0 model, which can be supported by a human–machine interface for its execution. Besides, process and product design are also activities of the Industry 4.0 field since the end-to-end engineering principle proposed by the Industry 4.0 concept requires product design to be connected with the manufacturing activities (Dalenogare et al., 2018). This activity is also highly dependent on workers, but these are different from the workers involved in the manufacturing routine since they execute highly cognitive, non-routine, and creative activities that also require the support of digital tools (Frey & Osborne, 2017). Therefore, this paper integrates these eight manufacturing activities, six from Segura et al. (2020) and two from complementary literature, to consider how Industry 4.0 technologies can support such activities. This study also aims to relate these manufacturing activities with the enhanced worker capabilities proposed by Romero et al. (2016) to provide a better overview of the use of Industry 4.0 technologies in work.

3. Research method

A Systematic Literature Review (SLR) was conducted to systematize the body of research on Industry 4.0 technologies and work (Okoli & Schabram, 2010). Five stages of SLR proposed by Denyer & Tranfield (2009) were adopted, which are (i) Research formulation; (ii) Studies identification; (iii) Selection and evaluation of studies; (iv) Analysis and synthesis of results and; (v) Presentation of results (the latter is presented in Section 4). Scholars have successfully implemented this method in the Operations Management field and the Industry 4.0 context (Liboni et al., 2019, Núñez-Merino et al., 2020, Rauch et al., 2020).

3.1. RESEARCH FORMULATION

Regarding the formulation of the research question, two main questions were defined, as presented in the introduction: How can Industry 4.0 technologies contribute to workers' activities for a Smart Working-based manufacturing system? Moreover: What are the contributions and limits of the use of such technologies? A conceptual framework was formulated to support the analysis of the research questions (Section 2). Eight manufacturing activities of workers were considered (Segura et al., 2020, Bueno et al., 2020, Hinckeldeyn et al., 2014): (i) assembly, (ii) maintenance, (iii) quality control, (iv) materials movement, (v) training, (vi) machine operation, (vii) production planning and control, and (viii) product and process design. Additionally, eight technology-enabled workers' capabilities proposed by Romero et al. (2016) for the Operators 4.0 were considered. The conceptual framework supported the investigation of technologies and data analysis.

3.2. IDENTIFICATION OF STUDIES

The second stage of the SLR method aimed to locate studies related to the research question and relevant to the intended analysis. Thus, an essential step comprised choosing the appropriate search engines, defining search queries, and using the conventions for search (Denyer & Tranfield, 2009). Scopus and Web of Science (WoS) databases were adopted as search engines because they comprehend most of the operations management and industrial engineering journals that comprise this study's scope (Meindl et al., 2021). As search queries, keywords and titles were reviewed to identify a set of Industry 4.0 and work terms. The search queries were defined based on keywords used in previous literature reviews addressing topics related to smart manufacturing and work (Kamble et al., 2018, Liao et al., 2017, Liboni et al., 2019, Núñez-Merino et al., 2020, Rauch et al., 2020, Zarte et al., 2020, Zheng et al., 2021). Furthermore, seminal studies in the Industry 4.0 field were included based on the number of citations and alignment with the research topic (e.g., Dalenogare et al., 2018, Frank et al., 2019, Romero et al., 2016). Hence, as the research objective of this paper is to offer an overview of Industry 4.0 technologies and manufacturing work activities, the research strings were designed to find the documents included in this intersection.

The search string was constructed using logical and Boolean operators to find studies with at least one of the keywords in each of the two main search query groups in the title, abstract, or keywords for Scopus database, and in the topic (title, summary, author's keywords, expanded keywords) in WoS. A total of nine keywords for the smart manufacturing set and nine for the work set were used. These keywords, as well as the strings used in the databases, are shown in

Table 1. The table also shows that the Industry 4.0 term was limited to the manufacturing domain since broader concepts may include the other smart dimensions described by Frank et al. (2019). However, this present study aimed to consider only the internal manufacturing processes in which Industry 4.0 technologies may support workers.

Table 1 - Search keywords and strings

Industry 4.0	Worker
"industry 4.0"	"work 4.0"
"industrie 4.0"	"operator 4.0"
"industrial internet"	"cyber physical human system"
"smart factory"	"human cyber physical system"
"smart manufacturing"	"smart work"
"digital manufacturing"	"work place"
"intelligent manufacturing"	Worker
"factory 4.0"	Employee
"smart production"	"human-centred"
"industry 4.0" *OR* "industrie 4.0" *OR* "industrial internet" *OR* "smart factory" *OR* "smart manufacturing" *OR* "digital manufacturing" *OR* "intelligent manufacturing" *OR* "factory 4.0" *OR* "smart production" *AND* "work 4.0" *OR* "operator 4.0" *OR* "cyber physical human system" *OR* "human cyber physical system" *OR* "smart work" *OR* "work place" *OR* worker *OR* employee *OR* "human-centred"	

By using these keywords and search terms, a total of 2307 articles were identified in the databases consulted, 842 of them in WoS and 1465 in Scopus. The terms used in the search were all in English, except for the German term Industrie 4.0, included because the concept was coined in Germany, and some papers still use the term in the original language.

3.3. Selection and evaluation of studies

The next step aimed to filter the studies found in the previous step and select relevant ones for the subsequent analysis (Okoli & Schabram, 2010). Fig. 1 represents the selection flow, in which some inclusion and exclusion criteria were defined to address the research questions. These criteria must be explicit so that decisions can be evaluated and updated (Denyer & Tranfield, 2009). First, some filters were applied in the databases to export the studies subject to more careful evaluation. Thus, the search was limited to studies published from 2011 to April 2021, i.e., from when the Industry 4.0 concept was coined at the Hannover Fair (Pfeiffer, 2017) until the date when this present research was performed. A filter was then used to limit the search fields to manufacturing, engineering, management, business, and applied computer sciences, which are the most commonly focused on the investigated topics (Meindl et al., 2021). Additionally, the document type filter was applied, selecting the option 'article' since these are the most relevant, peer-reviewed works to reinforce the scientific nature of this systematic review. Finally, a language filter was applied because the most relevant studies in the research area were published in English. Based on these filters, 152 articles were initially extracted from WoS and 383 from the Scopus database. Upon extraction, these studies were entered into a reference manager in which 125 duplicate articles were eliminated, resulting in a set of 410 studies. Next, the procedure was to verify whether the studies in the set had the full text available or not. Eight documents were removed because the full text was not available (only title, abstract, and keywords), resulting in 402 articles. Subsequently, the title, abstract, and keywords of the articles were manually analyzed. Studies that were not related to the research questions (322 exclusions) were excluded. In this case, articles that did not address Industry 4.0 technologies and/or manufacturing activities were excluded. As a result, 80 articles were read in full for the stage of analysis and detailed synthesis. The manual analysis of the initial refined sample (402 articles) and the complete review of the final 80 articles were performed by three researchers with the support of two research assistants. Fig. 2 summarizes the systematic review method adopted in this study, covering all stages and applied filters.

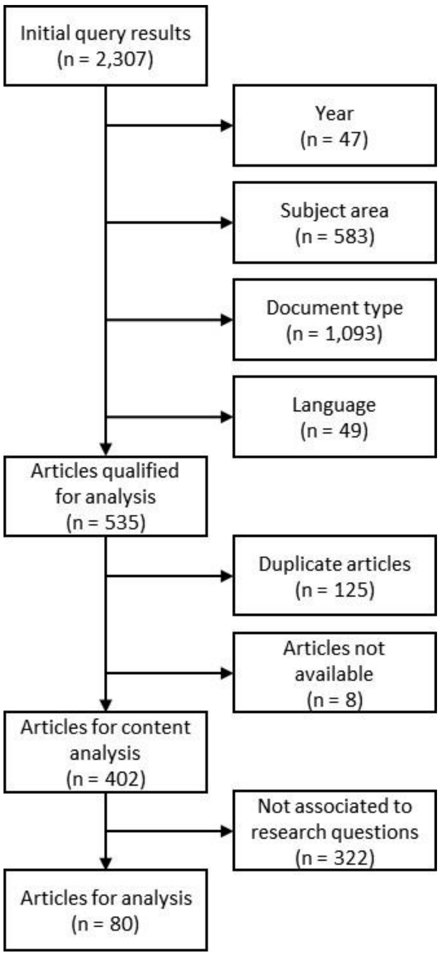

Figure 2 - Summary of the systematic review method

3.4. ANALYSIS AND SYNTHESIS OF THE RESULTS

The analysis and synthesis of results aimed to group the individual studies, describing their relations. Thus, information was first extracted and stored according to the investigated issues and the details observed were included (Denyer & Tranfield, 2009). Thus, this step was carried out by reading the selected documents in full, seeking to identify the intended elements of the research. In this sense, the procedure to identify and analyze Smart Working technologies and associate them with manufacturing activities and workers' capabilities was based on a content analysis approach in which the meaning and the categorization rules were used (Bardin, 1977). The meaning rule considers identifying common issues that are clustered according to the interpretation given to their meaning (Bardin, 1977). The categorization rule adopted defines the name of the groups at the end of the construction, according to the semantic criteria, and classified according to the general meaning of the elements from each category (Bardin, 1977). Thus, we grouped Industry 4.0 technologies cited in the work context to define their meanings and names at the end of the grouping process. The establishment of meanings supported by previous seminal studies related to smart, such as Romero et al., 2016, Frank et al., 2019, and Meindl et al. (2021). These studies helped create the initial meanings that define Smart Working technologies and workers' capabilities potentially enhanced by these technologies. The initial labels were expanded by reviewing the identified papers. The meaning rule demanded that the papers mention specifically Industry 4.0 technologies that help manufacturing workers. Thus, Industry 4.0 technologies were included in the Smart Working technologies list only when associated with workers.

Moreover, the meaning rule also considered manufacturing activities and workers' capabilities as described in Section 2.2. Synonyms related to these labels were used to capture the context described in the paper. For instance, when the technology was described as being used by workers to support their interaction with machines, better manufacture product parts, operate the production process, or any similar meaning, it was attributed to the 'machine operation' manufacturing activity. The description of what technologies do in such context also helped to classify the relationships. For instance, a paper describing how the worker handles equipment through a technology to manufacture a component was associated with 'machine operation' given its clear context-relation. Complementary information about these technologies' positive and negative impacts was extracted from those papers that mentioned such characteristics. Again, a meaning rule was used to adopt synonyms to positive or negative impacts, such as benefits and problems, advantages and disadvantages, etc. Some examples of excerpts that explain the positive effects of technologies on manufacturing processes are cited: “the collaborative robot enables the manipulation of large and heavy objects”, “augmented reality improves the efficiency and learning of workers", "through the use of wearable devices, production planning, and control workers can control and access real-time location information improving planning and control" and "through industrial social networks companies can establish and continuously update a repository of best practices for engineering problems". Some examples of excerpts collected in industry 4.0 technology studies that negatively impact workers are cited: "collaborative robots can reduce task efficiency since the robot can be slower than human", "with augmented reality the operator uses instructions in the field of view when performing an assembly task; however when the worker already knows the process it can generate worse results", "the size and culture of the company can impact the good use of wearable devices by operators" and "workers may hesitate to share knowledge through industrial social networks".

Three researchers helped to review the papers and classify the contents using these rules. Two of them had the main role of clustering technologies and relating them to manufacturing activities and workers' capabilities. At the same time, the third researcher acted as a judge of when different interpretations were given to a specific technology. After the second round of review, all cases achieve convergency between the researchers. An additional external validity approach was employed to reinforce the correct interpretation and ensure that there was no bias by the three researchers. The researchers compared the obtained results with empirical evidence from 46 business reports on Industry 4.0 and work to check for external validity. The most important reports from this list were: a) "MIT Work of the Future Final Report: The Work of the Future: Building Better Jobs in an Age of Intelligent Machines" (Autor et al., 2020), b) "Workforce of the future: The competing forces shaping 2030" (PWC, 2018), c) "Preparing Brazil for the future of work: jobs, technology and skills" (Mckinsey, 2018), d) "The Future of Jobs Report" (WEF, 2018), e) "The Future of Jobs: Employment, Skills and Workface Strategy for the Fourth Industrial Revolution" (WEF, 2016). Since such business Workforce report detailed case studies on different technologies, they were used to double-check the coherence of the analyses performed in this present study.

4. RESULTS AND DISCUSSION

The results were divided into three subsections. The first subsection conceptualizes each of the Industry 4.0 Smart Working technologies described in the literature. The second section shows how these technologies are related to the different workers' manufacturing activities. Finally, in the last section, several benefits and impacts described in the literature were analyzed and connected to the findings with the worker capabilities described by Romero et al. (2016).

4.1. WHICH INDUSTRY 4.0 TECHNOLOGIES CONTRIBUTE TO SMART WORKING

In the studies analyzed in this SLR (see Appendix), 15 technologies related to manufacturing work were identified, all Smart Working technologies, as shown in Table 2. Table 2 presents the technologies, their definitions concerning workers, and the studies in the sample citing these technologies.

Table 2 - Technologies related manufacturing activities

Technologies	Definitions	Studies
Augmented reality (AR)	The workplace is improved by facilitating the visualization of information from factory data relevant for the performance of workers' activities (Álvaro Segura et al., 2020).	[2] [3] [4] [8] [10] [11] [13] [14] [15] [16] [17] [18] [21] [23] [25] [27] [28] [29] [32] [34] [40] [48] [49] [50] [56] [60] [62] [74] [77] [78]
Collaborative robots (CR)	A collaborative robot (cobot) is a complex machine that can physically interact with operators during assembly and manufacturing activities by sharing the workspace safely and assisting repetitive and non-ergonomic tasks (Calzavara et al., 2020; Romero et al., 2016).	[1] [9] [11] [15] [20] [24] [31] [35] [38] [39] [41] [49] [52] [59] [60] [64] [65] [70] [79] [80]
Virtual reality (VR)	The virtual reality (VR) technology enables immersive interaction and simulation with security and real-time feedback, enabling the safe use of dangerous equipment and improving the learning of procedures (Romero et al., 2016; Álvaro Segura et al., 2020).	[10] [12] [17] [32] [37] [59] [60] [68] [69] [73]
Wearable devices (WD)	A wearable technology or wearable device can be described as a piece of clothing, bracelet, or smartwatch designed to collect workers' health data and track operator movement, promoting the best management of this information (Longo et al., 2020; Romero et al., 2016).	[3] [8] [33] [46] [55] [57] [59] [66] [67] [76]
Environment and machine sensors (SENS)	Sensors are used to capture data and communicate between various actors (machines, equipment, and people). Together with the IoT (Internet of Things), it allows for the detection of any object and its connection to a wider system allowing the operator to discover useful information and predict relevant events in real time (Boyes et al., 2018; Romero et al., 2016).	[7] [8] [24] [42] [53] [75] [76]
Automation (AUT)	Automation, also known as advanced robotics, can be characterized as adaptable and flexible robots without human intervention. The machines operate autonomously, guided by pre-established parameters, improving performance and enriching the work of operators (Margherita & Braccini, 2020; Sacomano et al., 2018).	[19] [36] [45] [49] [63]
Voice-enabled assistant (VEA)	Voice-enabled assistants (VEA) are technologies to interact with workers using voice, giving them intuitive access to varied information and improving the human-machine interface and information management (Longo & Padovano, 2020; Romero et al., 2016).	[50] [56] [59] [61]
Digital Twin (DT)	Digital twins can be thought of as computer models with accurate virtual copies of machines or systems that use data collected from sensors in real time, reflecting almost every facet of a product, process, or service. They support workers in conducting processes without blocking real production capacities (Horváthová et al., 2019; Tao et al., 2019).	[26] [30] [56] [58] [75]
Smart decision support systems (SDSS)	Smart decision support systems use learning and problem-solving techniques to solve complex problems in real contexts. They improve operator performance by providing detailed process optimization instructions. Some examples are machine learning,	[5] [36] [43] [44] [72]

	neural networks, and data mining (Margherita & Braccini, 2020; Russell & Norvig, 2016).	
Automated Guided Vehicle (AGV)	The AGV (Automated Guided Vehicle) is a self-guided vehicle with an integrated magnetic or optical sensor that follows a prescribed path and performs turning and parking functions. It is used in industrial applications, freeing the operator from activities that do not add value (Le-Anh & De Koster, 2006; Nunes & Barbosa, 2020).	[15] [36] [47] [70] [71]
Computer Vision (CV)	Computer vision can be defined as a technology for acquisition, analysis, and synthesis of visual data using computers that provide tools relevant to the analyzed context. This improves the operator's cognitive process involved in understanding and gaining manufacturing data (Posada et al., 2015; Álvaro Segura et al., 2020).	[4] [22] [54]
Industrial social networks (ISN)	Industrial social networks function as social media in manufacturing. They can strengthen corporate collaboration and provide a mechanism to capture knowledge that processes data/information and produces valuable knowledge to support operators in decision-making (Li & Parlikad, 2016; Romero et al., 2016).	[6] [60]
Exoskeletons (EXO)	An exoskeleton assists workers through a device that acts on the body mechanically in order to assist or increase the operator's strength (Constantinescu et al., 2016; Romero et al., 2016).	[15]
Visual Analytics (VA)	The analytical view helps operators interpret and understand large amounts of data and relationships through intuitive representations (Álvaro Segura et al., 2020).	[60]
Artificial intelligence (AI)	Artificial intelligence (AI) can be defined as a technology capable of developing thought processes like learning, reasoning, and self-correction similarly to humans in order to supplement and increase worker capabilities (Russell & Norvig, 2016; Zolotová et al., 2020).	[51]

As shown in Table 2, the most cited technology in the studies is augmented reality. AR is commonly used to assist operators and technicians in performing complex tasks more quickly and assertively (Uva et al., 2018). An additional, less common application of AR is to assist engineers in planning activities to improve the productivity and efficiency of these workers (Wang et al., 2020b). This leads to the understanding that the use of technologies that mix real and virtual environments can improve workers' performance (Lai et al., 2020, Segura et al., 2020, Uva et al., 2018).

Collaborative robots were also closely linked to manufacturing. Although applied in different activities, collaborative robots showed lower diversification in their application. This technology is commonly used to assist operators in repetitive tasks, freeing them to perform activities that require greater flexibility (Koch et al., 2017). Another relatively unusual application is in process design activities, helping engineers redesign workstations (Gualtieri et al., 2021). However, the fact that collaborative robots are used in activities indicates that companies understand that using robots with humans safely enhances productivity (Cherubini et al., 2019, Koch et al., 2017, Weckenborg et al., 2020).

Although not cited as often as AR and collaborative robots, virtual reality and wearable devices are also highlighted as technologies that support workers. These technologies have rather diversified applications, with VR being more versatile than collaborative robots in terms of their activities. The main use of VR is to assist operators and technicians in conducting and practicing their activities, making it possible to “learn by doing” (Abidi et al., 2019). Another application, although less usual, is the use of VR to assist engineers in the design and reconfiguration of products (Damiani et al., 2018). Wearable devices are commonly used to collect health and movement data from operators to improve their health and ergonomics (Guo et al., 2019, Sun et al., 2020, Sun et al., 2020). However, a not-so-common application assists engineers in locating operators, facilitating the allocation of multifunctional operators according to the nearest workstations (Kymäläinen et al., 2017). Therefore it is possible to affirm that the use of VR and WDs in manufacturing is a trend that is here to stay, given its potential to increase productivity in workers' activities and, more specifically, to enhance training in the case of VR (Gorecky et al., 2017, Muñoz-Saavedra et al., 2020, Roldán et al., 2019), and increase efficiency, improve workers' physical well-being and reduce workplace accidents, in the case of wearable devices (Khakurel et al., 2017, Knoch et al., 2020, Sun et al., 2020, Sun et al., 2020).

Automation and sensors were rarely mentioned by studies linking technologies to workers' activities, although they can be applied in a wide range of activities. This may be due to a lack of focus on how these technologies directly benefit workers. Automation is usually referred to in terms of production performance, without consideration to its potential benefits for workers (Atack et al., 2019, Atlas et al., 1996, Dinlersoz and Wolf, 2018). Nevertheless, automation can protect operators from difficult working conditions and ergonomic risks (Klumpp et al., 2019). Environment sensors can benefit operators by helping in the maintenance and improvement of the working environment, collecting, for instance, air quality information (Papetti et al., 2021). Machine sensors, in turn, help establish an effective human–machine interaction system by a precise recognition of human movements that will promote operators' safety and well-being (Wang et al., 2018). It should be noted, however, that although such uses are still largely unexplored in the literature, studies on the benefits of sensors for workers are expected to become more common as their prices decrease, and more companies and workers can reap the benefits of automatic assessment in their activities (Cheng et al., 2013, Schuh et al., 2020).

The same can be said about digital twins and smart decision support systems. Even though these are more commonly connected to advantages for the production line, the systematic review has evidenced advantages for workers (Horváthová et al., 2019, Margherita and Braccini, 2020, Peruzzini et al., 2020). Digital twins can help engineers find more efficient ways to conduct processes without blocking real production capabilities (Horváthová et al., 2019). Smart Decision Support Systems can help operators and managers analyze data in real-time to improve production time and costs (Margherita & Braccini, 2020).

Voice-enabled assistant technology was also rarely related to manufacturing activities in the literature. This can be explained by the fact that it is still little explored for these activities (Longo & Padovano, 2020). However, as it will be seen in the next subsection, this technology can offer several advantages to workers in manufacturing systems and be applied in different activities. For example, this technology commonly supports technicians and specialists during maintenance tasks at the factory by providing information and tips on how to act (Longo et al., 2020). The same can be said about the Industrial Social Network: although still rarely applied in manufacturing systems, it can strongly support workers' activities by, for instance, improving the exchange of information on issues and experiences between engineers (Mourtzis et al., 2016).

Finally, computer vision, exoskeleton, visual analytics, and artificial intelligence technologies were the least mentioned in the studies and few applications in different activities. Surprisingly, computer vision and visual analytics, i.e., visual computing technologies, were rarely mentioned despite their potential to support workers' decision-making (Posada et al., 2015, Segura et al., 2020, Soban et al., 2016). Such a scarcity of studies may be due to a lack of interest by scholars in surveying the impacts of these technologies on activities or to a lack of widespread implementation of these technologies in the industries. A possible reason for the little expressiveness of exoskeletons in the results is that their cost of implementation is still high, and its advantages as yet unknown (Calzavara et al., 2020, Spada et al., 2017). Besides, there are few implementation cases in the industries, which leads to an even smaller number of cases studied. The low number of studies on the applications of artificial intelligence in manufacturing activities may be related to the low degree of maturity of companies in Industry 4.0, since companies at more advanced maturity levels are the ones that implement this technology in their activities and still rather restrictedly, as pilot solutions (Frank et al., 2019, Longo et al., 2020).

The following section will present details on where each of these technologies is used in each activity.

4.2. Where Industry 4.0 technologies contribute to smart working

The data analysis identified the technologies cited in the literature to be used in each specific manufacturing activity, as shown in Table 3. The cells represent the association between the activity and the technology. They are filled in with the corresponding references listed in detail in Appendix A. Empty cells mean that no reference was identified in the literature for this relationship between the specific technology and the manufacturing activity.

Table 3 - Smart Working technologies and manufacturing activities

	AR	CR	VR	WD	AUT	SENS	VEA	DT	SDSS	AGV/AMV	ISN	CV	EXO	VA	AI
Assembly	[2] [8] [10] [14] [15] [16] [18] [23] [27] [32] [48] [49] [60] [74] [78]	[1] [15] [20] [24] [31] [35] [39] [41] [49] [52] [59] [60] [64] [65] [79] [80]	[4] [10] [12] [32] [37] [59] [60] [68] [69]	[8] [46] [55][57][59] [66] [67]	[36] [49] [63]	[7] [8] [24] [75]		[26] [30] [75]		[15][36]		[4]	[15]		
Machine Operation		[1] [11] [15] [38] [59] [60]	[32] [59] [60]		[36] [49]		[50] [56] [59] [61]	[56]	[5] [36]			[22]		[60]	
Maintenance	[18] [25] [29] [32] [50] [56] [60] [62]	[9] [59] [60]					[50] [56] [59] [61]	[56]						[60]	[51]
Training	[2] [8] [18] [32] [50] [60] [74]		[12] [32] [37] [59] [60] [68] [69] [73]	[8] [59]		[8]	[50] [59] [61]								[51]
Quality control	[18] [21] [25] [27] [40] [49] [77]				[19] [49]							[4] [54]			
Materials movement		[1] [15] [70]		[33] [76]	[45]	[7] [42] [76]				[15] [47] [70] [71]			[15]		
Process and product design	[13] [16] [17] [18] [34]	[35]	[17]			[53]					[6] [60]				
Production planning and control	[3] [17] [28]			[3]				[58]	[43] [44] [72]						

Note: AR (Augmented reality); CR (Collaborative robots); VR (Virtual reality); WD (Wearable devices); AUT (Automation); SENS (Environment and machine sensors); VEA (Voice-enabled assistant); DT (Digital twin); SDSS (Smart Decision Support Systems); AGV (Automated guided vehicle); AMV (Autonomous Mobile Vehicle); ISN (Industrial Social Networks); CV (Computer vision); EXO (Exoskeleton); VA (Visual analytics); AI (Artificial Intelligence).

The Assembly activity is carried out by shop floor operators and is the activity in which more technologies are implemented. In this activity, augmented reality is used for indicating the stages in the assembling of real objects (De Pace et al., 2019), signaling and preventing errors, and putting the operator in remote communication with a specialist in case of doubts (Calzavara et al., 2020), eliminating the need for face-to-face supervision of operators with disabilities (Simões et al., 2019) and assisting experienced operators in complex assemblies (Lai et al., 2020). Collaborative robots are used for handling large and heavy objects and performing difficult tasks (Cherubini et al., 2019), assisting the operator in assembling a product according to personalization requirements and in unknown work situations (Wang et al., 2019), intelligently distributing assembly tasks according to the skills of operators and machines (Scholer & Müller, 2017), and transforming complex assembly tasks into semi-automatic ones (Pérez et al., 2020). Virtual reality is one of the most versatile technologies for application in manufacturing activities. This technology is especially used in the assembly activity to guide operators through the correct sequence of operations (Tarallo et al., 2018). Several studies consider it part of both assembly and training activities, for example, in cases where its functionality may eliminate the need for expert instruction in assembly tasks (Roldán et al., 2019). Wearable devices are applied in the assembly to collect operator data in real-time, mainly related to movements and workflows (Knoch et al., 2020). This leads to optimizing operators' activities and the elimination of waste (Guo et al., 2019). Besides efficiency gains, real-time data collection provides direct feedback on ergonomics during the assembly activity (Römer & Bruder, 2015). Automation works in a complementary way in assembly: on the one hand, operators supervise automatic assembly operations and adjust them according to production needs; this, on the other hand, is reflected in significant changes in operators' skills and operations (Margherita & Braccini, 2020). The digital twin acts as an interface for the operator, enabling the monitoring of assembly activities and aggregating useful information such as postural assessment (Peruzzini et al., 2020). Sensors complement other technologies such as wearable devices and collaborative robots and are mainly applied to precisely measure operators' movements (Tao et al., 2019, Tao et al., 2019, Wang et al., 2018). AGV in the assembly activity acts as a facilitator, i.e., it helps assembly operators by transporting the parts and tools necessary for the performance of their activities (Margherita & Braccini, 2020). Computer vision in the assembly activity supplements information with multimedia details, improving operator support (Tarallo et al., 2018). Lastly, exoskeletons in the assembly activity facilitate operators' activities by increasing their strength and productivity (Calzavara et al., 2020).

Machine Operation activities are carried out by shop floor operators. As shown in the results, a large set of technologies can be implemented in this activity. In the case of collaborative robots, they are used for operating activities to simplify operators' activities and perform less ergonomic tasks (Calzavara et al., 2020). Virtual reality is used in operating activities to visualize operating scenarios from different points of view (Segura et al., 2020). Automation technologies are useful to increase operators' productivity, for instance, by making more cuts than in a process without technology's assistance. This implies a change in the responsibilities of the operators, who start supervising rather than u just operating the machines (Margherita & Braccini, 2020). Operators can use voice-enabled assistants to acquire information using a question-and-answer approach (Longo et al., 2017) to learn, for instance, how to conduct a machine correctly and safely (Longo & Padovano, 2020). A digital twin can be applied together with other technologies such as augmented reality in operational activities. It can streamline operations, avoiding delays in decision making due to questions such as “how to configure the printing machine for the next batch?” or asymmetric information like “what is the next batch to produce?” (Longo et al., 2019). The smart decision support system supports operators for the proper performance of their operating activities, for instance, by monitoring activities below expected standards of machinery operation or operator performance (Margherita & Braccini, 2020). Computer vision and visual analytics are used in operational activities to help operators understand the information generated from data or images (de Araujo and Lins, 2020, Segura et al., 2020).

Maintenance is an activity performed by technicians that include six applications of technologies. Augmented reality is used for maintenance activities mainly because it guides the technician in carrying out their activities (Segura et al., 2020) and communicating remotely and intuitively between the technician and a remote specialist (Park et al., 2020). Collaborative robots, in turn, are used for maintenance activities because they can do maintenance work while the technician works elsewhere. For example, a robot can perform the screwing activity while a technician performs other activities that the machine cannot execute (Koch et al., 2017). Voice-enabled assistants can be used in conjunction with augmented reality to support technicians and specialists during maintenance tasks (Longo et al., 2020). A digital twin is used in maintenance activities with other technologies, such as augmented reality and voice-enabled assistants. This technology is used to plan maintenance operations according to customer orders and production schedules (Longo et al., 2019). Visual analytics is often used for maintenance because it easily detects defective production situations or defines abnormal production conditions, for example, by evaluating the correlation of various production variables with a key performance indicator (Segura et al., 2020). Lastly, artificial intelligence is used for maintenance because it analyzes root causes, enabling predictive maintenance instead of preventive maintenance (Foresti et al., 2020).

Training activities are transversal to the other manufacturing activities. Therefore, they impact all workers, especially operators and technicians, including six applications of technologies. Augmented reality is used to train operators and technicians about their activities quickly and intuitively (Longo et al., 2017). Besides, with augmented reality in training, the performance of operators and technicians is leveled because it no longer depends on a worker remembering all the operations necessary to assemble a certain product, now that the augmented reality system can guide the worker (Segura et al., 2020). Virtual reality had the largest number of studies when it came to the training activity. This is because its main role is to simulate immersion in the real factory and emulate the decision-making process without interrupting production and equipment activities and without exposing the operator to risky situations before the necessary training base (Roldán et al., 2019). For the training activity, wearable devices and environment sensors complement the augmented reality functionality by collecting information from workers to improve their training (Tao et al., 2019, Tao et al., 2019). As in other activities that implement voice-enabled assistants, this technology is used to communicate between humans and machines, especially robots, so that instructions can help the workers' learning process (Longo & Padovano, 2020). On the other hand, artificial intelligence applied to the training activity eliminates the need for personnel training, replacing it with methods conducive to self-learning (Foresti et al., 2020).

Inspection operators carry out Quality Control activities. Three Industry 4.0-related technologies are cited in the literature as useful to this activity. The main use of augmented reality for quality control activities is the elimination of document checklists and the release of operators' hands at the moment of the verification (Ruppert et al., 2018), and the automatic detection of defects (Muñoz et al., 2019). In the case of automation, it is used in the quality control activity to detect product defects in synchrony with the camera system of the autonomous machine (Erasmus et al., 2018). As well as automation, computer vision is used in quality control activity to detect errors in real-time and synchronize quality-control data (Tarallo et al., 2018). These applications facilitate and improve operators' activities.

The Product and Process Design activities are performed by engineers. Five Industry 4.0 technologies are cited in the literature to support this activity. Augmented reality is used to anticipate potential problems and design changes, and obtain accurate feedback on human–machine interaction before product realization (Grandi et al., 2020) or to build a collaborative design of the process for workers' well-being (Peruzzini et al., 2018). In this activity, collaborative robots are used to design a more flexible process, including them in the production line, for example, to develop new means of interaction (Weichhart et al., 2019). Virtual reality and augmented reality are used for the design and reconfiguration of the product before it is manufactured (Damiani et al., 2018). Sensors are an element of manufacturing systems that, in the case of the product and process design activity, capture information to allow for the necessary adjustments in process and product design (Kareem, 2019). Finally, industrial social networks are used for communication within a company regarding ideas, suggestions, or solutions in a context of continuous improvement (Mourtzis et al., 2016).

The Production Planning and Control activity is carried out mainly by engineers. Five technologies were identified for this activity. Augmented reality can be used to access the automation system remotely (Kymäläinen et al., 2017). Besides, shop floor workers receive information, instructions, and guidance from the engineers according to schedules prepared in real-time (Wang et al., 2020). Wearable devices are used to collect information to enable operator monitoring and, together with other technologies, such as augmented reality, anticipate potential disruptions, record the operator's troubleshooting activities, and suggest various solutions that the engineer can choose from (Kymäläinen et al., 2017). In this activity, a digital twin allows to find more efficient ways of conducting processes without blocking real production capacities (Horváthová et al., 2019), while a smart decision support system is used to consolidate information from process planning, operation sequencing, and programming, automating the decision-making process as much as possible (Trstenjak & Cosic, 2017).

The Materials Movement activity is performed by shopfloor operators. The literature cites six technologies for this activity. Collaborative robots, when applied to the movement activity, serve to provide mobility in dynamic environments and to handle and transport bulky objects (Cherubini et al., 2019). In this activity, wearable devices are used to collect real-time data that will support decisions on measures to improve the work environment and locate operators on the shop floor (Sun et al., 2020). Automation in this activity protects operators in difficult working conditions and with major ergonomic challenges (Klumpp et al., 2019). Environment sensors applied in movement activities locate and track machines and equipment, like forklifts (Barral et al., 2019). Automated Guided Vehicles (AGV) and their derivatives – Autonomous Mobile Vehicles (AMV) – have the function of transporting materials on the shop floor, for example, from the warehouse to assembly stations (Nunes & Barbosa, 2020). Finally, in the movement activity, exoskeletons provide ergonomic assistance in handling activities, mainly heavy lifting and aerial work (Calzavara et al., 2020).

4.3. HOW INDUSTRY 4.0 TECHNOLOGIES CONTRIBUTE TO SMART WORKING

Table 4 summarizes all the related impacts of Industry 4.0 Smart Working technologies according to the investigated papers. The analysis was divided into positive and negative impacts of these technologies on manufacturing activities. As the table shows, although the literature acknowledges the contribution of these tools to workers' manufacturing activities, they also have several limitations that should be considered before implementing them in a company's manufacturing processes.

Table 4 - Impacts of Smart Working technologies on manufacturing activities

Industry 4.0 Technologies	Positive impacts	Negative impacts
Augmented reality	Training effectiveness; Improvement in the teaching and supervision of workers; Reduction in task completion time and number of errors; Reduction of cognitive load; Facility of performing tasks; Simplification of necessary skills; Improved security; Increased performance; Increased worker satisfaction; Supports decision-making; Facilitates error diagnosis; Facilitates the provision of information; Improves information exchange between professionals.	Visual fatigue; Distractions during use; User resistance; Lack of familiarity with the technology; Occlusion problems; Impairs vision; Unknown physical and psychological effects; Weight and discomfort of the device; Impoverishment of work; Increased pressure/stress; System failure may impair worker performance; Cybersecurity.
Collaborative robots	Simplifies operators' tasks; Replaces operators in less ergonomic tasks; Productivity improvement; Improves the safety of operation; Handles large and heavy objects; Performs difficult tasks; Reduces errors; Cost economy; Reduces manual labor; Assists workers with physical disabilities; Improves the ability to respond to market changes.	Collision control problems; Safety and ergonomics problems in the interaction; High investment; Increased anxiety; Lack of confidence in technology; Problems with the manipulation of deformable objects; Limited applicability; Slowness due to legislation and security issues.
Virtual reality	Helps to execute the correct sequence of operations; Improves speed in the execution of tasks; Reduces cost; Reduces time and errors; Facilitates knowledge transfer; Increases the cognitive abilities of workers and speed of learning; New solutions can be created quickly, easily, and intuitively; Reduces the stress produced in the man-machine interactions; Eliminates the need for written documents.	Problems related to field of view and device battery; Operators can ignore digital instructions and security; Decreases workers' ability to make decisions; Difficulty in the integration of corporate data sources; Difficulty in defining the authorship of the manuals; Difficulty in preparing the simulations; High cost of equipment; Uncomfortable due to weight and gesture interface; Difficulty in wearing glasses with safety helmets; Impairs visual acuity; Compromises the visual field and vision.
Wearable devices	Improvement of training and simulations; Real-time control of workers' location information; Improvement of safety at work; Increased movement recognition accuracy; Assists in decision making on health actions; Improvement of the operator's working conditions; Improved operator health and safety; Increased empowerment and engagement; Assists the measurement of	Data privacy concerns; Limited applicability due to company size and culture; Data integration problems; Fear or reluctance of operators; Difficulty in adapting to different body types; Psychophysical measurement may be invasive.

	time and quality in real time; Improved awareness of ergonomics at work.	
Automation	Maximize process flexibility and efficiency; Increased productivity; Reduction of human effort; Downtime reduction; Reduction of mental and body stress; Occupational health risk reduction; Lead time reduction; Defect rate reduction; Optimized use of production resources; Improved monitoring of the production process; Improved product tracking; Waste reduction; Improved product quality; Increased competitive advantage; Increased employee engagement and motivation; Increased attractiveness of jobs.	Limited speed for some processes; Replacement of some workers; Dependence on the robotic systems' proper functioning; Security issues; Complexity of workforce activities is increased; Difficulty in workers' acceptance.
Voice-enabled assistant	Intuitive access to information and knowledge; Maximizes users' cognitive efficiency; Facilitates information retrieval; Reduces the time to set up the operation; Waste reduction; Guides on the correct use of tools; Increases safety and decreases worker stress; Improves the operator's learning curve; Amplifies the learning effect; Accelerates the learning process.	Limited utility and acceptance by workers; Data corruption; Potential serious risks to the operation; Problems related to information reliability; Employees' resistance to change; Need for long technology configuration times; May discriminate against some workers for cultural and language reasons; Workers' dependence on technology; Need for fault tolerance and data recovery plans; Rapid prototyping tools are lacking.
Digital twin	Helps in planning operations; Facilitates information visibility; Minimizes the impact of unexpected disturbances; Improves the efficiency of daily tasks; Facilitates the reproduction of simulated actions realistically; Reduction of maintenance costs; Reduction of tasks execution time; Resource optimization; Reduction of setup times and cycle times; Reduction in the waste production rate; Reduction of configuration time; Better enjoyment of knowledge.	High initial investment; Problems with light interference and calibration problems can interfere with the model's construction; Difficulty in managing unexpected disturbances; Difficulty in data management and analysis; Cyber-attacks can steal industrial knowledge.
Environment and machine sensors	Early identification of worker fatigue or injury; Improves worker safety; Reduced downtime; Improves accuracy in recognizing human movements; Improves training; Improves accuracy in locating materials; Waste reduction; Reduction in the percentage of defective products; Optimization of resource usage.	High dependency on connectivity; High initial investment for connectivity.
Smart decision support system	Makes production more efficient; Improves coordination between units; Waste reduction; Decreases the defect rate; Decreases the time spent in the production stages; Increased speed of adjustment of production planning and control; Helps in obtaining quick responses to unforeseen incidents in manufacturing; Improves control and decision making; Facilitates real-time data recognition and analysis; Generates knowledge for continuous process improvement and optimization.	Workers' resistance to change and new operating processes; Complexity, usability, and acceptability can be challenging; Resistance of specialists to the need for change; Time-consuming deployment; High investment cost; System security concerns.
AGV/AMV	Improves efficiency; Time-saving; Avoids musculoskeletal disorders; Low investment; Possibility of use in confined spaces; Eliminates worthless activities like transportation, inventory, and waiting; Reduces the cycle time of factory processes;	Potential movement restrictions; Lack of system availability may compromise the operation; Operators are more stationary.

	Improves materials tracking; Reduces inaccuracy in order fulfillment.	
Industrial social network	Establishes and continually updates the best practices repository; Reduces the training curve for new employees; Decreases the incidence of recurring problems; Boosts the continuous improvement process.	Potential hesitation of workers to share knowledge; Lack of commitment to reporting new problems; Distraction with the use of mobile devices on the factory floor; Business intelligence protection issues.
Exoskeletons	Ergonomic assistance in weight lifting and overload; Reduction of the operator's physical effort; Reduction of work injuries; Improves operator productivity in a safe way; Benefits aging workers.	Investment is medium-high; Limits some body movements; Weight and discomfort may reduce operator acceptability; Existence of unanswered security issues; Increased worker anxiety about the use of technology on their bodies.
Computer vision	Reduction of measurement uncertainties; Low cost to perform configuration tasks; Improves operational efficiency; Improves task accuracy; Eliminates the requirement for a highly trained worker for inspection tasks.	N/R
Visual analytics	Improves the cognitive process; Helps to analyze data quickly and interactively; Extends the perception of data in less time; Improves efficiency in decision making; Enables a quick view of the complexities of performance tuning.	N/R
Artificial intelligence	Reduction of downtime; Reduction of failure; Reduction of training costs; Increased productivity; Reduction in after-sales assistance; Reduced activity costs.	Limited confidence on the part of workers; Ethical concerns.

Note: N/R corresponds to No Record in sample.

Amongst the several impacts mentioned in the literature, some positive and negative impacts stand out. The main positive impacts are waste reduction, improved workers' health and safety, time reduction, training effectiveness, and easy access to real-time information on activities. Waste reduction is related to improved use of materials and production resources, which eliminates defective products and reduces time spent in production activities (Longo et al., 2019, Margherita and Braccini, 2020, Nunes and Barbosa, 2020). The improvement of workers' health and safety derives from efficient use of information for the monitoring and improvement of working conditions (Klumpp et al., 2019; S. Sun et al., 2020), as well as to increase safety and reduce occupational accidents and ergonomics problems (Erasmus et al., 2018, Peruzzini et al., 2020). Time reduction means greater agility in processes due to technologies, including reductions in time for learning, task completion, and information analysis (Calzavara et al., 2020, Mourtzis et al., 2016, Tao et al., 2019, Tao et al., 2019). Training effectiveness means that one of the main benefits of technologies is related to the training of workers, including advantages such as effective knowledge transfer and retention, the release of specialists for the training of new operators, and avoiding unnecessary interruptions in production to conduct a training (Gorecky et al., 2017, Roldán et al., 2019). Finally, the facility of real-time access to information refers to simple and quick data access, allowing for viewing and analyzing large amounts of data about machines and operators in real-time (Guo et al., 2019, Knoch et al., 2020, Longo et al., 2020).

In contrast, the major negative impacts of technologies on manufacturing activities are worker resistance, device discomfort, technology failure, high investment, and a high level of technical skills required. Worker resistance is linked to fear or insecurity about technology, including fear of substitution, insecurity in use, reluctant acceptance of changing processes, and cultural aspects (Longo et al., 2020, Longo and Padovano, 2020, Römer and Bruder, 2015). As many of the technologies to support workers' activities require the use of devices, discomfort in device usage is a factor that can be interpreted negatively because their weight or imposed limitations can interfere with the good performance of the workers' activities (Calzavara et al., 2020, Herzog et al., 2018). Technology failure is also a negative impact caused by its implementation. With such systems remodeling, any failure can result in losses to the process and interfere with workers' performance (Cañizares et al., 2018, Longo et al., 2020). Another negative impact of these technologies is the high initial investment often required to implement them in manufacturing, involving actual technology costs and the investments required to set up the infrastructure necessary for their functioning (Calzavara et al., 2020, Kareem, 2019, Trstenjak and Cosic, 2017). With the implementation of technologies in activities, there is an increase in the complexity of tasks, which leads to the need for highly skilled workers to monitor the technical information and program technologies for substantial gains to be achieved (Margherita and Braccini, 2020, Pérez et al., 2020).

4.4. A FRAMEWORK OF INDUSTRY 4.0 SMART WORKING TECHNOLOGIES IN MANUFACTURING ACTIVITIES

As a final result of this SLR on manufacturing activities and Smart Working technologies, a framework was elaborated, shown in Table 5, which summarizes the applications of technologies in each manufacturing activity impacting workers. In this table, the worker capabilities enhanced by Industry 4.0 technologies (Romero et al., 2016) were related to the findings reported in Table 3 on the type of Smart Working technologies used in each manufacturing activity. For instance, Table 3 shows that the smart capability and the social capability are not highlighted in the literature addressing assembly capacity and Smart Working technologies. On the other hand, assembly activities require several worker capabilities and, consequently, many Industry 4.0 Smart Working technologies can support these activities to enhance capabilities.

Table 5 - How Industry 4.0-smart working technologies are related to manufacturing activities and workers' occupations

	Type of worker	**Operators**				**Operators/ Technicians**	**Technicians**	**Engineers**	
	Manufacturing activity	**Assembly**	**Machine Operation**	**Materials Movement**	**Quality control**	**Training**	**Maintenance**	**Planning and control**	**Product and process design**
Worker capability	**Super-strength capacity**	AUT; EXO	AUT	AUT; EXO	AUT				
	Augmented capability	AR			AR	AR	AR	AR	AR
	Virtual capability	VR	VR			VR	VR		VR
	Healthy capability	WD; SENS		WD; SENS		WD; SENS	WD; SENS	WD	SENS
	Smart capability		VEA			VEA	VEA		
	Collaborative	CR; AGV	CR	CR; AGV				CR	CR
	Social capability								ISN
	Analytical capability	DT; CV	DT; CV; VA		CV	AI	AI	DT; SDSS	

Note: AR (Augmented reality); CR (Collaborative robots); VR (Virtual reality); WD (Wearable devices); AUT (Automation); SENS (Environment and machine sensors); VEA (Voice-enabled assistant); DT (Digital twin); SDSS (Smart Decision Support Systems); AGV (Automated guided vehicle); AMV (Autonomous Mobile Vehicle); ISN (Industrial Social Networks); CV (Computer vision); EXO (Exoskeleton); VA (Visual analytics); AI (Artificial Intelligence).

Furthermore, according to the literature, the framework (Table 5) also highlights the main occupation of workers related to each manufacturing activity. Operators are related to assembly, machine operations, materials movement, and quality control (Cherubini et al., 2019, Marino et al., 2021, Sun et al., 2020, Sun et al., 2020). Since they are more often involved in handwork, robotics, for instance, is more used by this type of worker. Technicians, on the other hand, are more often related to artificial intelligence tools since they usually make operational decisions that can be supported by these tools (Shin & Prabhu, 2018). Table 5 shows that Engineers are dedicated to cognitive tasks and activities, such as production planning and control and product and process design, where augmented reality tools are much more used than other activities (Wang et al., 2020). These are just some examples of a complete picture shown in the table. It is worth noting that this final framework does not describe ideal relationships but the state-of-the-art of literature. Therefore, an unfilled box does not mean that a given capacity is not necessary for a specific type of worker and activity, but rather that the investigated papers did not introduce the use of any Industry 4.0 technology for that relationship. In this sense, the empty cells may represent opportunities for future research.

5. CONCLUSIONS

By reviewing 80 papers on Industry 4.0 and work, this paper answered two main questions: how Industry 4.0 technologies contribute to workers' activities for a Smart Working-based manufacturing system and what are the contributions and limits of the use of such technologies. Fifteen technologies were identified that make direct or indirect contributions to workers' activities, namely: augmented reality, collaborative robots, virtual reality, wearable devices, environment and machine sensors, task automation, voice-enabled assistant, digital twin, smart decision support systems, automated guided vehicles/ autonomous mobile vehicle, computer vision, industrial social networks, exoskeletons, visual analytics, and artificial intelligence. This paper showed how these technologies contribute to eight different manufacturing activities, namely: assembly, machine operation, maintenance, training, quality control, materials movement, process and product design, production planning and control. This paper also showed how these technologies create positive impacts on workers, but also carry some limitations in their usage, which is still a challenge in many manufacturing applications. Lastly, these technologies were related with the required enhanced capabilities of workers (i.e., super-strength capability, augmented capability, virtual capability, healthy capability, smart capability, collaborative, social capability, analytical capability), and with workers' occupational categories (operators, technicians, and engineers). This was all summarized in a final framework which brings contribution to both scholars and practitioners.

5.1. THEORETICAL CONTRIBUTIONS

As main theoretical contribution, this study is the first one that provides a wide and comprehensive concept of Smart Working in the manufacturing Industry 4.0-related field. From one hand, Smart Working has been previously addressed in managerial fields considering cognitive-related tasks that could be supported by digital tools. From the other hand, recent advances have considered the Operator 4.0 view by analyzing technological aspects that influence on manufacturing operational workers. This study provides a bridge between both perspectives by analyzing all types of digital enabled technologies that can support a large range of manufacturing activities, including both cognitive tasks (e.g., planning and design) and non-cognitive (e.g., machine operations) and at different hierarchical levels (e.g., operators, technicians, engineers). In this sense, we attend to the call for future research suggested by Cagliano et al. (2019), who pointed out the need of more research on the integration of smart manufacturing and workers' activities by clustering technologies on the basis of their different purposes and on the basis of associated tasks characteristics. The same need has been recently addressed by Meindl et al. (2021) when they showed that the interconnections between workers and technologies are still spread and not well connected, especially in the operations management literature. This study attends to such research gap and provides a big picture on how Industry 4.0-related technologies is being used for different purpose regarding the support of manufacturing workers. The created framework that connects technologies with occupations and workers required capabilities provides an integrative view on what has been investigated in the literature. It also enables new opportunities for scholars, since it shows 'empty cells' that opens opportunities for future investigation. Moreover, the results also showed limitations of Smart Working technologies, which is also important for the literature to avoid considering Industry 4.0 technologies as the remedy to any manufacturing challenge. The results shed light on these technologies' current problems, which can also help researchers focus on overcoming technological barriers in workers' activities. Still, Marcon et al. (2021) provided evidence on the role of considering socio-technical aspects in the Industry 4.0 implementation, especially regarding how workers adapt to technologies that can enrich and improve their activities. The present results complement such findings by providing details of the technologies used for specific purposes when manufacturing work is designed. The combination of such views helps to achieve a broader theoretical understanding of how to develop human-centered smart manufacturing systems, which is also a new trend in what some scholars and institutions have called Industry 5.0 (Breque et al., 2021).

5.2. Practical contributions

Practitioners can learn how to apply the Smart Working concept to develop an Industry 4.0 journey concerned with manufacturing workers. In this sense, the Smart Working concept calls the attention to practitioners to think Industry 4.0 not only as a set of technologies that will increase process efficiency but also as a set of technologies that can support the company's workers. Consequently, practitioners can learn through this study, firstly, the technologies that can contribute to the workers of their companies, the benefits and limitations of such technologies, and how manufacturing activities can be supported with these technologies. In this sense, practitioners can find in this paper several examples of the use of such technologies. This can help to increase practical understanding of several different potential applications. Secondly, the structured way the technologies were provided in this study can help practitioners develop a step-by-step analysis of their manufacturing activities for the potential development of Smart Working. For instance, operations managers can take the list of manufacturing activities and workers' capabilities provided in this study to investigate how these aspects happen in their field. Then, they can use the technologies presented in this paper to define how such technologies can enhance these manufacturing activities and workers' capabilities in their companies. Therefore, the structured analysis presented here to analyze the literature can also become a practical guideline for empirical designs of Smart Working environments.

5.3. Limitations and future research

This study is limited to journal papers and two specific journals' databases. Many industrial reports and conference papers could also be useful for this type of research, including, for instance, the recently launched MIT Work of the Future final report (Autor et al., 2020). However, the present research scope was delimited only to scientific journals to handle this growing literature appropriately. Future studies can complement the findings of this study with other sources of empirical evidence, including business reports or case studies that can expand the vision on Smart Working and Industry 4.0.

Meindl et al. (2021) have shown that the greatest potential for future studies on Smart Working is considering the interfaces between smart manufacturing and smart supply chain or smart product-service systems. Such interfaces were not possible to explore in this study, but they hold great potential for future investigation. In this sense, future works can investigate how Smart Working would look in the context of the service operator for smart product-service systems or the supply chain worker in smart supply chains. One may expect that digital technologies may be different in such environments than those considered here, especially because different operational activities must be executed and different workers' capabilities are required. Future research can explore more these fields of Smart Working.

Another limitation of this present study is that the way the workers adopt these technologies were not considered. The study pointed out some limitations regarding the normal use of such technologies, but some may need larger adaptation than others. Marcon et al. (2021) called attention to this point when they showed that the social manufacturing environment strongly influences adapting to new technologies. Moreover, Dalenogare et al. (2019) showed that smart glasses performance has high variation among workers, depending on the workers' individual characteristics. Therebefore considering these characteristics of the adoption of Smart Working tools, future research can investigate learning curves during the adoption of the considered technologies, individual characteristics that help or hinder such adoptions, or other social or cultural characteristics that need to be considered when such technologies are designed for their use in manufacturing activities.

Finally, as already highlighted in the theoretical contributions section, the empty cells of the framework proposed in this study are already suggestions for future research. Each empty cell indicates potential fields that are underexplored. For instance, the silence on artificial intelligence for Smart Working in machine operation is a surprising result. It is well known that artificial intelligence is used in the Industry 4.0 domain to increase machine processing capacity (Dalenogare et al., 2018). However, the findings suggest that the literature tends to focus on using this technology in the manufacturing process, overlooking its interaction with workers as a supportive tool. The same could be said about many other tools showing no relation to certain activities in the framework (e.g., few studies of the sample have investigated industrial social networks or visual analytics). Hence, our framework is also instrumental in identifying many opportunities for future research to define whether such absent relationships mean no actual contribution or a research gap on the topic.

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APPENDIX A – STUDIES SELECTED FROM THE SLR

Authors (with DOI link)	Technology 4.0	Manufacturing activities
[1] Cherubini et al. (2019)	Collaborative robots	Movement; Operation; Assembly
[2] De Pace et al. (2019)	Augmented reality	Training; Assembly
[3] Kymäläinen et al. (2017)	Augmented reality; Wearable devices	Planning and production control
[4] Tarallo et al. (2018)	Computer vision; Virtual reality	Assembly; Quality control
[5] Peruzzini & Pellicciari (2017)	Smart decision support systems	Operation
[6] Mourtzis et al. (2016)	Industrial social networks	Process and product design
[7] Wierschem et al. (2020)	Environment sensors	Assembly; Movement
[8] Tao et al. (2019)	Wearable devices; Environment sensors; Augmented reality	Training; Assembly
[9] Koch et al. (2017)	Collaborative robots	Maintenance
[10] Horejsi et al. (2020)	Virtual reality; Augmented reality	Assembly

[11] De Pace et al. (2020)	Augmented Reality; Collaborative robots	Operation
[12] Roldán et al. (2019)	Virtual reality	Training; Assembly
[13] Grandi et al. (2020)	Augmented reality	Process and product design
[14] Masood & Egger (2020)	Augmented Reality	Assembly
[15] Calzavara et al. (2020)	AGV; Exoskeleton; Augmented reality; Collaborative robots	Movement; Assembly; Operation
[16] Bruno et al. (2019)	Augmented Reality	Process and product design; Assembly
[17] Damiani et al. (2018)	Virtual reality; Augmented reality	Process and product design; Planning and production control
[18] Masood & Egger (2019)	Augmented reality	Quality control; Maintenance; Training; Assembly; Product and Process Design
[19] Bedaka et al. (2018)	Automation	Quality control
[20] Weckenborg et al. (2020)	Collaborative robots	Assembly
[21] Muñoz et al. (2020)	Augmented reality	Quality control
[22] de Araujo & Lins (2020)	Computer vision	Operation
[23] Simões et al. (2019)	Augmented reality	Assembly
[24] Wang et al. (2018)	Environment and machine sensors; Collaborative robots	Assembly
[25] Park et al. (2020)	Augmented reality	Maintenance; Quality control
[26] Guo et al. (2020)	Digital twin	Assembly
[27] Ruppert et al. (2018)	Augmented reality	Operation; Quality control; Assembly
[28] Wang et al. (2020)	Augmented reality	Planning and production control
[29] Uva et al. (2018)	Augmented reality	Maintenance
[30] Peruzzini et al. (2020)	Digital twin	Assembly
[31] Wang et al. (2019)	Collaborative robots	Assembly
[32] Ottogalli et al. (2019)	Virtual reality; Augmented reality	Assembly; Training; Maintenance; Operation
[33] Sun et al. (2020)	Wearable devices	Movement
[34] Peruzzini et al. (2018)	Augmented reality	Process and product design
[35] Weichhart et al. (2019)	Collaborative robots	Assembly; Process design
[36] Margherita & Braccini (2020)	AGV; Automation; Smart decision support system	Assembly; Operation
[37] Gorecky et al. (2017)	Virtual reality	Assembly; Training
[38] Eimontaite et al. (2019)	Collaborative robots	Operation
[39] Costa Mateus et al. (2018)	Collaborative robots	Assembly
[40] Muñoz et al. (2019)	Augmented reality	Quality control
[41] Scholer & Müller (2017)	Collaborative robots	Assembly
[42] Barral et al. (2019)	Environment sensors	Movement
[43] Sun et al. (2020)	Smart decision support system	Planning and production control
[44] Trstenjak & Cosic (2017)	Smart decision support system	Planning and production control
[45] Klumpp et al. (2019)	Automation	Movement
[46] Knoch et al. (2020)	Wearable devices	Assembly
[47] Nunes & Barbosa (2020)	AGV	Movement
[48] Lai et al. (2020)	Augmented reality	Assembly
[49] Erasmus et al. (2018)	Augmented Reality; Collaborative robots; Automation	Assembly; Quality control; Operation
[50] Longo et al. (2017)	Augmented reality; Voice-enabled assistant	Operation; Maintenance; Training
[51] Foresti et al. (2020)	Artificial intelligence	Maintenance; Training
[52] Pérez et al. (2020)	Collaborative robots	Assembly
[53] Kareem (2019)	Environment sensors	Process and product design
[54] Zhao et al. (2014)	Computer vision	Quality control
[55] Guo et al. (2019)	Wearable devices	Assembly

[56] Longo et al. (2019)	Digital twin; Augmented reality; Voice-enabled assistant	Maintenance; Operation
[57] Römer & Bruder (2015)	Wearable devices	Assembly
[58] Horváthová et al. (2019)	Digital twin	Planning and production control
[59] Longo et al. (2020)	Wearable devices; Virtual reality; Voice-enabled assistants; Collaborative robots	Assembly; Training; Maintenance; Operation
[60] Segura et al. (2020)	Visual analytics; Virtual reality; Collaborative robots; Augmented reality; Industrial social networks	Operation; Maintenance; Training; Assembly
[61] Longo & Padovano (2020)	Voice-enabled assistants	Operation; Maintenance; Training
[62] Wittenberg (2016)	Augmented reality	Maintenance
[63] Bortolini et al. (2020)	Automation	Assembly
[64] Weckenborg & Spengler (2019)	Collaborative robots	Assembly
[65] Lee et al. (2020)	Collaborative robots	Assembly
[66] Al-Amin et al. (2020)	Wearable devices	Assembly
[67] Kubenke & Kunz (2019)	Wearable devices	Assembly
[68] Abidi et al. (2019)	Virtual reality	Assembly; Training
[69] Zawadzki et al. (2020)	Virtual reality	Assembly; Training
[70] D'Souza et al. (2020)	AGV; Collaborative robots	Movement
[71] Tu et al. (2017)	AGV	Movement
[72] Alves et al. (2019)	Smart decision support system	Planning and production control
[73] Liagkou & Stylios (2019)	Virtual reality	Training
[74] Vidal-Balea et al. (2020)	Augmented reality	Training; Assembly
[75] Ruppert & Abonyi (2020)	Digital twin; Environment sensors	Assembly
[76] Papetti et al. (2021)	Environment sensors; Wearable devices	Movement
[77] Marino et al. (2021)	Augmented reality	Quality control
[78] Atici-Ulusu et al. (2021)	Augmented reality	Assembly
[79] Gualtieri et al. (2021)	Collaborative robots	Assembly
[80] Li et al. (2021)	Collaborative robots	Assembly

3. ARTICLE 2 - USING COLLABORATIVE ROBOTS TO CREATE INDUSTRY 4.0 SMART WORKING ENVIRONMENTS: IMPACTS ON MANUFACTURING WORKERS' SKILLS

Jéssica de Assis Dornelles[+]

Néstor Fabián Ayala[+]

Alejandro G. Frank[+]

[+] Organizational Engineering Group (*Núcleo de Engenharia Organizacional – NEO*), Department of Industrial Engineering, Universidade Federal do Rio Grande do Sul, Brazil.

***This paper will be submitted to the International Journal of Production Research (Taylor & Francis, IF = 8.568).**

ABSTRACT

We analyze the impact of collaborative robots (cobots) – substitution, deskilling, reskilling, and upskilling – on workers in quality control, assembly, material movement, and machine or manual operation of manufacturing processes, and through four levels of human-robot interaction – coexistence, synchronism, cooperation, and collaboration. We conduct a case study of a global cobot provider using technical reports on the implementation of 138 cobots implementation, interviews with two managers, and three manufacturing customers. We also followed a cobot implementation for six months and validated the results through interviews with two other competitors. Our results show that, in quality control, cobots are predominantly used to substitute workers, while in the other activities, cobots can also be used for deskilling and upskilling workers, or they can demand workers' reskilling to perform new activities like cobot programming and maintenance. Cooperation and collaboration are present in a few cases, and upskilling only happens in these two interaction types. Our findings show that, besides cobots implementation, these two interaction levels require a complete redesign of the workflow process from an anthropocentric perspective of the shop floor. We propose future pathways for advancing the contribution that cobots can make to Industry 4.0 smart working environments.

Keywords: Industry 4.0; Collaborative robots; Smart Working; Workers; Manufacturing.

1. INTRODUCTION

Digital transformation has triggered the fourth industrial revolution, also called Industry 4.0 (I4.0). Like prior industrial revolutions, I4.0 is rapidly changing the role of workers in manufacturing (Dornelles et al., 2022; Neumann et al., 2021). Although I4.0 is widely recognized for the integration of core technologies such as the Internet of Things, Cloud Computing, Big Data, and Artificial Intelligence, and of supporting technologies such as robotics, virtual and augmented reality, and wearable devices (Dalenogare et al., 2019; Frank et al., 2019), studies have shown that human work is still an essential part of smart factories (Fantini et al., 2020; Peruzzini et al., 2020). Therefore, recent studies on I4.0 have acknowledged the central role of workers in manufacturing systems and the need to empower workers through I4.0 technologies. This has been emphasized in different interrelated concepts such as the Operator 4.0 or Worker 4.0 (Romero et al., 2016), Smart Working 4.0 (Frank et al., 2019; Meindl et al., 2021), or Industry 5.0 (Breque et al., 2021). Dornelles et al. (2022) reviewed these different streams of the literature and integrated them under the conceptual umbrella of the Industrial Smart Working dimension of I4.0, showing that I4.0 can provide several technologies to enhance workers' activities and capabilities, and that these technologies can be used in several different manufacturing activities. Complementarily, Meindl et al. (2021) have investigated the literature of the last ten years of I4.0 and have called attention to the need for further understanding of the smart working dimension, which is the least investigated and the most promising area for the new generation of studies in this stream of research. There are many opportunities to investigate smart working technologies since current studies on I4.0 have not deeply assessed how technologies can affect workers, which is problematic for the success of I4.0 approaches or for workers who will have to deal with these technologies (Marcon et al., 2021; Neumann et al., 2021).

A prominent example of technology supporting manufacturing workers in the I4.0 context is collaborative robots (cobots), i.e., robots that can physically interact with operators during manufacturing activities, sharing the workspace safely with workers and assisting them in their tasks (Dornelles et al., 2022). This technology promotes human-robot collaboration, in which workers and robots can work side by side and share the same workspace, the same resources, and even the same tasks (Wang et al., 2019). The increased demand for cobots, which are expected to account for 13% of the global robotics market in 2022, evidences their contribution to industrial activities in the I4.0 context (Statista, 2021). However, despite the relevance of cobots to manufacturing activities, the current literature on this technology is mainly focused on practical aspects such as acquisition and development (Cohen et al., 2021; Ferraguti et al., 2019; Peron et al., 2020). On the other hand, there is a lack of studies investigating how this technology can impact workers in their activities, capabilities, and work environment (Neumann et al., 2021). In this sense, the MIT Work of the Future Initiative report, which summarizes a major initiative in the US on the impact of digital technologies on work, has highlighted that more investigation is needed in this direction since there is a common understanding that robots can replace jobs. Meanwhile, empirical evidence tends to show that workers and robots coexist in the same environment (Autor et al., 2020). Therefore, the following research question is proposed: How can the implementation of collaborative robots (cobots) impact manufacturing workers' activities?

To answer this question, this paper aims at understanding the impact of cobots on manufacturing workers' activities by considering effects such as substitution, deskilling, reskilling, and upskilling of workers when this technology is implemented in the manufacturing environment. To this aim, we conduct an inductive qualitative study combining documentary and empirical research related to one of the leading global providers of cobots. We use technical documents reporting on 138 cases of cobots implementation in manufacturing companies. In addition to these reviews, interviews were conducted with technology managers from the company and with three manufacturing customers. We followed the implementation of one cobot application for six months to understand the use of this technology in practice. Finally, we also interviewed two other robot and cobot providers to contrast and validate our findings. Our main findings show that, in quality control, cobots are predominantly used to substitute workers. In contrast, in the other activities, cobots can also be used for deskilling and upskilling workers, or they can demand a reskilling to perform new activities like cobot programming and maintenance. Cooperation and collaboration are present in a few cases, and upskilling only happens in these two interaction types. Our findings show that these two interaction levels require, besides cobot implementation, a complete redesign of the workflow process from an anthropocentric perspective of the shop floor. The main contribution of this study is that we provide an analytical framework for the implementation of cobots, which allows us to propose future pathways for advancing the implementation and contribution that cobots can provide for Industry 4.0 smart working environments. Scholars can learn the different impacts of cobots on workers and how these impacts happen. On the other hand, practitioners can learn about all the potential uses of cobots in smart working environments and what to consider to achieve higher levels of human-robot integration through the use of cobots in smart working environments.

2. THEORETICAL BACKGROUND

2.1. COBOTS IN MANUFACTURING ACTIVITIES

Manufacturing companies are continually seeking flexibility, versatility, and adaptability of their processes in response to different challenges imposed by the market, including mass customization, increased competition, and product complexity (Brettel et al., 2014). Faced with these challenges, one strategy is to implement advanced manufacturing technologies that can collaborate with workers safely and flexibly, combining the efficiency of robots with human cognitive abilities and skills (Sherwani et al., 2020). Among the advanced manufacturing technologies that companies implement to enable productivity improvement, flexibility, and quality, we have cobots (Bauer et al., 2016; Charalambous et al., 2016). Cobots are an automation technology designed to collaborate with humans in a safety approach, with easier programming features than usual robots, lightweight design, and implementation flexibility, primarily serving as a tool to assist manufacturing workers (Østergaard, 2017). Cobots can be integrated into manufacturing activities such as assembly, processing operation, maintenance, material movement, and product design (Dornelles et al., 2022). Within these activities, they can do tasks such as picking, packing, assembling parts, palletizing, welding, handling material, inspecting parts and products, machine tending, cleaning parts, finishing and bin picking and kitting, without needing to be isolated from the human workplace for compliance with safety standards (Antonelli & Bruno, 2019; Banaś & Olender, 2019; Vojić, 2020).

Due to the human-robot interaction capabilities provided by cobots, workers and robots can operate in a collaborative smart working configuration (Cohen et al., 2019, 2021; Ivanov et al., 2021). However, the literature still lacks an understanding of the different approaches that can be used to integrate cobots and workers in a smart working environment (Wang et al., 2019). The first contribution in this direction was made by Bauer et al. (2016), who conducted a study based on 25 applications of cobots in manufacturing activities and identified the main levels of interaction between workers and cobots: Coexistence, Synchronized, Cooperation, and Collaboration (Table 6).

Table 6 - Summary of levels of human-robot interaction

Levels of human-robot collaboration	Description
Coexistence	Workers and robots perform different activities in the same physical space without direct contact.
Synchronized	Workers and robots perform the same activity sequentially. While one works the other remains idle.

Cooperation	Workers and robots work on the same part sharing productive resources based on the programming design.
Collaboration	Workers and robots act simultaneously (real-time response) on the same part to complete the activity.

Source: Adapted from Bauer et al. (2016) and Wang et al. (2019).

Workers and cobots work side by side at the Coexistence level, but they do not share the same activities (Bauer et al., 2016). This means that both cobots and workers share the same physical space. However, the process is executed independently by each of them without direct contact (Wang et al., 2019). At the Synchronized level, workers and cobots share a workplace, but only one of them actually operates at each time in the activity (Bauer et al., 2016). In this case, the interaction occurs through an alignment between cobot and worker, with one of them guiding or controlling the other. Thus, they perform the same activity but complete each task sequentially (Wang et al., 2019). At the Cooperation level, the worker and the robot perform tasks simultaneously in the working area. However, they do not act on the same object (Bauer et al., 2016). Therefore, in cooperation, there is a sharing of productive resources in seeking to complete the tasks of both workers and robots without direct contact, and, although in some cases they work simultaneously, they may need to wait for the availability of productive resources (Wang et al., 2019). Finally, at the Collaboration level – the highest level of integration– both the worker and the cobot work simultaneously on the same object (Bauer et al., 2016). Therefore, collaboration implies that workers and cobots, guided by the same objective, carry out tasks jointly, coordinately, and synchronously (Wang et al., 2019). This highest level represents what the norm ISO 10218-2 (ISO, 2011) considers a human-robot collaboration system in the production context, which is defined as a situation where worker and robot can work in the same collaborative space, performing tasks simultaneously or together.

Moreover, Dornelles et al. (2022) conducted a deep investigation on I4.0 smart working technologies and showed the current association of cobots with different manufacturing activities. This means that, besides the levels of human-cobot interaction, cobots can be used for different manufacturing processes. The analysis of Dornelles et al. (2022) built on prior studies from Segura et al. (2020), Bueno et al. (2020) and Hinckeldeyn et al. (2014) to study eight manufacturing activities in which digital technologies can support workers, namely: assembly, machine/manual operation, maintenance, training, quality control, materials movement, process and product design, and production planning and control. According to Dornelles et al. (2022), most studies on cobots have highlighted their applications for activities such as assembly, machine operation, maintenance and material movement. However, as pointed out in their literature review, there is a lack of empirical investigation in the several other potential applications and limits of such applications.

2.2. DIGITAL TECHNOLOGIES IMPACTING WORKERS' SKILLS

A smart working environment enabled by I4.0 digital technologies aims to influence workers' skills to increase outputs such as productivity, quality, and flexibility (Dornelles et al., 2022; Frank et al., 2019). Therefore, it is important to evaluate the best way to share tasks between humans and technology to take the advantages that each of them can provide to the manufacturing system (Sheridan, 1995). In this sense, digitally-enabled technologies can create three situations in manufacturing activities. They can substitute tasks performed by workers, simplify workers' tasks (deskilling) or enrich workers' tasks (upskilling) (Dworschak & Zaiser, 2014; Hirsch-Kreinsen, 2016).

In the case of Substitution, the digitally-enabled technologies take on workers' tasks, resulting in the transfer of workers to other functions or, eventually, in workers' layoff (Frey & Osborne, 2017; Pfeiffer, 2018). A case of Substitution is the case of an Italian manufacturer of custom kitchen furniture that transformed the movement of furniture parts inside the warehouse into an autonomous process. In the warehouse, finished products are sorted and grouped according to customer order and delivery destination to optimize space. In this case, the technology replaced the workers, which were relocated to other, manual functions (Margherita & Braccini, 2020). In an I4.0 factory concerned with socio-technical factors, Substitution should be seen as a strategy to increase workers' safety and life quality by allocating them to better activities and adopting technologies to replace them in harmful tasks (Marcon et al., 2021). In the case of Deskilling, digitally-enabled technologies simplify workers' tasks, allowing workers to focus on specialized tasks and become more productive (Jarrahi, 2019; Wurhofer et al., 2018). This simplification of tasks is used when workers' activities are very complex and affect productivity or increase the risk of human mistakes. In other cases, the companies may want to become less dependent on highly specialized and experienced workers. One example of this approach is the case of Airbus. The company's automation system is designed to prevent the pilot from exceeding safety limits. The system automatically performs activities that should normally be done by a pilot, obliging the pilot to follow the decisions made by the automated system (Young et al., 2007). Upskilling occurs when the technology helps the worker to execute an activity even better (Kagermann, 2015; Pfeiffer, 2016). One example is Boeing, which strongly advocates self-awareness and promotes more human-centric automation as a tool to help pilots gain ultimate control of the automation system by preventing the system from overriding the pilot's decision (Young et al., 2007).

In addition to these three situations (substitution, deskilling and upskilling), the increase in complexity caused by the implementation of digital technologies can demand a requalification of workers (reskilling) to build their capacities to develop new tasks in interaction with the technology (Margherita & Braccini, 2021; Romero et al., 2020; Vanderstraeten, 2018). In a reskilling situation, the worker needs to learn new skills to perform activities with the new technology (Waschull et al., 2020). An example is the case of a small factory that produces parts for small and medium-sized engines. The factory changed its manual assembly line to one with automated robotic systems. With this modification, shop floor workers in the assembly line, who had no experience working with robots and automation technology, needed to learn new skills to adapt to the new system and work environment. Thus, they developed skills to understand the process, the robotic system, the screen-based system information, and systematic and analytical skills for problem-solving (Rangraz & Pareto, 2021).

Cobots can be used for different purposes in the smart working environment of I4.0 (Dornelles et al., 2022). The literature has evidenced the contribution of this technology to increase the operational performance of manufacturing companies (Dalenogare et al., 2018; Frank et al., 2019). Some empirical studies have argued that, in a broader sense, this new generation of robots is not massively substituting workers (Autor et al., 2020), which may suggest that other purposes, including the support of existing workers, are being pursued with this technology. However, the literature lacks a detailed investigation of how cobots are used in practice. This study aims to fulfil this gap by considering the different levels of human-machine interaction involved in the use of cobots for manufacturing activities (Section 2.1) and the purposes of their application in smart working activities (Section 2.3).

2.3. A CONCEPTUAL FRAMEWORK OF COBOTS AND SMART WORKING

Based on the concepts introduced in Sections 2.1. and 2.2, we built a conceptual framework to guide our empirical investigation. The framework is shown in Figure 1 and summarizes three main dimensions that we combine to investigate the use of cobots in an I4.0 smart working environment. Firstly, the framework considers the human-robot interaction types proposed by Bauer et al. (2016), which presents maturity levels ranging from less integrative to more integrative interaction processes. Secondly, our framework acknowledges that the use of cobots can happen in different manufacturing activities, as pointed out previously by Dornelles et al. (2022). Finally, by relating manufacturing activities with human-robot interaction types, the framework analyses the impact of the technology on workers' skills, considering that workers can be reskilled, upskilled, deskilled, or substituted by cobots.

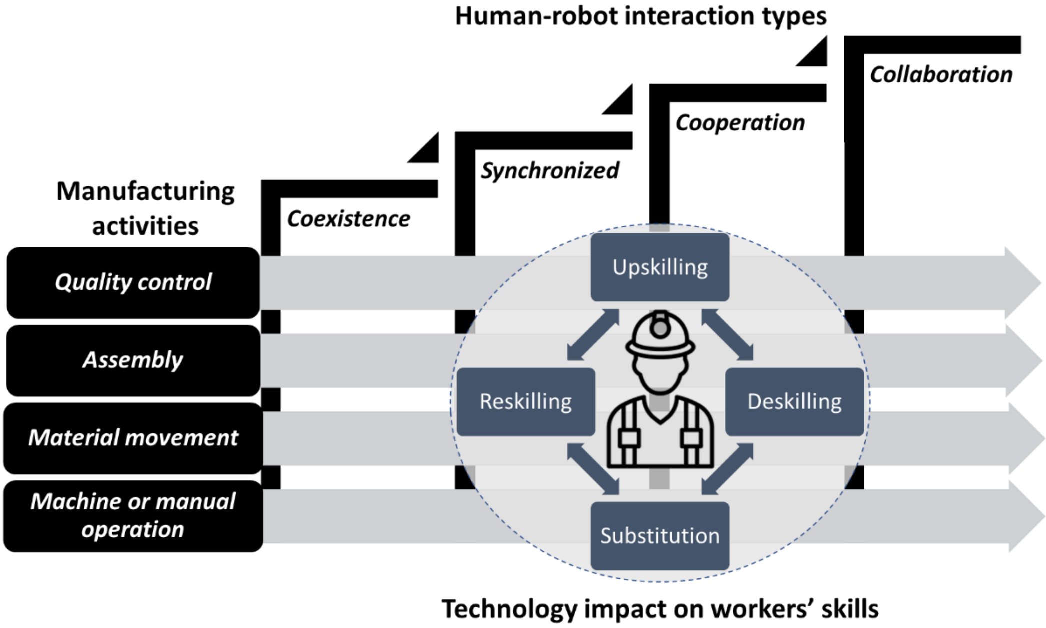

Figure 3 - Conceptual framework for the analysis of the use of cobots in smart working environments

3. RESEARCH METHOD

Recent studies in the I4.0 literature have adopted a technology provider perspective to investigate how digital technologies are developed and implemented in practice. This view allows to obtain a broader perspective on the wide range of I4.0 technology applications (Benitez et al., 2020). We followed this perspective to investigate how cobots are used in practice to create smart working environments in several manufacturing activities. Moreover, we aimed to understand how the implementation of this technology affects workers' skills. Thus, we adopted an inductive qualitative case study approach (Yin 2009). This methodological approach allows to obtain detailed information to build a theory and expand the understanding of a phenomenon (Voss et al., 2002). In this case, cobots contribute smart working practices, as described in the conceptual research framework that guided our investigation (Figure 3).

3.1. CASE STUDY SELECTION AND DATA TRIANGULATION

The case study was conducted in a multinational company that is one of the world's largest suppliers of cobots and a leader in innovation in this market. The selected case is representative since this company holds one of the largest shares in the market of cobots for the manufacturing sector, thus ensuring access to a diversity of cases of cobot application in manufacturing activities. Moreover, as the cobots provided by this company are considered some of the most flexible for manufacturing activities, we could observe a wide range of situations in which they can be used, as proposed in our conceptual framework of manufacturing activities and human-robots interaction (Figure 3). Finally, we aimed to investigate multiple sources of information (triangulation) to ensure reliability, data consistency, and construct validity in this qualitative study (Goffin et al., 2019; Yin, 2009). In this sense, we selected this company because we had access to technical reports on cobot applications since the company used a structured business case report. The company also provided us access to managers and customers so that we could interview them and learn how they are implementing the technologies in different applications. The main data sources used in this case study are represented in Figure 4 and explained next. In sum, the representativeness of this case and the necessary data accessibility defined this as an appropriate case for investigation.

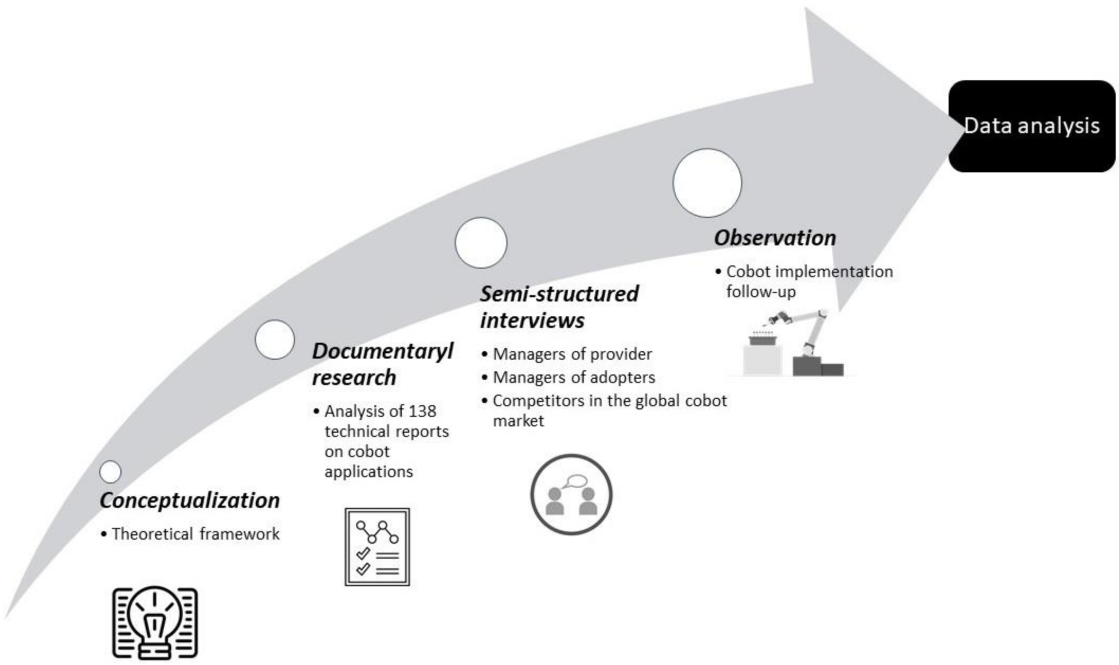

Figure 4 - Main sources of data triangulation for the case study research

To establish the case study scope, we focus our analysis on cases in which cobots were implemented in manufacturing activities as a smart working technology (Dornelles et al., 2022). This means that we did not analyze any cases from other industry sectors where these cobots could be applied. Besides, we did not analyze activities in which interaction between workers and cobots was not intended (In some situations, companies acquire cobots to expand to new activities to be performed without workers, such as new tests and new processing operations. Such types of implementation were ignored in our study). Within this scope, we selected 138 successful cases of the company (i.e., implementation was finished and the outputs were measurable), implemented in 34 different countries and 17 manufacturing sectors (see Appendix A). We also interviewed two managers from the company to obtain more details on the documentary analysis conducted in the company. We interviewed the provider's sales development manager and the company's business development manager for Latin America (approximately 1 hour each interview). They provided us with complementary supplementary information about the business cases and the profile of cobot implementation in the manufacturing field.

Additionally, we interviewed three manufacturing customers of the cobots companies with advanced factories in Brazil (Figure 4). The cases are from companies considered leaders in Industry 4.0 implementation in this country, with advanced implementation of cobots. We aimed to complement our documentary analysis with the 'customer voice', considering particularities of cobots' utilization in their factories. The contacts were provided by the cobots vendor, but we made independent contact with them to avoid any conflict of interest between the vendor and the customer. We interviewed the person in charge the ideation, adoption, and implementation of cobots in Brazilian plants. Details on these three customers (Companies A, B, and C) are provided in Table 7.

Table 7 - Companies interviewed (customers and competitors of the focal company investigated)

Companies	Sector	Country of Origin	Global Number of Employees	Plant Location (State)	Interviewee's Position	Interview Time
Company A	Industry and Commerce of Health Products	USA	128,000	Amazonas	Production Manager	50 minutes
Company B	Truck and Bus Manufacturing	Germany	289,000	São Paulo	Manufacturing engineering manager	59 minutes
Company C	Computer Equipment Manufacturing	China	54,000	São Paulo	System & Automation Manager	45 minutes
Company D	Robots and Cobots manufacturer	Germany	5,000	São Paulo	Sales Manager	55 minutes

Company E	Robots and Cobots manufacturer	Japan	40,000	São Paulo	Sales Manager	47 minutes

As a third source of data for triangulation (Figure 4), we followed the implementation of a cobot in an Industry 4.0 manufacturing project. In this project, eight companies contributed with different resources to develop a joint solution, and the cobot provider was one of these companies. The other companies were 3D printing, SCADA/MES, classic automation and sensors providers, all collaborating to implement an integrated manufacturing production cell for an electronics assembly company. The project was developed by an industry-university partnership in Brazil that aims to evaluate Industry 4.0 technologies in real-world cases. We followed the cobot implementation since the first step, when the technology utilization was designed. We followed the definition of requirements, cobot programming, preliminary tests and the final application in the manufacturing cell where it interacted with workers. This participant observation aimed to identify the limitations and implementation characteristics of this technology in real-world situations (Yin et al., 2009). Finally, to reduce potential bias from using a single case study, we interviewed two competitors who also produce cobots for the global market (Table 7). These interviews provided a comparative overview of how cobots are used in smart working environments.

3.2. RESEARCH INSTRUMENTS AND DATA COLLECTION PROCEDURES

The documentary analysis (Figure 4) consisted of 160 reported cases with a written structured report and audiovisual content. The written report contains the following main topics: (i) challenges to be solved, (ii) solutions developed, (iii) tasks impacted, and (iv) identification data of the adopting company and its production characteristics. Complementary videos about the implementation cases support the written reports. After reading all the cases in full and watching the available videos, we discarded 22 cases that did not fit our scope (for example, we excluded cases of application in educational institutions and testing laboratories in the manufacturing environment). After raw data extraction, each case was classified according to its identified impact typology and related manufacturing activity, following the categories proposed by Dornelles et al. (2022) in Appendix A. The researchers carried out this classification jointly, according to the constructs described in the conceptual framework of Figure 1.

Regarding the semi-structured interviews with customers (Figure 4 and Table 7), we followed an interview guideline (Appendix B) to analyze the phenomenon and understand the elements of the conceptual framework (Figure 3). Complementary interviews (Figure 4) were conducted with two competitors, as described in Section 3.1 and following similar procedures. The interviews were conducted via videoconference and had an average duration of 50 minutes each. At least two researchers participated in each interview, one of the researchers being the interview moderator and the other acting as an assistant and taking notes. The interviews were recorded and fully transcribed for further content analysis.

Finally, the participant observation was conducted by two of the main researchers of this study with the support of three research assistants. The activity involved a weekly interaction with the implementation team, which considered full days in the factory and regular videoconference meetings to decide on the steps of the implementation project. The team collected notes and insights by introducing questions and discussions during the sessions. During the six months of interaction, the collected data were recorded in electronic notes and processed by the main research team.

3.3. DATA ANALYSIS

We used the content analysis technique to analyze the collected data, following Miles & Huberman (1994). According to these authors, content analysis should be carried out in three steps: (i) data reduction, (ii) data display expansion, and (iii) conclusion drawing and verification. These steps will be described for each of the data sources. Regarding external validity, the desk research results were presented to respondents from the three multinational companies participating in the study that implemented cobots with different types of impact of technologies on workers' skills. In addition, to present their vision and reality with this implementation, the interviewees also validated the classifications according to the constructs defined for each of them. In addition to the interviewees from the adopting companies, two managers technological responsible from the supplier company were interviewed. They also confirmed the constructs and suggested the aforementioned companies for validation.

3.3.1. ANALYSIS OF DOCUMENTS

In the data reduction stage, business case reports data were disaggregated in a summarized format based on the sets of challenges to be solved, solutions developed using the cobot, and impacted tasks. By analyzing the data from these three dimensions, in the stages of expansion of data display and conclusion drawing and verification, we sought to identify the impacts resulting from the implementation of cobots on workers' skills as presented in Section 2.2. The cases were allocated according to the main manufacturing activities in which the cobots were used (Dornelles et al., 2022), linked to a typology of technologies impact on workers' skills and type of interaction between the workers and cobots. Regarding the impact on workers, Substitution happens when the operator is replaced by the cobot and moved to a new activity, unrelated to the cobot. In the case of Deskilling, the operator will perform an easier task than before, such as feeding the cobot that will perform what used to be the worker's task. In the Reskilling situation, workers learn how to perform another activity to handle the cobot. This is the case when the operator receives training to program cobots. In Upskilling, cobots should collaborate with workers, for instance, when the cobot does not replace human presence but rather helps the operator in welding tasks or component assembly.

Regarding the interaction types, in the case of coexistence, the cobot carries out its work without interaction with the worker. In the synchronized type, the activity is conducted sequentially by cobot and worker. In the cooperation type, the cobot and the worker do not work on the same part, although they are working in the same activity. Finally, in the collaboration type, both the worker and the cobot perform the same activity and work simultaneously on the same part. We used these rules to codify the interactions and conceptually define what happens in each business case analyzed.

3.3.2. ANALYSIS OF INTERVIEW DATA

Again, we used content analysis to analyze the interview data (Miles & Huberman, 1994). We analyzed recordings and transcriptions, and common phrases were highlighted for each of the questions addressed. From the reductions carried out, it was possible to organize the findings in terms of the types of application and interaction types of each company. Thus, it was possible to draw conclusions that, together with the documentary analysis, provided this study's main findings. As shown in Appendix B, the interviews were guided to answer questions raised in the previous stage of documentary analysis. Therefore, unlike the first stage, content analysis focused mainly on the aim of answering the questions raised in this research, as the documents had not been originally prepared to do so.

3.3.3. ANALYSIS OF PARTICIPANT OBSERVATIONS

Participant observations were used to enlighten practical issues that were unclear to the team in the former two stages, especially regarding cobots limitations and detailed aspects that need to be considered for their integration with workers on the shop floor. The codification of our notes followed the structure of the conceptual framework described in Figure 3. In this sense, the observations were guided by the framework, and notes were taken regarding unclear specificities in the documents and interviews.

4. RESULTS

Table 8 summarizes the observed frequencies of each human-robot interaction situation in the 138 business cases reviewed (documentary analysis). As detailed in Appendix A, several cases presented more than one interaction situation (observed frequency), especially when several cobots are implemented in the same case for a mix of activities. In this table, it is possible to observe that most applications were for material movement (28.5%), machine operation (38%), and substitution purposes (70%). The coexistence between workers and robots is the most frequent interaction type (83.5%). Such descriptive data suggests that companies are using cobots mostly to replace workers in workplaces where cobots can coexist with other workers. Yet, we also identified more advanced types of interaction, evidencing the possibility of such use to create smart working environments. The only case containing only basic levels of interaction (coexistence) was in quality control, where cobots are used for substitution. It is worth noting that deskilling and reskilling impacts were similar in terms of frequency of observation (14% and 13%, respectively), while upskilling was the least observed (3%) in the business cases analyzed.

Table 8 - Observed frequencies of cases in the data analysis*

Manufacturing Activities	Workers' impact	Interaction Type				
		Coexistence	Synchronized	Cooperation	Collaboration	Totals
Material movement	Substitution	41	2	-	-	**57 (28.5%)**
	Deskilling	2	1	-	-	
	Reskilling	8	2	-	-	
	Upskilling	-	-	1	-	
Machine operation	Substitution	49	2	-	-	**76 (38%)**
	Deskilling	9	2	1	-	
	Reskilling	12	-	-	-	
	Upskilling	-	-	1	-	
Manual operation	Substitution	12	-	-	-	**18 (9%)**
	Deskilling	-	3	1	-	
	Reskilling	1	1	-	-	
	Upskilling	-	-	-	-	
Assembly	Substitution	14	2	2	-	**33 (16.5%)**
	Deskilling	1	4	4	-	
	Reskilling	2	-	-	-	
	Upskilling	-	-	2	2	
Quality control	Substitution	16	-	-	-	**16 (8%)**
	Deskilling	-	-	-	-	
	Reskilling	-	-	-	-	

Upskilling	-	-	-	-
Totals	**167 (83.5%)**	**19 (9.5%)**	**12 (6%)**	**2 (1%)**
Totals	Substitution = **140 (70%)**	Deskilling = **28 (14%)**	*Reskilling =* **26 (13%)**	*Upskilling =* **6 (3%)**

* Note: Frequencies are above the 138 business cases because some cases contain more than one observed situation about human-robot interaction

To discuss the documentary observations of the frequencies reported in Table 8, we complemented them with interviews with manufacturing customers, as described in Table 9. In the case of Company A, three impact types on workers' skills were identified considering the pick-and-place tasks (packaging) and palletizing of products. In the cell where the pick-and-place task is performed, before cobot implementation, there were three workers to carry out the packaging of the products, that is, place the bottles (primary packaging) inside the cardboard box (secondary packaging) and seal this box. Two workers were reassigned to other cells when the cobot was implemented in this cell, which characterizes a substitution effect. In contrast, the worker who remained in the cell where the cobot was deployed was affected in two ways: deskilling and reskilling. First, the cobot was designed to perform the primary and secondary packaging tasks, and the worker remained to seal the boxes. In this case, by staying in the cell, the worker began to perform fewer tasks (deskilling) and serve the cobot to ensure that the necessary supplies for its operation were available. However, this same worker also needed reskilling to learn how to operate the cobot. Regarding the palletizing task, a single worker was previously responsible for the cell, performing all the necessary manual tasks. After cobot implementation, this same worker underwent a reskilling to learn some commands to operate the cobot and supervise its operation. Regarding the type of human-robot interaction (considering the operators who work in the same cell as the cobot), we identified that synchronized interaction occurs in all analyzed situations (packing and palletizing) because the interaction occurs through the command given by the operator to the cobot, and the activities performed in the cell are performed sequentially.

Regarding Company B, the four effects of technologies on workers were identified, considering the tasks of dispensing glue (manual operation) and assembling the general switch (assembly). Regarding the glue dispensing task, three effects were identified. Before the cobot was implemented, the worker performed the tasks of dispensing glue and then welding in the same production line. After the cobot implementation, the worker remained in the same operator station. However, he was replaced by the cobot in the glue dispensing task and continued to perform the subsequent task, which is welding. In addition, this worker also experienced deskilling, as he started to serve the cobot to supply it with the necessary inputs to dispense glue. On the other hand, this same worker also experienced reskilling as he had to learn new skills to operate the cobot. Regarding the general switch assembly activity, the implementation of this cobot has enabled people with special needs to perform this complex assembly, which consists of handling parts for assembly. In this case, we identified an upskilling effect because, without the help of technology, it would not be possible for people with certain limitations to perform such a complex assembly task. For the glue dispensing task, the type of interaction is Synchronized, as the cobot performs one part of the activity (glue distribution and parts handling), and then the worker performs another part of the activity (welding). As for the general switch assembly activity, the interaction type is Cooperation. This is because the cobot moves and reaches the parts while the operator performs the assembly without acting on the same part simultaneously.

Finally, in the case of Company C, we only identified the effect of substitution when the technology was implemented. This is because, by implementing the cobot, the company seeks to eliminate a human worker from the screwing activity. This elimination consists of relocating the worker to another manual activity or another production line. However, although the company seeks to replace workers in the activity in which the cobot is implemented, the interaction between humans and cobots is synchronized because production is in line and the cobot performs one of the tasks of assembling the final product.

Table 9 - Summary of interview findings

Company	Sector	Manufacturing activity	Task	Impact Typology	Interaction Type
Company A	Industry and Commerce of Health Products	Material movement	Packaging	Substitution Reskillling Deskilling	Synchronized
			Palletizing	Reskillling	Synchronized
Company B	Truck and Bus Manufacturing	Manual operation	Dispense glue	Substitution Reskilling Deskilling	Synchronized
		Assembly	General switch assembly	Upskilling	Cooperation
Company C	Computer Equipment Manufacturing	Assembly	Screwing	Substitution	Synchronized

The documental analysis summarized in Table 8 and the interviews summarized in Table 9 were complemented with the interview with competitors and the participant observation of the cobot implementation, as explained in the methodological procedures of Section 3. In the next subsections, we summarize the qualitative findings regarding these different impacts on workers through the different ways cobots are used.

4.1. COBOTS AND HUMAN-ROBOT INTERACTION LEVELS

As shown in Table 8 and corroborated by the interviews, most cobot applications focus on coexistence and synchronized activities. Few cases are reported for cooperation (6%) and even fewer for collaboration (1%). As explained by one of the managers of the cobot vendor, there are important barriers to implementing higher levels of interaction in a smart working environment. The first barrier is that manufacturers need to look at cobots as a technology different from traditional robots with different capabilities. As explained by this manager: "Many companies adopt cobots because they think that they can reduce their workforce payroll, and we have the challenge of showing them that cobots can do something much better than competing with workers". As explained in this interview, the second barrier is that higher levels of interaction require redesigning of the workflow process and manufacturing tasks and activities. As mentioned by the interviewee: *"It is different how you will perform an activity synchronized with a cobot and how you will effectively collaborate in the same activity with the cobot"*. Therefore, higher levels of interaction like cooperation and collaboration demand that workers' activities be designed for cobots. As few companies have such skills and vendors are more concerned with selling cobots than supporting such activities redesign, the resulting scenario is presented in Table 8, where workers' substitution and coexistence of cobots with workers are highly correlated and concentrated in terms of observed cases. These results were also evidenced in the three cases of adopters. They stated that the smart working approach was something new for the companies, although they have been implemented for almost eight years in Industry 4.0 related technologies. These companies are currently more concerned with the increased flexibility of their operations and decided to focus mainly on smart working technologies. However, as this journey is new for them and they also need convergence between their cobots activities, operations management methods, and worker practices, they consider the human-robot integration to be still in its early stages.

It is also worth noting that, when collaboration occured in the human-robot interaction (two cases of the documentary analysis), the activities were related to assembly and involved workers' upskilling. In the first case, the company (Company 38, Appendix A) implemented a collaborative approach for handling glue dispensing in the manufacture of door handles. In this case, the cobot now dispenses the glue with speed and precision, working in perfect collaboration with the operator who places the button on the rod after the glue is applied. This joint effort doubled person-hour output on the high-volume/low-volume production line. The second case (Company 85, Appendix A) was from a metal and machining company that uses cobots to assemble dental sterilization equipment in collaboration with the workers. In this case, the cobot is equipped with a force sensor enabling the operator to simply touch the cobot to activate it. Upon being touched, the cobot positions and holds the part for the operator to insert the pin into the assembled part, acting in a combined assembly process.

4.2. COBOTS AND SUBSTITUTION OF WORKERS

From the information analyzed, and as mentioned above in the human-robot interaction types, we found that substitution is the most common typology among cobot applications in manufacturing industries, and it can occur in activities such as quality control, material movement, assembly, and machine or manual operation. In the case of quality control, the cobot can autonomously inspect parts and tests, eliminating the need for a worker. To do so, it can use the support of other technologies such as visual computing and artificial intelligence. To exemplify the integration of these other technologies, in case 18, the cobot can be integrated into a vision system that, with the help of artificial intelligence, guides the cobot to the correct position for the expansion of the copper tube. In material movement, the cobot can replace the worker in pick and place, palletizing, labelling, machine feeding, and packaging, for example. In assembly, the cobot can replace the worker using box assembly, bolting, glue dispensing functions for joining product parts and labelling products. In machine and manual operation, the cobot can replace the worker in the autonomous operation of a CNC machine by loading the raw material into the machine and unloading the finished machine parts, operating injection moulding machines, and performing naturally manual operations such as welding and finishing. Among the types of interaction that can occur within the substitution type, cases of coexistence, synchronized, and cooperation were identified. Coexistence cases are the most common within this typology, and they cover all types of activities related to substitution. This happens, for instance, when the cobot performs an autonomous inspection of a product (e.g., Company 1, and 64, Appendix A), when it takes the boxes from a conveyor and places them on a pallet (e.g., Company 10 and 22, Appendix A). Also, when it screws a part (e.g., Company 69, and 97, Appendix A) or when it performs the entire machining process of a component (e.g., Company 23, and 39, Appendix A) without any direct contact with the worker, this technology is replacing a worker in a coexistence mode. Another type of interaction that can occur in substitution is synchronized in assembly, machine and manual operation, and material handling. In this case,

for example, when the cobot performs the dispensing of glue and joining the pieces (e.g., Company 12, Appendix A), when it operates a press or welding equipment (e.g., Company 112, Appendix A), or when they choose parts from the manufacturing line and place them in boxes (e.g., Company 111, Appendix A), completing each step sequentially, worker replacement takes place synchronously. As for cooperation, it can happen in an assembly activity in which the cobot works side by side with operators in a shared space (e.g., Company 113, Appendix A).
All the three companies interviewed have at least one substitution case. In the application of Company A, for the material handling activity, only one out of three operators remained at the station, i.e., two operators were replaced in that activity. In the application of Company B, for the glue dispensing, the cobot acts this task in the place of the welder, so the cobot performs the activity that another operator could perform. In Company C, for the assembly activity, the cobot acts instead of an operator. In this case, operators are reallocated to other manual activities, which is the main purpose of implementing cobots in this company's production line. Several cases and interviews report that the operator is removed from repetitive, stressful, or tedious tasks to perform a better role when substituted by cobots, assuming more complex activities that actually require human skills, such as control, supervision, and problem-solving. In this sense, all interviewees (suppliers, adopters and competitors) emphasized that the implementation of the technology is usually not focused on dismissing workers, but rather aims at automating dangerous or excessively repetitive activities so that workers be of more benefit in activities that really add value to the process and increase work quality and satisfaction.

4.3. COBOTS AND DESKILLING

According to the information analyzed, it was found that workers' deskilling is the second most common typology among cobot applications in the manufacturing industries, and that it can happen in the activities of assembly, material movement, and machine or manual operation. When it comes to assembly, the cobot performs a part of the assembly, for example, tightening screws or gluing parts, tasks that the operators would previously perform (e.g., Company 49, Appendix A). In addition, worker's deskilling can also happen when, instead of carrying out the activity, the operator starts to feed the cobot with the items necessary to carry out the tasks, which can be made to increase productivity (e.g., Company 128, Appendix A). In material movement, workers undergo deskilling when they need to feed cobots to carry out handling tasks such as packaging, palletizing, pick and place, and labelling. In these cases, the operator acts as an assistant to the cobot, preparing what is necessary for the cobot to perform the activities to which it was deployed (e.g., Company 111, Appendix A). In the case of machine or manual operation activities, worker's deskilling happens when the worker only delivers and collects boxes with the elements that need to be processed instead of being present in the machines and equipment for operation (e.g., Company 6, and 11, Appendix A). In these cases, an example is filling a container with parts that correspond to several hours of cobot operation and randomly checking the task status. There are also cases of deskilling in welding tasks, where, for example, instead of the welder performing the manual operation, he watches the cobot move and weld. In this case, an operator can take care of the cobot welder, which characterizes a case of deskilling (e.g., Company 47, 82, and 99, Appendix A).

The coexistence, synchronized, and cooperation types were identified when it comes to the types of interaction in which deskilling can occur. Coexistence cases are the most common within the deskilling impact, followed by synchronized cases. Coexistence cases occur in assembly, material movement, and machine operation. For example, when the cobot performs bolting tasks using the parts package provided by the worker while the worker performs other activities outside the cobot's operating area (e.g., Company 100, Appendix A). Or when the cobot performs its tasks, such as packaging, palletizing, pick and place, in a workspace not shared with the worker (e.g., Company 22, Appendix A). Another case is when the operator only powers the cobot, and the operator performs his activities independently and simultaneously without sharing the same workspace (e.g., Company 100, Appendix A). In deskilling with synchronized interaction, the reported cases refer to assembly activities, material movement, and machine or manual operation. It happens, for instance, when the cobot performs one part of an assembly and the operator performs another (e.g., Company 49, Appendix A); when the cobot performs the packaging, and the operator performs the closing of the boxes (e.g., Company 111, Appendix A; or when the cobot performs a part of the welding, and then the operator performs another part (e.g., Company 82, Appendix A). In these cases, the cobot and the worker share the same workspace but work sequentially, characterizing cases of synchronized interaction. When it comes to cooperation, it can occur in the assembly and machine or manual operation. An example is when, while a cobot uses the pre-assembled package positioned by the operator, it performs marking and screwing activities (e.g., Company 55, Appendix A). During the process, the worker folds the shipping boxes and cleans the finished parts with a cloth (e.g., Company 5, Appendix A). In these cases, the worker and the cobot operate in the same workspace and are dedicated to completing the same task. However, they are not simultaneously working on the same part/product, which characterizes a case of cooperation.

Among the companies interviewed, Company A and B have cases of deskilling. In the case of Company A, the application was carried out in the material movement activity, in the packaging task. According to the respondent, the deskilling case happened because the operator is responsible for ensuring that everything necessary for the cobot to operate is available. In this case, the operator acts as the cobot's feeder instead of carrying out the activities. The application of Company B is in manual operation, specifically in the task of dispensing glue for sealing. In the case of glue dispensing, before implementing the cobot, the welder was responsible this task, for the sealing, and then for the welding of components to the vehicle. After implementation, one of the welder's functions became to supply the cobot so that it would perform the glue dispensing activity, resulting in improved quality, ergonomics, and productivity.

Although most cases of deskilling occur with the cobot being fed by the operator to carry out activities in his stead, these applications can increase worker productivity by allowing the same worker to work at different stations, ensuring that cobots have the necessary inputs to carry out the activities for which they are intended. Still, as in substitution cases, even when cobots cause the deskilling of the worker, most of the tasks that the cobot performs are repetitive, exhausting, and difficult to access for the worker, or require great worker precision during processing.

Furthermore, it is important to point out that deskilling cases often happen together with substitution and reskilling cases, impacting operators differently. This happens because, when a technology is implemented to perform a certain activity, the way people are considered in these projects will vary, causing different types of impacts.

4.4. COBOTS AND RESKILLING

The results show that reskilling is the third most common impact on workers from cobot applications. As in deskilling, the reskilling effect occurs in assembly, material movement, and machine or manual operation (Table 3). In assembly activities, cobots carry out the assembly, but workers keep their positions for programming and operating activities 'on' the cobots. In this case, the operators' scope of work changes through requalification with training about how to program and operate cobots, including tasks such as program cycles, performing adjustments, and identifying the central point of gravity of the tool in the cobot (e.g., Company 13, and 26, Appendix A). In material movement, packaging, palletizing, and pick-and-place tasks, workers start the program, operate, and supervise the execution of these tasks by the cobot (e.g., Company 93, Appendix A). These activities performed by the workers allow to develop and raise the level of professional qualification of employees through interaction with the cobot. In machine or manual operation activities, workers also undergo Reskilling for cobot programming, operation, and supervision. For example, in some cases, a welder operator is re-qualified and starts programming and operating the cobot that performs the welding task (e.g., Company 7, Appendix A). In addition, due to the reskilling, workers start to operate, program, and supervise the cobots in more than one machine on the shop floor, becoming multifunctional.

Regarding the types of interaction identified through case analysis and interviews, it was verified that coexistence and the synchronized type could occur. The cases of coexistence are triggered by the ones that occur the most within this typology. For instance, although workers are responsible for operating, scheduling, and supervising the cobots, the latter can carry out the tasks to which they have been deployed autonomously. As a result, workers no longer need to share the workspace with the cobot (e.g., Company 50, Appendix A), since now repetitive tasks are carried out by the cobot while the worker can engage in different tasks. In cases where the synchronized interaction type exists, for example, when a batch is completed, the cobot directly alerts the operator responsible for supervising it about the completion. In this way, the cobot communicates with the worker, and the worker decides on the next steps to be taken, modifying the cobot's programming or operating mode (e.g., Company 7, Appendix A).

Regarding the interviews with adopters, the companies that presented cases of reskilling were Company A and Company B. In Company A, the case of reskilling took place within the activity of moving materials in the packaging and palletizing tasks. In the packaging task, the operator who remained at the workstation (two others were removed to other production lines) was retrained to learn how to operate and supervise the cobot. In the case of the palletizing task, the workers needed to learn how to supervise and operate the cobot. As reported by the respondent, “this is the least 'noble' application of a cobot because it is used only for this purpose. However, it is the workplace where workers are most satisfied with their work”. An interesting issue highlighted by the respondent is that the company is considered one of the best places to work in Brazil according to the Great Place to Work survey (GPTW, 2020), and one of the difficulties the company faces is in the availability of training outside the company to help meet today's technological demands. Thus, the company created an internal team of three employees to develop solutions, program, and train operators to operate and supervise the cobots. The application of Company B was carried out in a manual operation activity, specifically in the task of dispensing glue. In this case, the welder responsible for the activity was requalified to operate the cobot in addition to welding, while the cobot took over the glue dispensing activity. In this case, as highlighted by the interviewee, in addition to employee safety and product quality, they observed that they are developing other skills in the team, not only for production but also in monitoring and operating the cobot.

When it comes to reskilling, companies choose not to incorporate highly specialized people to handle a state-of-the-art cobot but rather to develop capacities and train internal team specialists, thereby increasing the level of workers’ skills. One of the managers of the cobot vendor interviewed explained that such a strategy allows the company to increase productivity in the production process and also helps to preserve the essence of teamwork by valuing the workers that have been part of the operations. In this sense, the reskilling approach is not only focused on the benefits of cobot adoption but also on a socio-technical perspective of the factory. This aims to evaluate workers and their history in the company, which should also result in more openness to the adoption of new technologies, as stated by Company B. However, we also observed some cases of reskilling that happen together with cases of substitution. In these cases, not all workers in the production line were qualified to operate, program, and supervise the cobots. In such cases, the reallocation strategy was adopted in factories where job preservation was a value of the company.

4.5. COBOTS AND UPSKILLING

According to the cases and interviews, the upskilling typology is the least recurrent among the typologies and it can occur in assembly and material movement activities. In assembly, the upskilling situation occurs when the cobot performs activities collaborating with the workers and helping them to do the activity even better, for instance, helping to put components together or supporting the part while the worker performs a task on it (e.g., Company 87, Appendix A). In the case of material movement, the cobot performs activities that do not add value to the process, such as moving parts removed from an injection molding machine for the operator to carry out inspection activities (e.g., Company 71, Appendix A). In this case, the operator continues to perform the activity, but with the cobot helping to move the parts.

Cooperation and collaboration were identified as the two human-robot interaction types related to upskilling. In cooperation cases, both the cobot and the worker perform the activity simultaneously in the same workspace and share resources, although they do not act simultaneously on the same part. For example, while cobots perform high-risk tasks such as welding and separating cut parts, workers may be in the same workspace performing less dangerous tasks to complete the same activity (e.g., removing burrs from the metal parts welded by the cobot) (e.g., Company 103, Appendix A). In cases where collaboration occurs, both the cobot and the worker act on the same part simultaneously, for example, in assembly cases where the cobot dispenses glue so that the operator can fit the part (Company 38) or when the cobot reaches and holds the part for the operator to assemble (Company 85).

Among the companies interviewed, just Company B presented an upskilling situation. In this company, the activity in which the Upskilling took place is assembly, specifically in the complex task of assembling a vehicle's general switch. In this case, the cobot helps the operator in complex manual assembly to such an extent that now it is possible for operators with special needs to perform one of the most complex tasks within an automotive assembly line, with the cobot moving and reaching the parts for the operator to make the assembly.

These results show that upskilling is highly correlated with the cooperation and collaboration human-robot interaction types. In Section 4.1. we explained the difficulties and challenges of implementing cooperation and collaboration interaction types in manufacturing due to the need of redesigning the manufacturing workflow. Therefore, although cobots can help workers be upskilled, this can only happen when the complete system is designed for smart working between workers and cobots, requiring an anthropocentric perspective on the use of cobots on the shop floor.

This was also evidenced during the follow-up of the implementation project in which the researchers were involved. The manufacturing company wanted to develop an Industry 4.0 production line that supported its workers in the assembly and production decision-making. One of the technologies considered for the production line was cobots, but the company was only interested in this technology after it moved to a new plant, where the production line could be redesigned from the ground up. The cobots were integrated into a new modular production cell in which both cobots and workers' stations are flexible to be added or retired based on the production routes and capacity available. The combination was designed for collaboration on the same component: while the worker assembles the components, the cobot activates the quality and reliability tests on the component, thus requiring less of the worker's attention to those repetitive, simpler tasks of the assembly activity. Upskilling was possible in such a situation because now less of the worker's attention is required to complementary tasks, and thus he can execute the main activities faster and assemble a greater variety of components in the same production line. However, the company only considered such an integration because it redesigned its layout. As stated by the operations manager: *"our previous production line was rigid, we could not use the same workplace to have both a cobot and a worker. The production line was linear"*.

5. DISCUSSIONS

Our main findings are summarized in Figure 5, which represents the conceptual framework from Figure 3 revisited based on the empirical results described in Section 4. This figure shows the impacts on workers that were possible to observe in the qualitative research reported. Next, we discuss the main findings obtained.

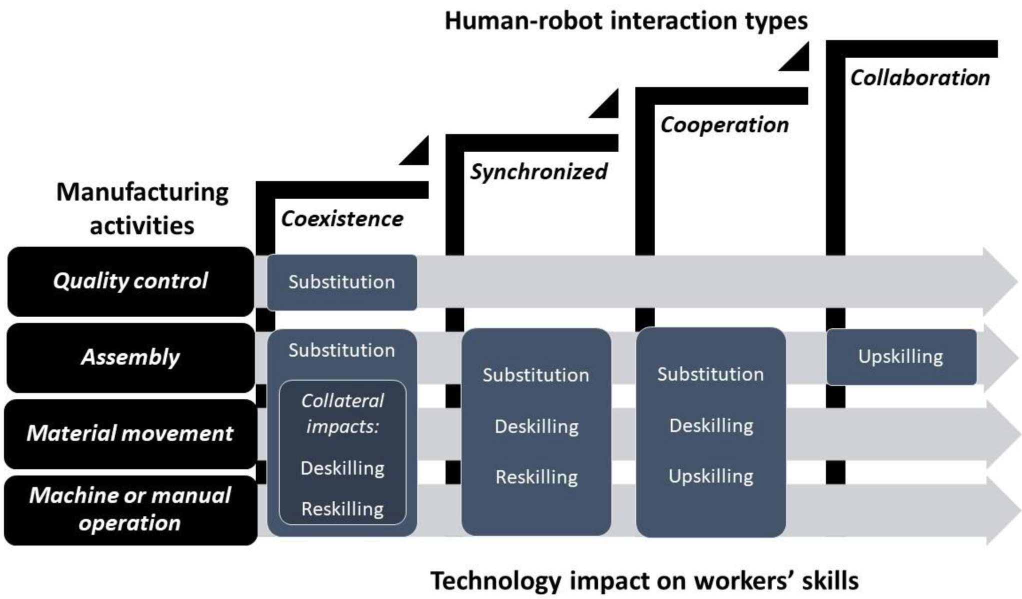

Figure 5 - Main findings about the impact of cobots on operators in smart working environments

Firstly, our findings showed that quality control is dominated by the implementation of cobots to substitute workers in an environment where cobots can coexist with other workers. In this manufacturing activity that is necessary but does not add value to the manufactured product, companies aim to reduce worker activity and focus on automating repetitive inspection tasks. This is in line with other quality control-oriented Industry 4.0 solutions. The literature has also reported the adoption of automated processes rather than workers supported by technologies (Hrehova et al., 2021). Furthermore, our results described substitution of workers also in assembly, material movement, and machine operation, usually when there are highly repetitive and/or dangerous tasks. In such cases, we observed that cobots are no different from traditional robots, except that they can coexist with other workers in the manufacturing environment (Dornelles et al., 2022). Thus, we present the following proposition:

Proposition 1: *Cobots are used for substituting purposes when there are highly repetitive and/or dangerous activities and tasks. In such situations, the coexistence of cobots with human operators characterizes the type of interaction that differentiates cobots from traditional robots.*

In the case of substitution of workers and coexistence of the implemented cobots with other operators in the assembly, material movement and machine or manual operation activities, we also observed complementary or collateral impacts related to the deskilling or reskilling of workers that remained in the production line, as described in Figure 2. When the cobot substituted a worker, we also observed that other workers needed to be trained to provide support to the cobot (for instance, in programing or maintenance), i.e., they were upskilled. In other cases, the activities of the worker who remained in that task became simpler, like checking the cobot's execution of the tasks (deskilling). Therefore, as previously suggested in the socio-technical theory of manufacturing systems (Marcon et al., 2021), cobots should not be seen in coexistence interactions as an isolated and independent technology that simply substitutes workers. Instead, they can produce changes in the environment, demanding broader adaptations of the workers that are coexisting with the cobots. As pointed out by recent studies in the Industry 4.0 context, social aspects of the workers coexisting with a new digital technology need to be considered, especially regarding the new skills they will need to acquire (Marcon et al., 2021; Neumann et al., 2021). Thus, our observations lead to the following proposition:

Proposition 2: *When cobots are used for substituting purposes, coexisting with workers who remain, they can generate collateral impacts on them. Such impacts can be related to reskilling or deskilling, depending on how workers will coexist with the cobot. Therefore, a broader analysis needs to be considered to assess the impact on the substituted workers and on the remaining workers as well.*

Regarding the synchronized and cooperation interaction types, Figure 1 shows that they presented the highest variation in the types of impacts for three of the four manufacturing activities. As these are the two main ways in which human-robot interaction happens, they are rather flexible to attend numerous options of applications, pointing to the flexibility of cobots (Enrique et al., 2022). However, while cooperation presented the four types of interaction in the observed cases, synchronized interaction did not show upskilling situations. This is because there is sequential activity between worker and cobot in synchronized activities, but the cobot does not directly support the worker to improve task execution. As upskilling involves an enhancement of workers' capabilities through digital technologies (Dornelles et al., 2022), cobots are not in touch with the worker in synchronized activities but focused on a specific task, which is complementary to the one performed by the worker, and this impact is not present. Thus, we summarize this situation in the following proposition:

Proposition 3: *When cobots are used for synchronized and cooperation interaction types, the highest variation of types of impacts on manufacturing workers can be present. However, synchronized interaction does not comprise workers' upskilling, remaining this one only for cooperation activities where the cobot will support the worker.*

Finally, for the collaboration situation, our findings showed only upskilling impacts on workers. The collaboration type of interaction is focused on producing a smart working environment in which the cobot supports the worker so that the worker can better execute the manufacturing activities (Frank et al., 2019; Dornelles et al., 2022). The literature has already suggested that this is one of the least explored aspects in the Industry 4.0 domain (Meindl et al., 2021), which is corroborated by the fact that our investigation found only two cases. Recent studies have shown that when cobots collaborate with workers, productivity can be increased, and workers' learning curve to implement new tasks can be reduced in the workstations (Cohen et al., 2021). Besides, cobots can help increase operational flexibility in the production line, since they can adapt workers' activities and provide more flexibility for the worker execute a wider range of tasks, while the cobot is focused on complementary repetitive operations (e.g., the worker assembles different product parts while the cobot helps the worker by tightening the screws in such product parts) (Enrique et al., 2022). Thus, we propose:

Proposition 4: *Collaboration interaction between workers and cobots is intrinsically related to upskilling situations. Cobots are used as assistants to workers' tasks and activities so that workers can enhance their capabilities and take more advantage of capabilities that differentiate human workers from automation technologies.*

6. CONCLUSIONS

This study investigated the use of cobots to create an Industry 4.0 smart working environment in different manufacturing activities. We used a large amount of qualitative data on the application of cobots to analyze how cobots are used in manufacturing activities for different types of human-robot interactions to understand how such configurations can impact workers' skills. Our findings show that this Industry 4.0 technology presents different impacts on workers' skills, ranging from the substitution of workers to their deskilling, reskilling and upskilling. Our results suggest that this will depend on the type of manufacturing activity in which the cobot will be used and on the level of interaction with operators for which the working process was designed. Our study brings important contributions to the Industry 4.0 theory, as it sheds light on the various ways cobots can be used in manufacturing activities. In this sense, this study meets the demand for more research on Industry 4.0 smart working technologies, as recently suggested by Meindl et al. (2021). Moreover, a recent literature review from Dornelles et al. (2022) on smart working technologies showed that cobots are one of the emerging technologies most commonly used in manufacturing applications, and called for deeper investigation into the details of how such cobots are used. Our findings help to fulfil these gaps and demonstrate how cobots can be effectively adopted in smart working environments. We also provide propositions that can drive future empirical studies on cobots adoption in smart working environments.

6.1. MANAGERIAL IMPLICATIONS

Practitioners can use this study as a guideline for the implementation of cobots. The proposed framework can help in the decision-making process of implementing cobots for different activities. Practitioners can learn what kinds of training they will need for their workers and what kinds of impact their workers will suffer from cobots implementation. Moreover, they can also learn what is required in each level of human-robot interaction since the applications with the highest level of collaboration are the least explored. Our results also reported the difficulty of convincing companies to think of the adoption of cobots in another way, which can also be useful to help practitioners reflect on how they will adopt cobots in the manufacturing system.

6.2. LIMITATIONS AND FUTURE RESEARCH

One limitation of this study is that we used a single cobot provider as source of evidence. Although we took some caution by interviewing two competitors to validate our findings, we believe that future studies should consider the nuances and differences between cobots providers. There is a risk that some cobots can be more useful for collaborative activities than others. Such undesirable effects on the research can be only fully controlled when several brands are compared. On the other hand, our study has the advantage of capturing a very deep analysis based on the multiple and extensive sources of qualitative data we used. Second, we provided four propositions in this study that should open opportunities for future research. Such propositions can be deployed in hypotheses to be tested with empirical data from survey studies. Finally, more research is needed in the smart working context of Industry 4.0 since the literature lacks knowledge on how smart working technologies like cobots can be integrated and connected to other smart working tools to create a really immersive experience for workers on the shop floor. Today, cobots and most smart working technologies focus on the workers, but they are not interconnected to create a fully integrated smart working experience. A study on how cobots can be integrated with other tools would be valuable for production research.

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APPENDIX A - BUSINESS CASES OF COBOT APPLICATION OF THE SUPPLIER COMPANY

Companies	Country	Sector	Manufacturing activities	Typologies	Types of Interaction
Company 1	India	Metal and machining	Quality control	Substitution	Coexistence
Company 2	USA	Metal and machining	Manual operation	Substitution	Coexistence
Company 3	Germany	Electronics and Technology	Assembly	Deskilling	Cooperation
Company 4	USA	Electronics and Technology	Material movement	Substitution	Coexistence
Company 5	Japan	Automotive and subcontractors	Machine operation	Deskilling	Cooperation
Company 6	Poland	Metals and Treatment, and Polymers	Machine operation	Substitution	Coexistence
Company 6	Poland	Metals and Treatment, and Polymers	Machine operation	Deskilling	Coexistence
Company 7	Finland	Metal and machining	Manual operation	Reskilling	Synchronized
Company 8	New Zealand	Furniture and equipment	Assembly	Deskilling	Coexistence
Company 9	Czech Republic	Automotive and subcontractors	Machine operation	Substitution	Coexistence
Company 10	India	Science and research	Material movement	Substitution	Coexistence
Company 11	Czech Republic	Metal and machining	Machine operation	Substitution	Coexistence
Company 11	Czech Republic	Metal and machining	Machine operation	Deskilling	Coexistence
Company 12	Romania	Furniture and equipment	Assembly	Substitution	Synchronized
Company 13	Thailand	Electronics and Technology	Assembly	Substitution	Coexistence
Company 13	Thailand	Electronics and Technology	Assembly	Reskilling	Coexistence
Company 14	Poland	Metal and machining	Machine operation	Substitution	Coexistence
Company 14	Poland	Metal and machining	Machine operation	Reskilling	Coexistence
Company 15	New Zealand	Metal and machining	Assembly	Substitution	Coexistence
Company 16	Germany	Electronics and Technology	Assembly	Deskilling	Cooperation
Company 17	Denmark	Metal and machining	Manual operation	Substitution	Coexistence
Company 17	Denmark	Metal and machining	Machine operation	Substitution	Coexistence
Company 18	India	Electronics and Technology	Manual operation	Substitution	Coexistence
Company 19	Germany	Automotive and subcontractors	Material movement	Substitution	Coexistence
Company 19	Germany	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 20	France	Automotive and subcontractors	Machine operation	Substitution	Coexistence
Company 20	France	Automotive and subcontractors	Machine operation	Reskilling	Coexistence
Company 21	France	Metal and machining	Machine operation	Substitution	Coexistence
Company 21	France	Metal and machining	Quality control	Substitution	Coexistence
Company 22	Italy	Food and agriculture	Material movement	Substitution	Coexistence
Company 22	Italy	Food and agriculture	Material movement	Deskilling	Coexistence
Company 23	Great Britain	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 24	Spain	Automotive and subcontractors	Material movement	Substitution	Coexistence
Company 24	Spain	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 25	USA	Electronics and Technology	Assembly	Substitution	Coexistence
Company 26	USA	Electronics and Technology	Assembly	Substitution	Coexistence
Company 26	USA	Electronics and Technology	Material movement	Reskilling	Coexistence
Company 26	USA	Electronics and Technology	Material movement	Substitution	Coexistence
Company 27	Czech Republic	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 27	Czech Republic	Plastic and polymers	Material movement	Reskilling	Coexistence
Company 28	USA	Metal and machining	Machine operation	Substitution	Coexistence
Company 28	USA	Metal and machining	Machine operation	Reskilling	Coexistence
Company 29	Sweden	Food and agriculture	Material movement	Substitution	Coexistence
Company 30	India	Automotive and subcontractors	Material movement	Substitution	Coexistence
Company 30	India	Automotive and subcontractors	Machine operation	Substitution	Coexistence
Company 30	India	Automotive and subcontractors	Assembly	Deskilling	Cooperation
Company 31	United Kingdom	Plastic and polymers	Manual operation	Substitution	Coexistence
Company 31	United Kingdom	Plastic and polymers	Machine operation	Deskilling	Synchronized
Company 32	Singapore	F&B, home care, personal care, oils	Material movement	Substitution	Coexistence
Company 33	Czech Republic	Metal and machining	Machine operation	Substitution	Coexistence
Company 33	Czech Republic	Metal and machining	Machine operation	Deskilling	Coexistence
Company 34	USA	Pharma and chemistry	Material movement	Substitution	Coexistence

Company 35	India	Automotive and subcontractors	Machine operation	Substitution	Coexistence
Company 35	India	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 36	USA	Electronics and Technology	Material movement	Substitution	Coexistence
Company 37	USA	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 37	USA	Plastic and polymers	Assembly	Deskilling	Synchronized
Company 38	USA	Furniture and equipment	Assembly	Upskilling	Collaboration
Company 39	Germany	Metal and machining	Machine operation	Substitution	Coexistence
Company 40	India	Metal and machining	Machine operation	Substitution	Coexistence
Company 40	India	Metal and machining	Machine operation	Reskilling	Coexistence
Company 40	India	Metal and machining	Machine operation	Deskilling	Coexistence
Company 41	Norway	Metal and machining	Machine operation	Substitution	Coexistence
Company 41	Norway	Metal and machining	Manual operation	Substitution	Coexistence
Company 41	Norway	Metal and machining	Material movement	Substitution	Synchronized
Company 42	Canada	Furniture and equipment	Material movement	Substitution	Coexistence
Company 43	USA	Plastic and polymers	Assembly	Substitution	Cooperation
Company 43	USA	Plastic and polymers	Material movement	Substitution	Coexistence
Company 44	Germany	Metal and machining	Manual operation	Substitution	Coexistence
Company 44	Germany	Metal and machining	Quality control	Substitution	Coexistence
Company 45	Netherlands	Metal and machining	Machine operation	Substitution	Coexistence
Company 45	Netherlands	Metal and machining	Assembly	Substitution	Coexistence
Company 46	Switzerland	Metal and machining	Machine operation	Substitution	Coexistence
Company 47	USA	Metal and machining	Machine operation	Substitution	Coexistence
Company 47	USA	Metal and machining	Manual operation	Deskilling	Synchronized
Company 47	USA	Metal and machining	Manual operation	Reskilling	Coexistence
Company 48	Romania	Automotive and subcontractors	Manual operation	Substitution	Coexistence
Company 48	Romania	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 49	Switzerland	Furniture and equipment	Assembly	Deskilling	Synchronized
Company 50	Germany	Metal and machining	Machine operation	Reskilling	Coexistence
Company 51	USA	Metal and machining	Machine operation	Substitution	Coexistence
Company 52	Denmark	Furniture and equipment	Material movement	Substitution	Coexistence
Company 52	Denmark	Furniture and equipment	Manual operation	Substitution	Coexistence
Company 53	Japan	Automotive and subcontractors	Assembly	Substitution	Coexistence
Company 53	Japan	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 54	USA	Pharma and chemistry	Machine operation	Substitution	Coexistence
Company 55	France	Automotive and subcontractors	Assembly	Deskilling	Cooperation
Company 56	China	Metal and machining	Machine operation	Substitution	Coexistence
Company 57	Germany	Electronics and Technology	Material movement	Substitution	Coexistence
Company 58	Germany	Metal and machining	Material movement	Substitution	Coexistence
Company 59	Netherlands	Metal and machining	Machine operation	Reskilling	Coexistence
Company 60	Germany	Electronics and Technology	Machine operation	Substitution	Coexistence
Company 61	Singapore	Metal and machining	Machine operation	Substitution	Coexistence
Company 62	USA	Metal and machining	Machine operation	Substitution	Coexistence
Company 63	Denmark	Electronics and Technology	Material movement	Substitution	Coexistence
Company 63	Denmark	Electronics and Technology	Machine operation	Substitution	Coexistence
Company 64	Slovenia	Electronics and Technology	Quality control	Substitution	Coexistence
Company 65	Austria	Metal and machining	Material movement	Substitution	Coexistence
Company 65	Austria	Metal and machining	Machine operation	Substitution	Coexistence
Company 66	Finland	Metal and machining	Machine operation	Substitution	Coexistence
Company 67	Finland	Metal and machining	Machine operation	Substitution	Coexistence
Company 68	Japan	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 69	Germany	Automotive and subcontractors	Manual operation	Substitution	Coexistence
Company 70	Sweden	Metal and machining	Machine operation	Substitution	Coexistence
Company 71	Italy	Plastic and polymers	Material movement	Upskilling	Cooperation
Company 71	Italy	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 72	Italy	Electronics and Technology	Manual operation	Substitution	Coexistence
Company 73	Czech Republic	Automotive and subcontractors	Manual operation	Deskilling	Cooperation
Company 74	Denmark	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 75	USA	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 76	India	Pharma and chemistry	Material movement	Substitution	Coexistence
Company 77	Slovakia	Automotive and subcontractors	Assembly	Substitution	Coexistence
Company 78	Spain	Automotive and subcontractors	Machine operation	Deskilling	Synchronized
Company 78	Spain	Automotive and subcontractors	Machine operation	Upskilling	Cooperation
Company 79	Italy	Pharma and chemistry	Assembly	Substitution	Coexistence
Company 80	Austria	Electronics and Technology	Material movement	Substitution	Coexistence
Company 81	Island	Food and agriculture	Material movement	Substitution	Coexistence
Company 82	USA	Metal and machining	Manual operation	Deskilling	Synchronized
Company 83	Czech Republic	Metal and machining	Machine operation	Substitution	Coexistence
Company 84	Brazil	Pharma and chemistry	Material movement	Substitution	Coexistence
Company 85	France	Metal and machining	Material movement	Substitution	Coexistence
Company 85	France	Metal and machining	Machine operation	Substitution	Coexistence
Company 85	France	Metal and machining	Assembly	Upskilling	Collaboration

Company 86	Japan	Pharma and chemistry	Material movement	Substitution	Coexistence
Company 86	Japan	Pharma and chemistry	Assembly	Substitution	Coexistence
Company 87	Japan	Automotive and subcontractors	Assembly	Upskilling	Cooperation
Company 88	Sweden	Food and agriculture	Quality control	Substitution	Coexistence
Company 88	Sweden	Food and agriculture	Material movement	Substitution	Coexistence
Company 89	Norway	Food and agriculture	Material movement	Substitution	Coexistence
Company 90	India	Automotive and subcontractors	Machine operation	Substitution	Coexistence
Company 90	India	Automotive and subcontractors	Machine operation	Reskilling	Coexistence
Company 91	Denmark	Metal and machining	Machine operation	Substitution	Coexistence
Company 91	Denmark	Metal and machining	Machine operation	Reskilling	Coexistence
Company 92	Germany	Automotive and subcontractors	Assembly	Substitution	Coexistence
Company 92	Germany	Automotive and subcontractors	Assembly	Reskilling	Coexistence
Company 93	Sweden	Food and agriculture	Material movement	Reskilling	Coexistence
Company 94	Denmark	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 94	Denmark	Plastic and polymers	Material movement	Substitution	Coexistence
Company 95	Denmark	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 96	Canada	Electronics and Technology	Manual operation	Substitution	Coexistence
Company 97	China	Automotive and subcontractors	Manual operation	Substitution	Coexistence
Company 98	USA	Metal and machining	Quality control	Substitution	Coexistence
Company 98	USA	Metal and machining	Material movement	Substitution	Coexistence
Company 99	USA	Metal and machining	Manual operation	Deskilling	Synchronized
Company 99	USA	Metal and machining	Machine operation	Substitution	Synchronized
Company 100	Sweden	Metal and machining	Machine operation	Deskilling	Coexistence
Company 100	Sweden	Metal and machining	Machine operation	Reskilling	Coexistence
Company 101	Switzerland	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 102	Australia	Plastic and polymers	Assembly	Substitution	Coexistence
Company 103	Indonesia	Electronics and Technology	Assembly	Upskilling	Cooperation
Company 104	Czech Republic	Pharma and chemistry	Material movement	Substitution	Coexistence
Company 105	Spain	Cosmetics and fragrances	Material movement	Reskilling	Synchronized
Company 106	Poland	Metal and machining	Quality control	Substitution	Coexistence
Company 106	Poland	Metal and machining	Material movement	Substitution	Coexistence
Company 107	USA	Furniture and equipment	Machine operation	Substitution	Coexistence
Company 108	Italy	Furniture and equipment	Assembly	Substitution	Synchronized
Company 109	France	Health Care	Material movement	Substitution	Coexistence
Company 110	Denmark	Food and agriculture	Material movement	Substitution	Coexistence
Company 111	Bulgaria	Electronics and Technology	Material movement	Substitution	Synchronized
Company 111	Bulgaria	Electronics and Technology	Material movement	Deskilling	Synchronized
Company 111	Bulgaria	Electronics and Technology	Material movement	Reskilling	Synchronized
Company 112	USA	Electronics and Technology	Machine operation	Substitution	Synchronized
Company 113	Spain	Automotive and subcontractors	Assembly	Substitution	Cooperation
Company 114	USA	Aerospace and defense	Machine operation	Substitution	Coexistence
Company 115	Singapore	Metal and machining	Machine operation	Deskilling	Coexistence
Company 115	Singapore	Metal and machining	Machine operation	Reskilling	Coexistence
Company 116	India	Machines and equipment	Material movement	Reskilling	Coexistence
Company 117	Denmark	Plastic and polymers	Machine operation	Deskilling	Coexistence
Company 117	Denmark	Plastic and polymers	Machine operation	Reskilling	Coexistence
Company 118	Czech Republic	Metal and machining	Machine operation	Substitution	Coexistence
Company 119	Denmark	Metal and machining	Material movement	Reskilling	Coexistence
Company 120	USA	Automotive and subcontractors	Material movement	Substitution	Coexistence
Company 120	USA	Automotive and subcontractors	Material movement	Reskilling	Coexistence
Company 121	New Zealand	Plastic and polymers	Machine operation	Substitution	Coexistence
Company 122	USA	Metal and machining	Machine operation	Deskilling	Coexistence
Company 123	New Zealand	Plastic and polymers	Assembly	Substitution	Coexistence
Company 124	Taiwan	Electronics and Technology	Machine operation	Substitution	Coexistence
Company 125	Germany	Metal and machining	Machine operation	Substitution	Coexistence
Company 126	USA	Automotive and subcontractors	Machine operation	Substitution	Coexistence
Company 126	USA	Automotive and subcontractors	Assembly	Deskilling	Synchronized
Company 126	USA	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 127	USA	Metal and machining	Machine operation	Substitution	Coexistence
Company 128	USA	Metal and machining	Assembly	Deskilling	Synchronized
Company 129	USA	Metal and machining	Machine operation	Substitution	Coexistence
Company 130	Korea	Automotive and subcontractors	Machine operation	Reskilling	Coexistence
Company 130	Korea	Automotive and subcontractors	Machine operation	Deskilling	Coexistence
Company 131	Taiwan	Plastic and polymers	Material movement	Substitution	Coexistence
Company 131	Taiwan	Plastic and polymers	Material movement	Deskilling	Coexistence
Company 132	Poland	Food and drinks	Material movement	Substitution	Coexistence
Company 132	Poland	Food and drinks	Material movement	Reskilling	Coexistence
Company 133	Japan	Food and agriculture	Material movement	Substitution	Coexistence
Company 133	Japan	Food and agriculture	Material movement	Reskilling	Coexistence
Company 134	Vietnam	Metal and machining	Material movement	Substitution	Coexistence
Company 135	USA	Plastic and polymers	Material movement	Substitution	Coexistence

Company 136	China	Furniture and equipment	Material movement	Substitution	Coexistence
Company 136	China	Furniture and equipment	Assembly	Substitution	Coexistence
Company 137	Japan	Metal and machining	Material movement	Substitution	Coexistence
Company 138	USA	Automotive and subcontractors	Material movement	Substitution	Coexistence
Company 138	USA	Automotive and subcontractors	Quality control	Substitution	Coexistence
Company 138	USA	Automotive and subcontractors	Assembly	Substitution	Coexistence

APPENDIX B – INTERVIEW GUIDELINE

1) We would like to ask you to introduce yourself and talk a little about your experience with technology and cobots.
2) According to your experience, what is the main use of cobots in relation to workers? For example, does the robot do some of the work and then the operator does it, or do they work together, moving the same part simultaneously? Do you have any examples of this?
3) In your perception, what normally happens to workers when a cobots is implemented? For example, is the worker replaced, or can he perform the same task better using the cobot? Can you name a case?
4) According to your experience, what is companies' main motivation for adopting technologies such as cobots? For example, do they seek to improve conditions for workers, increase product quality, reduce labor, create better jobs?
5) How do you believe cobots can impact workers' skills? For example, can they lose some of their skills because the cobot simplifies their work, or can they improve their skills with retraining?
6) Our study analyzed 138 cobot application cases in companies worldwide. We verified that there are four potential impacts on workers with implementing this technology. One is substitution, where the cobot starts doing the operator's task, and it is shifted to another function or laid off. Another is deskilling, in which the operator starts to serve the cobot, which simplifies his task. Another is reskilling, where, due to the implementation of the cobot, the operator learns how to perform a new role to use the technology. The last one is an upskilling, in which the cobot helps the operator to do the same activity he was already doing but better. Based on your experience, have you ever witnessed any of these cases? Could you describe?
7) Could you name the main challenges with the process of ideation, implementation, and post-implementation of cobots?

4. FINAL CONSIDERATIONS

4.1. CONCLUSIONS

This dissertation brings contributions to the development of Smart Working environments in manufacturing industries, especially related to the activities of workers and the effects that technologies can generate. In the first paper, we sought to identify the SWT related to the main manufacturing activities. As a result, we obtained 15 SWTs that support workers in eight manufacturing activities. In addition, we also identify the possible negative and positive impacts of these technologies on workers. From this, we were able to link the SWTs to the capabilities of the workers, according to Romero et al. (2016), showing that the implementation of such technologies can contribute to the improvement and empowerment of workers. As the main theoretical contribution of the first article, we point out the 15 main SWTs applied in manufacturing activities, and that contribute to the support of workers, according to the literature: augmented reality, collaborative robots, virtual reality, wearable devices, environment sensors and machines, automation, voice-enabled assistant, digital twin, smart decision support systems, automated guided vehicles/autonomous mobile vehicle, computer vision, industrial social networks, exoskeletons, visual analytics, and artificial intelligence. As a main practical contribution, we emphasize that managers interested in implementing technologies can use the study to identify ways to apply these technologies, i.e., in which manufacturing activities there are cases of application as well as the impacts that each of them can generate on workers, which can better prepare them to face the uncertainties of a technological application.

The second paper investigated in depth the effects of SWTs on the manufacturing workers' activities, i.e., what can happen to these workers when these technologies are implemented in their processes. We carried out a case study focused on collaborative robots, as this technology is one of the most relevant for workers and manufacturing (Dornelles et al., 2022). In this way, we investigated application cases and conducted interviews and observations regarding technology implementation in workers' manufacturing activities. From this, we conceptualized four types of SWT effects on workers: Substitution, Deskilling, Reskilling, and Upskilling. This classification is the main theoretical contribution of this paper and the dissertation since it demonstrates how the same technology can have different effects on workers' skills according to the way and strategy with which it is implemented. As practical contributions of this paper, we highlight that the classification of effects can help industries that want to implement technologies understand how companies have been implementing technologies and bring to light the importance of aligning strategy with the effects of technology implementation. Along with this, it is also useful for SWT providers to offer their products, considering that technologies, in addition to improving the process, can also impact workers and outline strategies to provide more complete solutions.

The results obtained in the second article, which used the initial conceptual base from Article 1, were focused on collaborative robots as a mean to analyze in depth the contributions of a smart technology on workers. As a conceptual extension of the study presented in Article 2, the final conceptual framework represented in Figure 6 shows how the analysis of collaborative robots could be extended to any kind of smart working technology (SWT). These means that this dissertation opens an avenue to replicate our study in other types of technologies related to workers in the Industry 4.0 context. Therefore, as final contribution, this study provides a framework useful to conduct similar studies but applied to other technologies in which the impact on workers' skill can be very different from those observed in this dissertation for collaborative robots.

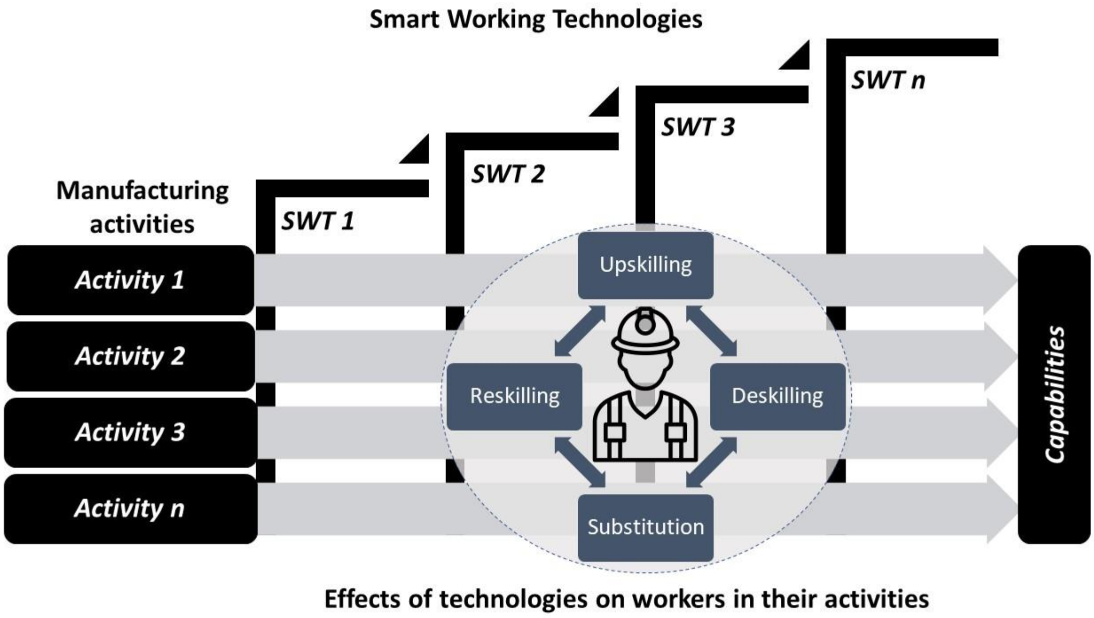

Figure 6 - Final generic conceptual framework

4.2. FUTURE RESEARCH

Our findings can provide support for future work. In this sense, new studies can identify new manufacturing activities that will arise from the technology's implementation. With this, other effects of technologies on workers can appear.

It is also important to investigate whether the effects elucidated in this dissertation apply to another SWT since the concepts were validated considering cobots. Despite having relative importance among SWTs, they have specific characteristics and are not applied to all manufacturing activities previously analyzed in Article 1. Therefore, other studies could validate these concepts to consolidate the previously proposed classification.

Based on this, other studies could verify if and how SWTs interact with each other to create an anthropocentric environment. That is, to investigate whether technologies can be integrated to create a smart work environment that empowers workers in real-time. This premise analyzes from another perspective the I4.0 maturity model proposed by the German Academy of Sciences and Engineering (ACATECH) (Schuh et al., 2020), in which the highest level would be autonomous targeting the so-called “dark factories” without the need of the worker. On the contrary, the anthropocentric perspective aims to place the worker at the centre of the production system, i.e., as the main resource of the organization, and the integrated technologies used to improve the activities performed by workers aiming at greater productivity, quality, and flexibility of the process.

Finally, this dissertation also serves as a subsidy for other studies to identify the skills that must improve in workers, both dealing with technologies and adapting to the new type of production system. As mentioned by (Frank et al., 2021), new professions will emerge through the implementation of technologies, which leads to the belief that new skills will also be necessary for adapting workers to this context. Therefore, it would be interesting to identify the required skills and training workers.