

Jobs and Skills of Production Workers at Manufacturing SMEs

An empirical exploration of smart technology adoption

Koen Nijland
Dennis Trotta
Paul Preenen
Sebastian Thiede

Abstract

The skillsets of production workers are crucial for the effective adoption of smart technologies which are largely shaped by work design. However, current literature lacks comprehensive insights into the skills and work designs of production workers, hindering the adoption of Industry 5.0. Grounded in work design and skills literature this study explores the required skills of employees and perceived work design characteristics for adoption of AI, AR/VR, and Robotics in Dutch Manufacturing SMEs. This qualitative study involved semi-structured interviews with experts, managers and production workers. Results reveal a need to reassess traditional job profiles, as two distinct production workers roles emerge from AI, AR/VR and robotics adoption. Machine operators face potential deskilling through low feedback from the job, low task variety and low job complexity. Foreman-production workers require additional skills due to job enlargement and enrichment. However, they seem to be put in this job role due to the lack of various professional and transversal skills to fully utilize smart technologies, and to accommodate a viable return on the technology investment. This highlights the importance of balancing job resources and requirements in work design, training programs for I5.0 skill development, and understanding contextual design elements of manufacturing systems contributing to viable I5.0 adoption in SMEs. Finally, sustainability, self-awareness, and self-reflection skills are not considered by professionals, displaying unawareness of its importance for I5.0 implementation practices.

Keywords: Industry 5.0, SMEs, production workers, smart technology, workplace innovation, work design, skills

Introduction

In the last decade, a lot of attention has been paid to Industry 4.0 (I4.0) which was predominantly focused on digitalization and the implementation of smart technologies (e.g., Robots, AR/VR, AI) to create more efficient and flexible factories (Ammirato et al., 2023; Meindl et al., 2021; Müller, 2021). Recently, a new concept has emerged: Industry 5.0 (I5.0). This concept represents the next wave in manufacturing, promoting the integration of advanced digital technologies while prioritizing employee well-being and job quality (Breque et al., 2021; Ghobakhloo et al., 2023). I5.0 advocates that technology adoption should ensure sustainability, human-centricity, and resilience toward industry, the economy, and society including its members (Breque et al., 2021; Xu et al., 2021). In this feat, the evolution from I4.0 to I5.0 does not seem to change what smart technologies are used. Instead, it predominantly changes how smart technologies are adopted, and the level of digitalization required in SMEs to accommodate sustainability, resilience, and human centricity requirements of smart technologies (Akundi et al., 2022; Alojaiman, 2023; Ammirato et al., 2023; Barata & Kayser, 2023; Leng et al., 2022). Moreover, I5.0 shifts from I4.0's technological determinism to a more inclusive approach based on technology appropriation. Technology appropriation emphasizes adoption, modification and customization of technology and manufacturing processes to meet user requirements and needs (Carroll et. al., 2003; Dix, 2007). Therefore, true adoption of technology in I5.0 automatically implies appropriation of these technologies by definition (Oeij et al., 2024).

Meanwhile, AI, AR/VR, and Robotics are smart technologies that have become rapidly available to manufacturing organizations (Maddikunta et al., 2022, Noghabaei et al., 2020, Zhang et al., 2021). These technologies present opportunities for SMEs in areas such as production planning and control, energy management, quality management, and maintenance management (Zheng et al., 2021). The integration of smart technologies into everyday business allows SMEs to shift towards more efficient, agile, and competitive production processes (Chavez et al., 2023). In addition, example cases emerge that show benefits of AI, AR/VR and robotics in terms of more resilient production systems (Bortolini et al., 2018; Dohale et al., 2024), enhanced understanding of sustainability in production (e.g., Daut et al., 2017; Liu et al., 2019), and enhanced well-being and performance through human-centered use of smart technologies (e.g., Bal et al., 2021; Kim et al., 2019; Mark et al., 2021; Vukicevic et al., 2019). Hence SMEs, who account for 4 million jobs in the Dutch economy, are increasingly implementing these technologies to reap the benefits (European Commission, 2023a; Frank et al., 2019).

The adoption of AI, AR/VR, and robotics also brings about significant challenges, especially for Small and Medium-sized enterprises (SMEs) (Maddikunta et al., 2022). These challenges encompass (1) increased job complexity (Hecklau et al., 2016), (2) the need to learn new skills (Müller, 2021), (3) new job profiles being required (Wilson et al., 2017), and (4) a potential decrease in job quality (Spencer, 2018). Production workers are at the core of I5.0 and require specific skills to fully leverage smart technologies (Nair et al., 2024). However, these skills seem scarce across Europe (Büth et al., 2017; European Commission, 2023b; George & George,

2023). In response to this skills scarcity, SMEs are focusing on developing their existing workforce (European Commission, 2023b). In this vein, workplace innovation (WPI) gained attention, as it explores practices for effective integration of smart technologies while also ensuring the well-being and development of their production workers (Dhondt et al., 2015; Kopp et al., 2019; Oeij et al., 2017; Oeij, Preenen, & Dhondt, 2021). More specifically, WPI refers to practices that structurally (division of labour) and/or culturally (empowerment) enable employees to participate in organizational renewal and improvement to enhance the quality of working life and organizational outcomes (Oeij et al., 2017). This means that manufacturing processes can be adapted to the (development) needs and current capabilities of production workers (Breque et al., 2021) and work designs can be shaped such that they facilitate the exhibition and development of required skills (Eurofound & Cedefop, 2020; Humphrey et al., 2007; Parker & Knight, 2024).

Despite these initiatives, successful adoption of I5.0 is lacking at SMEs (Maisiri et al., 2019; Mavrikios et al., 2018). This seems to be due to various challenges such as data security, required investments, and human resource requirements in terms of time and effort invested and skills required to work with smart technologies (Adel, 2022; Leng et al., 2022; Lewandowska et al., 2023). In this paper, the focus is on the skills challenge. The novelty of I5.0 concept has resulted in limited understanding of skills that are required to work with smart technologies in an I5.0 context (European Commission, 2023c; Oeij et al., 2024).

Additionally, whilst technology affects jobs (Parker et al., 2017) research on how these changed jobs look like is lacking (Pejic-Bacht et al., 2019). In particular for production workers, as they are traditionally underrepresented in research on jobs and learning (Koen et al., 2013; Preenen et al., 2015). Moreover, although research on the jobs and skills of production workers in I4.0 can provide a foundation, skills and jobs are context-specific and vary from organization to organization, depending on different factors, including the maturity of the implemented technologies (Dalenogare et al., 2018; Parker et al., 2017). For instance, the extent to which a decision support technology can support increasingly complex decisions is reliant on the technological maturity and can impact the job complexity of a production worker. Further empirical data on skills and work design is necessary (European Commission, 2023c; Oeij et al., 2023; Rus et al., 2019). Therefore, to bridge the skills gap for SMEs, there is a need to specify the required skills and current work design of production workers into the context of specific smart technologies in a manufacturing system.

Overall, a comprehensive understanding of the current skills landscape could facilitate a smooth transition to I5.0. To achieve this, a review of existing literature has been conducted to identify the spectrum of skills in I4.0 that are relevant to I5.0. The skills identified are often broad categories (i.e., technical skills, personal skills) that necessitate interpretation within specific contexts (Dalenogare et al., 2018). Production workers, defined as those directly involved in the operational processes of manufacturing and handling technology daily, are experiencing and adapting to I5.0 in their daily work. Understanding their perspective is crucial, as they are not just users of technology but are also significantly impacted by its

integration in their work environment. To further enhance comprehension of this perspective it is important to understand the context within which a smart technology is adopted. In this sense, it is critical to model the manufacturing processes (Havey, 2005). In this study, it is explored how production workers can be fostered to adopt three smart technologies: (1) AI, (2), AR/VR, and (3) Robotics. Striving for achieving the I5.0 vision, the identification of specific skills, and how jobs look like dependent on the manufacturing processes that they work on has become crucial. These two challenges result in the following two main research questions: Which skills do production workers need to work with AI, AR/VR and Robotics within manufacturing SMEs that strive for I5.0?

How do production workers experience work design characteristics when working with AI, AR/VR and Robotics within manufacturing SMEs that strive for I5.0?

Theoretical foundations for smart technology adoption

This study is grounded in skills (e.g., van Laar et al., 2020) and work design theory (Humphrey et al., 2007) in the context of I5.0 manufacturing. Given the limited literature specific to I5.0, this study draws primarily from I4.0 research, adapting these insights to the I5.0 context. The European Commission highlighted human-centricity, sustainability, and resilience as the core principles of the I5.0 concept (Breque et al., 2021). Human-centric technology adoption means that technology is used to adapt production processes to the needs of the worker whilst ensuring smart technologies do not impinge on workers' fundamental rights to privacy, autonomy, and human dignity (Breque et al., 2021). Sustainability requires technology adoption to enhance circular processes, reduce waste, and decrease environmental impact of manufacturing systems such that energy consumption and greenhouse emissions are reduced. Finally, smart technology adoption should contribute to the resilience of organisations through increased robustness in industrial production. Manufacturing systems should be armed better against disruptions and provide better security for critical industrial infrastructures in times of crisis (Breque et al., 2021)

This chapter outlines the key concepts of work design and skills that are crucial for innovating manufacturing workplaces with smart technologies. To select these concepts we specifically looked at scientific and grey literature that fulfil the predetermined selection criteria: (1) production workers, (2) level of abstraction, and (3) duplicates.

1. Skills and work design characteristics that are specifically relevant to production workers in manufacturing SMEs. This means identifying skills and work design characteristics that are important for people who work directly in manufacturing processes.
2. Skills and work design characteristics that are described in a more concrete and practical way. In particular, skills and work design characteristics that are more directly related to the actual tasks and activities carried out by production workers.
3. If there are skills or work design characteristics that appear multiple times in the papers or overlap with each other, duplicates are removed. This means if a skill is mentioned more than once, it is included once in the skills synthesis.

Work design and smart technology adoption

Work Design can be defined as the process of structuring work and defining the roles and responsibilities within an organization. It involves determining the division of work tasks assigned to individuals, specifying not only what workers do but also how and why these tasks are performed. Designing jobs encompasses the analysis of task requirements, the methods used to complete these tasks, and the relationships involved in the job (Morgeson & Humphrey, 2006). This analysis is done on the level of work design characteristics which can be defined as “the attributes of the task, job, and social and organizational environment” (Humphrey et al., 2007, P. 1333).

In general, Humphrey et al. (2007) distinguish three categories of work design that contain several work design characteristics. First, motivational characteristics refer to individual job components such as the skill, task and knowledge demands of work. Second, social characteristics pertain to interactional components of work such as interdependence, feedback, and social support from others. Third, work context relates to contextual elements of a job which can be physical demands, ergonomics of the workplace, and noise in the surrounding workplace (Humphrey et al., 2007).

The introduction of smart technology can have various effects on work design depending on the context. Industry 4.0 is associated with more job variety and an increase in the cognitive predominance of the tasks executed. However, Industry 4.0 can also lead to deskilling and lower autonomy due to changes in job content (Shaba et al., 2019). While Industry 4.0 has been associated with affecting job enlargement and job enrichment by pushing workers at the shopfloor level to constantly monitor the production processes (Lagorio et al., 2021), Waschull et al. (2022) highlight a trend in job simplification for production workers, mainly from a technological push perspective. These contrasting findings highlight the context-specific nature of technology effects on the workforce. Shaba et al. (2019) found that these effects are dependent on a control-oriented organizational design or a commitment-oriented organizational design.

In the same vein, Parker et al. (2017) claim that the implementation of smart technologies affects work design both positively and negatively. In the context of Industry 4.0, the level of implementation has different effects on job complexity, skill variety, and job autonomy (Waschull et al., 2019). Hirsch-Kreinsen (2016) distinguishes between polarized organizations, where there are simple tasks and a need for highly skilled professionals for the execution of complex tasks. On the other hand, there are large groups of organizations where simple activities are completely automated. Lastly, as a result of new technologies, several job profiles are modified or newly created: industrial engineers (Cimini et al., 2020), data scientists (Pejic-Bach, 2020), AI engineers, cloud services managers, data security administrators (Pontes et al., 2021), cybersecurity managers, cobot programmers, cobot users, additive manufacturing experts, human-machine interface programmers & users (Leitao et al., 2020), augmented reality experts (Ras et al., 2017), robot coordinators, maintenance of smart

systems, software engineers for CPS, process analysts, bionics experts, and programmers (Jerman et al., 2019).

In conclusion, extant literature focused mainly on the impact of I4.0 technologies on work design of production workers. Automation, as opposed to augmentation, seems to be the preferred use by manufacturing SMEs and other sectors such as logistics (Hosseini et al., 2023). In addition, human-centricity has been limitedly applied to technology adoption (Kwiatkowska, 2022) which is integral to both the socio-technical approach (Trist, 1980) and the I5.0 concept (Beque et al., 2021). Despite the growing interest in the he social system, it represents a very marginal amount of the literature (Kadir & Broberg, 2021). The lack of attention to the social component aspect of this system is partially related to the failure to recognize the complexity of technology adoption (Schumacher et al., 2016). Table 1 provides an overview of the job characteristics that are considered within the three identified work design categories. These allow for further investigation of the effect of smart technology adoption for the work designs of production workers in an I5.0 context.

Table 1. Work design categories, characteristics, and their definitions adopted from Humphrey et al. (2007)

Category	Job characteristic	Definition
Motivational characteristics	Autonomy: • Work scheduling autonomy • Work methods autonomy • Decision making autonomy	The freedom to control the schedule and timing of work. The freedom to control which methods and procedures are utilized. The freedom to make decisions at work.
	Skill variety	The knowledge and skills necessary to perform a job.
	Task variety	The extent to which an individual performs different tasks at his/her job.
	Task significance	The extent to which a job impact's others' lives.
	Task identity	The extent to which an individual can complete a whole piece of work.
	Feedback from the job	The extent to which a job imparts information about an individual's performance.
	Information processing	The extent to which the job necessitates an incumbent to focus on and manage information.
	Job complexity	The extent to which a job is multifaceted and difficult to perform.
	Specialization	The extent to which the job involves the performance of tasks requiring specific knowledge and skill.
	Problem solving	The extent to which a job requires the production of unique solutions or ideas.
Social characteristics	Interdependence	The extent to which a job is contingent on others' work.
	Feedback from others	The extent to which other organisational members provide performance information.
	Social support	The extent to which a job provides opportunities for getting assistance and advice from either supervisors and co-workers.

	Interaction outside the organization	The extent to which a job requires and incumbent to communicate with people external to the organisation.
Work context characteristics	Physical demands	The amount of physical activity or effort necessary for a job.
	Work conditions	Aspect of the work environment such as health hazards, temperature, and noise.
	Ergonomics	The extent to which the work permits appropriate posture and movement.

Skills for smart technology adoption

The current study is based on the definition of skills given by Peterson and Van Fleet (2004) who define skills as “the ability either to perform some specific behavioural task or the ability to perform some specific cognitive process that is functionally related to some particular task” (P. 1298). Tasks are units of activity that produce output (Autor, 2013). While literature often distinguishes between competencies and skills, this study treats them as synonyms, reflecting their interchangeable use in I4.0 and I5.0 research.

One stream of research sees the change of work as so extensive that authors label new production workers as "Operator 4.0" (Bousdekis et al., 2020; Romero et al., 2016, 2020). Such Operator 4.0, or "smart worker," is skilled enough to perform not only "cooperative work" with robots but also work aided by machines. Hence, the relevance of acquiring a set of skills to cope with cyber-physical systems. Studies on the Operator 4.0 (e.g., Hecklau et al., 2016) have identified personal skills, social and interpersonal skills, technical skills, and methodological skills as important for the new workforce. Moreover, the significance of interpersonal skills lies in the fact that it is a crucial domain where humans can outperform machines, and they will be required in all the new job profiles (Alhoul & Kiss, 2022). The prominence of technical skills is also emphasized by Pinzone et al. (2017), who focused on the technological skills needed to operate in I4.0, particularly in areas where the most attention is needed (i.e., operations management, supply chain, product-service innovation management, data science management, IT-OT integration management).

The World Economic Forum has investigated the skills required on more than one occasion (2017, 2020, 2023) and identified some of the most important skills: analytical thinking, active learning, complex problem solving, critical thinking and analysis, creativity, leadership and social influence, technology use, technology design, resilience, stress tolerance, flexibility, and reasoning. Similarly, Islam (2022) found that business skills, such as critical thinking, cognitive flexibility, complex problem-solving, adaptive thinking abilities, qualitative skills, and communication skills, as well as technical skills, including programming, quantitative skills, data interpretation, data visualization, and virtual collaboration, are also essential for employability in Industry 4.0. According to Karacay (2018), all employees in an Industry 4.0-based system must have information and communications technology (ICT) skills and soft skills, such as collaboration, communication, and autonomy. According to Mudzar et al. (2022), three skills are crucial: high-level technical skills (e.g., deep understanding of

technologies), higher-order cognitive skills (e.g., problem-solving and critical thinking), and human and interpersonal skills (e.g., interpersonal and leadership).

The aforementioned paragraphs highlight either technical skills, non-technical skills (soft skills), or both. Janis and Alias (2018) have made a clear distinction between these two types of skills. A similar distinction has been made by Rampelt et al. (2019), who identify specific skills and general skills. The former is concerned with content-specific skills required to carry out a job, and the latter is concerned with a broader spectrum (e.g., literacy). Similarly, Maisiri (2021) distinguishes between technical skills (technological, programming, digital skills) and soft skills (thinking, digital, social). Praj et al. (2022) have investigated the crucial competencies for Industry 4.0, making a distinction between must-have skills (e.g., ability to interact with modern equipment), should-have skills (e.g., knowledge management), and could-have skills (e.g., programming skills). However, despite this overview, no distinction has been made or attention paid to the different roles and technologies independently. This specification to roles and technologies was also missing in the overview of Prifti et al. (2017) who identified eight critical areas and the associated skills required to effectively perform in I4.0 companies.

Finally, after a literature review, Kohlgrüber et al. (2021) propose a new classification of the skills needed for the future of work. This classification consists of five primary areas: digital skills, personal skills, social skills, methodological skills, and professional skills.

In conclusion, early literature focused mainly on the technological skills of the workforce to operate with Industry 4.0 technologies. More recent publications are focusing to a greater extent on non-technical skills. These align well with tasks of workers in the human-centric, sustainability, and resiliency views of I5.0 (Oeij et al., 2024). However, the dimensions identified as being of interest tend to be broad categories that require interpretation in specific contexts. A summary of the main skills associated with smart technologies can be found in appendix 1.

To achieve a comprehensive list of skills, the starting point is the skillset identified by Kohlgrüber et al. (2021) due to the notable effort in mapping many studies comprehensively about skills and the seeming relevancy of the study in an I5.0 context. Further understanding of skills in the I5.0 context is derived from a study done by Oeij et al. (2024) who proposed a categorization for skills according to general, human-centric, resilient, or sustainable abilities of production workers. Human-centricity in I5.0 requires production workers to work with assistive technologies, communicate in participation processes, participate in (re)design / change processes, and make use of learning opportunities and being empowered (Oeij et al., 2024). This aligns with digital- and technical skills that enable production workers to engage in human-machine interaction and tailor technology to their needs for task support and interaction needs. Examples of these skills could be human machine interface skills and process management. Resilience requires production workers to engage in lifelong learning, develop the ability to adapt and be creative, reflect on and respond to the resilience of work processes, analyse and solve resilience-related problems at system-level, and be self-organising and manage yourself (Oeij et al., 2024). This production work in I5.0 can be

implicitly attributed to some personal skills such as flexibility and cognitive flexibility, learning skills and self-awareness. Finally, sustainability requires production workers to understand circularity, conduct lifecycle and environmental impact assessments, evaluate contributions of smart technologies to sustainability goals, and elaborates resources efficiency (Oeij et al., 2024). These tasks could be attributed to both green and personal skills. In sum, although most literature has focused on an I4.0 context, the skills derived from main skills literature seem to cover elements of the production work in I5.0 described by Oeij et al. (2024).

Overall, a synthesis of the skills was created that clearly distinguishes between Transversal skills and Professional skills. Transversal skills are not limited to a specific job or domain but are generally required in the digital transformation. This category includes digital skills, personal skills, social skills, methodological skills, and green skills. Professional skills are specific and specialized skills relevant to a particular field of work, discipline, or occupation. They contrast with general skills as they pertain to the application of specific knowledge. Professional skills refer to the technical skills specific to the context under investigation and are needed to conduct the tasks associated with the job. Table 2 allows for analysis of the skills that production workers require to work with smart technologies in an I5.0 context.

Table 2. Skills synthesis of skills for I5.0

Skill Category	Skill subcategory	Skills	References
Transversal (generally required)	Personal	Self-reflection, self-awareness; Learning skills / lifelong learning; Integrity / ethics; Responsibility, attitude (individual values); Flexibility & Cognitive flexibility; Emotional Intelligence.	(Behrend et al., 2022; Büth et al., 2017; Corporaal et al., 2021; Hecklau et al., 2016; Islam, 2022; Janis & Alias, 2018; Prifti et al., 2017; Probst et al., 2019; van Laar et al., 2020)
	Social	Teamwork; Collaboration; Intercultural skills; Mediating, Negotiating and persuasion.	(Behrend et al., 2022; Büth et al., 2017; Hecklau et al., 2016; Janis & Alias, 2018; Maisiri et al., 2019; Mudzar et al., 2022; Prifti et al., 2017)
	Methodological	Problem-solving skills; Creative thinking; Analytical thinking; Critical thinking; Decision making.	(Behrend et al., 2022; Büth et al., 2017; Hecklau et al., 2016; Islam, 2022; Mudzar et al., 2022; Prifti et al., 2017)
	Green / Sustainability	Environmental awareness; Energy efficiency; Water reduction; Waste reduction and management; Resource re use/ recycling.	(Hecklau et al., 2016; Schröder et al., 2024)

	Digital	Basic digital skills (use of PC, browse Internet, finding information, storing data); Moderate digital skills (Word-processing, working on documents, working on spreadsheets); Advanced digital skills (Programming).	(Behrend et al., 2022; Bouwmans et al., 2024; Kohlgrüber, 2021; Maisiri, 2021; Schröder et al., 2024)
Professional (subject related)	Technical (subject related)	Specialized and expert knowledge; Process management; Human machine interface; Trouble shooting and maintenance; Analysis, modelling and simulation of production based on big data from sensors and devices; Use of digital devices (e.g. tablets, smartphones, smartwatches) for production monitoring and control; Programming and use of relevant technology (e.g. Collaborative robots, VR); Use of additive manufacturing technologies; Remote system monitoring and supervision of maintenance interventions; Use of virtual and augmented reality for instruction and support of maintenance interventions.	(Acatech, 2016; Büth et al., 2017; Kohlgrüber et al., 2021; Mudzar et al., 2022; Pinzone et al., 2017; Prifti et al., 2017)

Methodology

To answer the research questions, this study adopted a qualitative research approach, because firstly, interviews allow for in-depth exploration of interactions between production workers and advanced technologies which are needed given the novelty and rapid evolution of the I5.0 concept. Secondly, a qualitative method allows capture of the variability in job roles and manufacturing processes that typifies SMEs operating in I5.0.

Sample and research design

The research involved 19 semi-structured interviews with two respondent groups: work design or technological experts (e.g., senior researchers, professors, and a technology supplier, N = 7X), and professionals from 6 SMEs (managers as well as production workers, N

= 12). The four semi-structured interviews with work design experts focused on all three technology contexts. Additionally, one interview with a technological expert focused on the AI context, one interview was conducted on the AR/VR context, and one interview addressed the AI and robotics context. The combinations of insights from the expert interviews with the 6 SME cases has allowed for a multi-perspective view.

The inclusion criteria for experts were threefold: (1) distinguished academics in related fields of work design, sociology of work, AI, AR/VR or Robotics, (2) actively engaged with research on I5.0, (3) familiar with the technical aspects of the technologies. Manufacturing SMEs were included in the sample if (1) the company adhered to SME size requirements defined by *OPOCE* (n.d.), and (2) if professionals use AI, AR/VR or Robotics technologies in a smart manufacturing system. It was assessed which smartness characteristics the technology of interest contributes to the manufacturing system through an adaptation of the smart manufacturing characteristics by Mittal et al. (2019). Below, table 3 describes which expert interviewees relate to which SME case, the smartness characteristics of the manufacturing system, and the application of smart technology.

Table 3. SME sample including Smart technology applications

Organisation ID	Respondent ID	Related Expert	Smartness characteristics	Technology application
SME1	PM1 PW1	WDE1- WDE4 TE3	Connectivity	Bending bench robot: Automation of picking up, bending, and depositing products CO ₂ laser cutting robot: Automation of the laser cutting process
SME2	PM2 PW2	WDE1- WDE4 TE3	Decision-support, connectivity, and Monitoring and interpretation through sensors	Fiber and CO ₂ laser cutting robot: Automation of the laser cutting process Maintenance monitoring support Quality control of end products Decision support for final product quality
SME3	PM3 PW3	WDE1- WDE4 TE3	Connectivity, monitoring and interpretation through sensors	Fiber and CO ₂ laser cutting robot: Automation of the laser cutting process Maintenance monitoring support Quality control of end products

SME4	PM4 PW4	WDE1- WDE4 TE1 TE3	Connectivity and interoperability	AI-enabled Planning and control system: Automation of production control in robot cell Pallet-loading and spark robot: Automation of pallet loading Automation of sparking process Quality control of end products
SME5	PM5 PM5	WDE1- WDE4 TE1 TE2	Connectivity and interoperability , monitoring at distance	AI-enabled Work scheduling system: Automation of order scheduling Digital work schedule Digital work instructions
SME6	PM6 PW6	WDE1- WDE4 TE1 TE3	Monitoring and interpretation through sensors	Robotics and AI: Automation of substantive production processes such as milling Automation of production control in robot cell Automation of pallet loading

Based on a synthesis of literature from Work design (Morgeson & Humphrey, 2006) and skills (e.g., Kohlgrüber et al., 2021; van Laar et al., 2017) two semi-structured interview protocols have been developed: one for experts, and one for production workers and managers. The exploration of Work Design and required skills included an investigation of the manufacturing context in which production workers adopted smart technologies. In order to achieve this, the measurement instrument was enriched with elements drawing from business Process Modeling (Havey, 2005) and Technology Appropriation (Caroll et al., 2002). Business processes modelling was utilized through the creation of a flowchart that visualizes the detailed production steps, responsible person or machine, and flow of information and materials when producing a typical product for which they utilize the respective smart technology. Finally, elements of technology appropriation are utilized to capture required skills for modification and customization of technology and manufacturing processes to meet user requirements and needs.

The expert interview protocol assessed their views on two main elements: (1) Industry 5.0 and work design, and (2) skills for appropriation of technology. An example of a question targeting work design in I5.0 is: *"How has [the work design characteristic mentioned by the expert] evolved during one or two critical stages of implementing technologies like AI, VR, or Robotics in (I5.0) manufacturing?"*

The production workers interview protocol assessed three elements: (1) the current manufacturing process, and an assessment of (2) required skills and (3) current work design characteristics in the current manufacturing process. This focus on current processes is crucial because it establishes a baseline for understanding how I5.0 adoption may necessitate

new skills or changes in how workers interact with the manufacturing system. An example of a question is: *“What did you already need to be able to do before you first started to collaborate with the technology?”*

The data was collected through a combination of on-site (professionals) and online interviews (experts). The interviews with the professionals were supplemented by a workplace visit of the production workers and managers to further enhance understanding of the manufacturing process and work design. All interviews were recorded, with professional interviews transcribed in full and expert interviews transcribed selectively. Data analysis employed a deductive thematic analysis approach, utilizing both detailed transcripts and summaries. This variation in transcription allowed for in-depth analysis while balancing resource constraints based on the interviewee's role and the depth of technical process insights.

Results

Results indicate several insights which are structured according to the two research questions in the following sections: (1) required skills, and (2) work designs.

Required skills by production workers

Although green/sustainability skills are recognized as significant in the I5.0 literature, they were notably absent in the perspectives of interviewees. Similar results are shown for self-reflection and self-awareness which could be attributed as a skill for resilience. Instead, interviewees highlight the critical importance of digital skills, and technical skills such as human-machine interface skills. For instance, professionals indicated that manufacturing could be halted if production workers are unable to interact with the robot (interface). Experts further highlighted the importance of human-machine interaction for obtaining feedback from the job, maintaining job complexity, and maintaining task variety. Table 4 summarizes the perceived importance of skills in an I5.0 context.

Table 4. Composed list of required skills and their importance indicated in the interviews

Skill Category	Skill sub-category	Skills	Importance
Transversal (generally required)	Personal	Integrity / ethics; Learning skill; Self-reflection, self-awareness; Responsibility, attitude (individual values); Flexibility & Cognitive flexibility; Emotional Intelligence.	+ +++ 0 + ++ +
	Social	Collaboration; Teamwork; Intercultural skills;	+ ++ 0 +

		Mediating, Negotiating and persuasion.	
	Methodological	Creative thinking; Problem-solving skills; Analytical thinking; Critical thinking; Decision making.	+++ + +++ +++ +
	Green / Sustainability	Environmental awareness; Can identify appropriate approaches to mitigate, adapt and potentially solve sustainability problems; Challenge the status quo, and reflect on how personal, social and cultural backgrounds influence thinking and conclusions; Identify responsibility and accountability for unsustainable behaviour, and demand effective policies for sustainability.	0 0 0 0
	Digital	Basic digital skills (Use of PC, Browse Internet, Finding Information, Storing data); Moderate digital skills (Word-processing; Working on documents; Working on spreadsheets); Advanced digital skills (Programming).	+++ +++ ++
Professional (subject related)	Technical (subject related)	Process management; Human machine interface; Troubleshooting and maintenance; Analysis, modelling and simulation of production based on big data from sensors and devices; Use of digital devices (e.g. tablets, smartphones, smartwatches) for production monitoring and control; Programming and use of relevant technology (e.g. Collaborative robots, VR); Use of additive manufacturing technologies; Remote system monitoring and supervision of maintenance interventions; Use of virtual and augmented reality for instruction and support of maintenance interventions.	+++ +++ ++ +++ +++ ++ + + 0

Note. '0' indicates that the skill is not mentioned in the interviews.

Perceived work designs by production workers

Within the companies of this exploration, the gradual adoption of smart technologies has led to an incremental increase in technological sophistication. Consequently, distinctions between 'smart technology' and just 'technology in general' are not always salient for

production workers and managers. Some production workers have difficulties pinpointing changes in their jobs due to smart technology, given that they have been using the technology at hand for a prolonged period. This phenomenon is exemplified by the perception among production workers that smart robots do not seem to have not caused drastic changes to the work design compared to previous technologies, in the perception of these production workers:

"No, I think the tasks are pretty much the same as they were before. Only the process becomes much faster, and more products are created, when compared to ten years ago." – PW1

Although human-technology collaboration and augmentation are dominant pillars in I5.0 that give direction to desired work designs of production workers, the manufacturing SMEs mainly utilized smart technologies for automation purposes. Robotics and AI are the two main smart technologies that are adopted with various applications and levels of technological capabilities. Most notably AR/VR was absent in the SMEs under study.

Interviews with managers highlighted the crucial role of Total Productive Maintenance. Automated tasks by robots enable the possibility of almost 24/7 activity in the manufacturing process. For instance, workers are often asked to start large orders near the end of the working day such that these larger orders can be performed by robots throughout the night. The next day, production workers perform control measures on the completed tasks. In this way, sequential interdependence is established in the human-machine interaction. In addition, AI-applications suggest work schedules and work instruction to production workers. In this vein, job autonomy seems to be contingent on the design of the manufacturing system. Generally, there is a high degree of autonomy between manufacturing processes, and a low degree of autonomy within manufacturing processes. Finally, interviewees unanimously agreed that task automation with Robotics alleviate the physical strain on humans through physical support.

Two clearly distinct main job profiles emerge, namely 'foreman-production workers' and 'machine operators'. Typically, organizations have a few foreman-production workers as opposed to a larger group of machine operators. Professionals indicate that this results from the current skills gap that SMEs are faced with in relation to skills such as programming, work process overview and troubleshooting. Foreman-production workers are characterized by their expertise in programming, understanding of work process, and troubleshooting. The responsibility for addressing machine failures and programming machines has shifted away from machine operators to foreman-production workers. Otherwise, with more complicated errors, the manufacturer of the machines is contacted; they will attempt to solve the problem via the telephone, but if this does not work, they will visit the company themselves. The production workers' hierarchy as mentioned here is illustrated by the following quote:

"If a problem arises, not all production workers will be able to tackle it. [...] We definitely need the top layer for that." – PM3

The criteria for advancing machine operators to supervisory positions emphasize both domain-specific expertise and cross-functional skills such as digital skills, learning skills, cognitive flexibility, analytical thinking, and critical thinking. Professionals indicated plenty of social support, within and outside the company, for machine operators that want to learn to work with smart technology. However, upskilling is required if machine operators are tasked with performing the work of a foreman-production worker. Experts indicate that upskilling requires practices such as user participation, user-centered design of smart technologies, on-the-job feedback, and possibility to customize work processes. However, these practices are rarely indicated by the professionals under study. Overall, the effect of smart technologies seems contingent on the job role of production workers and mainly distinct in the task and knowledge characteristics category. Table 5 provides an overview of the perceived work design of production workers who adopted smart technologies.

Table 5. Perceived work design characteristics subdivided by job role indicated by professionals

Work design category	Work design characteristic	Machine operators	Foreman-production workers
Task characteristics	Autonomy – within a manufacturing process	–	–
	Autonomy – between manufacturing processes	+ / –	+
	Task identity	–	+
	Task variety	–	+
	Feedback from the job	–	+
Knowledge characteristics	Job complexity	–	+
	Problem solving	–	+
	Specialization	–	+ / –
Social characteristics	Interdependence	+ / –	+ / –
	Interaction outside the organization	+/-	+
	Feedback from others	+	+
Contextual characteristics	Physical load	–	–

Note. ' + ' indicating high, ' + / – ' moderate, and ' – ' low perceived level.

Discussion

This study offers valuable insights into the implications that smart technology adoption has on the required skills and the work designs of production workers. The following discussion highlights key points for practitioners, policymakers, and workplace innovation scholars that emerged from the analysis.

Implications for practitioners

While the effect of technologies on work design has been long established (Hirsch-Kreinsen, 2016; Parker et al., 2017; Waschull et al., 2019; Waschull et al., 2022), professionals experience difficulty in assessing the direct impact of smart technologies on their work. Although all precautions were established to have all interviewees fully grasp the content, machine operators remain a challenging group when discussing complicated topics such as work design, skill requirements, and smart technology adoption. This may be further complicated by the gradual adoption of smart technologies.

Moreover, the context-specific effect of smart technologies on different job profiles remains an open challenge for practitioners. Implications for machine operators can be detrimental as low levels of task and knowledge characteristics, as indicated by professionals, is associated with various deskilling (Shaba et al., 2019) and motivational challenges (Humphrey et al., 2007). At the same time, the foreman-production worker experienced job enlargement and job enrichment. Consequently, they run similar risks for motivational challenges if their skillset and additional job resources do not suffice for the additional job requirements they experience (Humphrey et al., 2007). This highlights the importance of practitioners that integrate job quality, productivity, and well-being of production workers evenly when adopting technology. In this feat, practitioners could consider a SMART work design for their production workers as a starting point when adopting human-centric technologies (Parker & Knight, 2024). Finally, the consideration of human-centric technologies such as assistance systems present another opportunity for practitioners as it ‘supports the production worker during manufacturing or assembly work tasks without replacing him, without overruling him and without posing any danger to the worker’ (p. 228) (Mark et al., 2021). This could contribute to enhanced capabilities of production workers to perform their job.

Another important observation is the absence of explicit discussion around green and sustainable skills, despite their growing importance in literature (Hecklau et al., 2016; Schröder et al., 2024). As organizations strive to adopt smart technologies, practitioners should recognize the criticality of equipping production workers with the necessary skills to contribute to sustainable manufacturing practices. Integrating green and sustainable skills into workforce development strategies and training programs should be a priority (de Sousa Jabbour et al., 2018; Schröder et al., 2024).

The study's findings on the return on investment (ROI) of technology for SMEs highlight a practical consideration that warrants attention. While the human-centered approach to smart

technologies is desirable, it must align with a viable business case for these organizations (Borchardt et al., 2022). The focus on maximizing the utilization of available technologies, rather than extending human capabilities, suggests that practitioners must carefully balance the investment in technological solutions with the need to maintain a sustainable and competitive operation. To make human-centered adoption of these technologies financially viable and more accessible to SMEs, practitioners could explore innovative business models (Waheed et al., 2022), lean manufacturing principles (Bittencourt et al., 2019), skills development in interorganizational learning communities (Schipper et al., 2023), learning factories (Büth et al., 2020), or government incentives (Mukherjee et al., 2023). Overall, the wide variety in different directions highlights the complexity and multidimensionality of the challenge that practitioners face.

Implications for workplace innovation scholars

The results of this study underscored divergent skill requirements and perceptions of work design between machine operators and foreman-production workers, once again, challenging a one-size-fits-all approach to WPI in the I5.0 era (De Spiegelaere et al., 2012; Putnik et al., 2019). This differentiation could lead to positive effects for foreman-production workers due to job enlargement, but potentially negative effects such as deskilling for machine operators. These varying effects call attention to a contingent approach to WPI such as various scholars have highlighted (Oeij, Dhondt, & McMurray, 2021; Oeij et al., 2023). Practitioners and researchers must recognize the diverse implications of smart technologies on various job profiles and develop customized strategies to address the unique challenges and opportunities faced by each group of workers.

One key implication for workplace innovation scholars to consider is the potential impact on the job quality of machine operators. The findings suggest that the introduction of smart technologies may have led to a reduction in the task and knowledge characteristics of the work. These changes could potentially lead to deskilling (Shaba et al., 2019) and eventually a reduction in perceived job quality (Bakker & Demerouti, 2007). This is an important consideration, as maintaining or improving job quality should be a critical goal when implementing workplace innovation practices for I5.0 adoption (Oeij et al., 2017; Oeij et al., 2019).

Avenues for future research

The insights from this exploratory study point to several promising avenues for future research.

Firstly, addressing the methodological challenges of assessing the direct impact of smart technologies on work design characteristics is critical. This study considered context aspects in which the effect of smart technology on work design is assessed. For instance, the study considers a healthy mix of different manufacturing types used in SMEs, such as line manufacturing and cellular manufacturing. However, these differences were not considered

in the analysis of this study. Future research should explore how these manufacturing approaches influence the relationship between I5.0 adoption and work design, given the significant differences in work design between line manufacturing and cellular manufacturing (Sengupta & Jacobs, 2004). Moreover, other contextual elements in the manufacturing system such as technological maturity (Zizic et al., 2022), technology type (Dhondt et al., 2020), existing production workers skills (Nair et al., 2024), and the design and capabilities of the technology itself (Mark et al., 2021) should be considered when investigating context-specific adoption of smart technologies in manufacturing systems. Longitudinal studies and comparative analyses can provide a more comprehensive understanding of the dynamic and evolving nature of these relationships across specific contexts. For example, AR/VR applications were ultimately not utilized in the SMEs under study despite rigorous efforts. This warrants further exploration in terms of technology type.

Secondly, the role of green and sustainable skills when innovating workplaces warrants deeper exploration. Researchers should investigate the integration of sustainability skills and work design elements that support environmentally conscious manufacturing processes and examine how organizations are adapting their training and development programs to address this emerging need. This research could contribute to a more holistic understanding of the evolving skill landscape in smart manufacturing environments.

Thirdly, the study's findings on the affordability of smart technologies for SMEs and their focus on maximizing technology utilization rather than extending human capabilities open up new research questions. Future studies could investigate how an I5.0 approach to technology adoption can provide a viable business case for manufacturing SMEs. Such research requires a system-approach that includes a thorough understanding of contextual elements in manufacturing systems and their outcomes.

To achieve this, scholars could explore specific strategies and interventions to improve job quality for production workers with human-centric smart technology. Human-centric technologies such as assistance system could be a potential solution for both machine operators and foreman-production workers (e.g., Pacaux-Lemoine et al., 2022; Wotschack et al., 2023). However, much uncertainty remains regarding the context-specific adoption in which assistance systems contribute and which additional strategies and interventions support the positive effects of these human-centric technologies (Kleineberg et al., 2017; Mark et al., 2022; Oestreich et al., 2020; Romero et al., 2016). Future research could examine how job roles and responsibilities can be restructured to increase task variety, autonomy, and skill utilization, evaluating the effectiveness of upskilling and reskilling programs to equip machine operators and foreman-production workers with necessary competencies, assessing the role of worker involvement in the design and implementation of assistance systems, and exploring the influence of organizational policies, practices, and the physical work environment on the job quality and well-being of machine operators. Conducting longitudinal studies to track the long-term effects of assistance system adoption and performing comparative analyses across different organisations, industries and regions could help identify best practices and contextual factors that influence job quality outcomes for

production workers, contributing to the development of evidence-based strategies to maintain or enhance their job quality in the face of technological change.

Finally, researchers should investigate the specific mechanisms by which the job role of machine operators may have been affected. This could involve examining changes in task variety, autonomy, skill utilization, and other key job characteristics that contribute to overall job quality. Understanding these underlying drivers will be crucial in identifying ways to mitigate potential negative impacts. Given the challenging nature of doing research with machine operators, researchers should consider strengthening co-creation of business process models, and semi-structured interviews with observations and think-aloud protocols to get a more reliable view of mechanisms by which the jobs of machine operators may have been affected.

Conclusion

This study offers insights into work designs and required skills for production workers in manufacturing SMEs striving for I5.0 adoption. This research suggests that whilst machine operators can experience deskilling due to reported low feedback from the job, task variety and job complexity (Shaba et al., 2019), foreman-production workers require additional skills due to job enlargement and job enrichment (Lagorio et al., 2021). Moreover, both job roles required a combination of transversal and professional skills to effectively leverage these smart technologies. On the contrary, the absence of sustainability, self-reflection, and self-awareness skills in the perspectives of production workers and managers signals a potential blind spot in current I5.0 implementation practices. This, once again, highlights the importance of practices for fostering autonomy, collaboration, and continuous learning in the workplace to ensure a successful I5.0 transition (Oeij et al., 2017; Prus et al., 2017).

In addition, the observed shift towards more cognitively demanding tasks and increased job variety necessitates (1) a re-evaluation of traditional job profiles (e.g. Wilson et al., 2017), (2) training programs (Leesakul et al., 2022), (3) and a balance between job demands and resources within SMEs (Bakker & Demerouti, 2007). Human-centric technologies such as assistance systems show great promise regarding the latter point through physical, sensorial, or cognitive assistance (Mark et al., 2021).

Moreover, capturing context-specific elements has proven to be crucial for a comprehensive analysis of current work designs and required skills of production workers that adopted smart technologies. Technological maturity (Zizic et al., 2022), type of technology (Dhondt et al., 2020), existing skills of production workers (Nair et al., 2024), and the design and capabilities of the technology itself (Mark et al., 2021) could contribute to enhanced understanding of the creation of a viable business case for human-centric smart technology adoption at SMEs.

In conclusion, while smart technologies offer significant potential for enhancing productivity in manufacturing SMEs, their successful implementation requires careful consideration of skill

development, work design across different job roles, and contextual elements of the manufacturing system at hand.

References

- Acatech, D. A. D. T. (2016). Kompetenzentwicklungsstudie Industrie 4.0.
- Adel, A. (2022). Future of industry 5.0 in society: human-centric solutions, challenges and prospective research areas. *Journal of Cloud Computing*, 11(1), 40.
- Alhloul, A., & Kiss, E. (2022). Industry 4.0 as a Challenge for the Skills and Competencies of the Labor Force: A Bibliometric Review and a Survey. *Sci*, 4(3), 34.
- Ammirato, S., Felicetti, A. M., Linzalone, R., Corvello, V., & Kumar, S. (2023). Still our most important asset: A systematic review on human resource management in the midst of the fourth industrial revolution. *Journal of Innovation & Knowledge*, 8(3), 100403.
- Akundi, A., Euresti, D., Luna, S., Ankobiah, W., Lopes, A., & Edinbarough, I. (2022). State of Industry 5.0—Analysis and identification of current research trends. *Applied System Innovation*, 5(1), 27.
- Alojaiman, B. (2023). Technological modernizations in the industry 5.0 era: A descriptive analysis and future research directions. *Processes*, 11(5), 1318.
- Autor, D. H. (2013). The "task approach" to labor markets: An overview. *Journal for Labour Market Research*, 46(3), 185–199. <https://doi.org/10.1007/s12651-013-0128-z>
- Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of managerial psychology*, 22(3), 309-328.
- Bal, M., Benders, J., Dhondt, S., & Vermeerbergen, L. (2021). Head-worn displays and job content: A systematic literature review. *Applied Ergonomics*, 91, 103285.
- Barata, J., & Kayser, I. (2023). Industry 5.0—past, present, and near future. *Procedia Computer Science*, 219, 778-788.
- Behrend, C. R., Götting, A., Kohlgrüber, M., Pomares, E., Wright, S., Dhondt, S., & Barnes, S.-A. (2022). *Understanding future skills and enriching the skills debate*. 8222296, 1–84. <https://beyond4-0.eu/publications>
- Bittencourt, V. L., Alves, A. C., & Leão, C. P. (2019). Lean Thinking contributions for Industry 4.0: A systematic literature review. *IFAC-PapersOnLine*, 52(13), 904-909.
- Borchardt, M., Pereira, G. M., Milan, G. S., Scavarda, A. R., Nogueira, E. O., & Poltosi, L. C. (2022). Industry 5.0 beyond technology: an analysis through the lens of business and operations management literature. *Organizacija*, 55(4), 305-321.
- Bortolini, M., Galizia, F. G., & Mora, C. (2018). Reconfigurable manufacturing systems: Literature review and research trend. *Journal of manufacturing systems*, 49, 93-106.
- Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). A human cyber physical system framework for operator 4.0—artificial intelligence symbiosis. *Manufacturing letters*, 25, 10-15.
- Bouwman, M., Lub, X., Orlowski, M., & Nguyen, T. V. (2024). Developing the digital transformation skills framework: A systematic literature review approach. *PloS one*, 19(7), e0304127.
- Breque, M., De Nul, L., & Petridis, A. (2021). Industry 5.0: towards a sustainable, human-centric and

- resilient European industry. *Luxembourg, LU: European Commission, Directorate-General for Research and Innovation*, 46.
- Buer, S. V., Strandhagen, J. O., & Chan, F. T. (2018). The link between Industry 4.0 and lean manufacturing: mapping current research and establishing a research agenda. *International journal of production research*, 56(8), 2924-2940.
- Büth, L., Bhakar, V., Sihag, N., Posselt, G., Böhme, S., Sangwan, K. S., & Herrmann, C. (2017). Bridging the Qualification Gap between Academia and Industry in India. *Procedia Manufacturing*, 9, 275–282. <https://doi.org/10.1016/j.promfg.2017.04.009>
- Büth, L., Juraschek, M., Sangwan, K. S., Herrmann, C., & Thiede, S. (2020). Integrating virtual and physical production processes in learning factories. *Procedia Manufacturing*, 45, 121-127.
- Carroll, J., Howard, S., Vetere, F., Peck, J., & Murphy, J. (2002, January). Just what do the youth of today want? Technology appropriation by young people. In *Proceedings of the 35th Annual Hawaii International Conference on System Sciences* (pp. 1777-1785). IEEE.
- Chavez, Z. Z., Arvidsson, A., Hauge, J. B., Bellgran, M., Birkie, S. E., Johnson, P., & Kurdve, M. (2023, September). From Surviving to Thriving: Industry 5.0 at SMEs Enhancing Production Flexibility. In *IFIP International Conference on Advances in Production Management Systems* (pp. 789-802). Cham: Springer Nature Switzerland.
- Dalenogare, L. S., Benitez, G. B., Ayala, N. F., & Frank, A. G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of production economics*, 204, 383-394.
- Daut, M. A. M., Hassan, M. Y., Abdullah, H., Rahman, H. A., Abdullah, M. P., & Hussin, F. (2017). Building electrical energy consumption forecasting analysis using conventional and artificial intelligence methods: A review. *Renewable and Sustainable Energy Reviews*, 70, 1108-1118.
- de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Godinho Filho, M. (2018). When titans meet– Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, 132, 18-25.
- De Spiegelaere, S., Van Gyes, G., & Hootegeem, G. V. (2012). Job design and innovative work behavior: one size does not fit all types of employees. *Journal of Entrepreneurship, Management and Innovation (JEMI)*, 8(4), 5-20.
- Dhondt, S., Oeij, P. R. A., & Preenen, P. T. Y. (2015). Working in the digitalized world: The meaning of the link between advanced manufacturing and Workplace Innovation in the EU growth strategy. In C. M. Schlick (Ed.), *Arbeit in der digitalisierten Welt* (pp. 155-170). Frankfurt/New York: Campus Verlag. ISBN 978-3-593-50502-2/9.
- Dhondt, S., Van der Zee, F., Preenen, P. T. Y., Kraan, K., & Oeij, P.R.A. (2020). Dominant technology and organization: Impact of digital technology on skills. In: Schaffers, H., Vartiainen, M., & Bus, J. (Eds.), *Digital Innovation and the Future of Work* (pp. 259-283). Gistrup (Denmark): Rivers Publishers.
- Dix, A. (2007, September). Designing for appropriation. In *Proceedings of HCI 2007 The 21st British HCI Group Annual Conference University of Lancaster, UK*. BCS Learning & Development.

- Dohale, V., Akarte, M., Gunasekaran, A., & Verma, P. (2024). Exploring the role of artificial intelligence in building production resilience: learnings from the COVID-19 pandemic. *International Journal of Production Research*, 62(15), 5472-5488.
- Eurofound and Cedefop (2020), European Company Survey 2019: Workplace practices unlocking employee potential (G. Van Houten and G. Russo). European Company Survey 2019 series. Luxembourg: Publications Office of the European Union.
- European Commission. (June 27, 2023a). Number of people employed by small and medium-sized enterprises (SMEs) in the Netherlands from 2008 to 2023, by enterprise size [Graph]. In Statista. Retrieved from <https://www-statista-com.saxion.idm.oclc.org/statistics/1140442/netherlands-sme-employmentby-size/>
- European Commission, Directorate-General for Employment, Social Affairs and Inclusion, Duell, N., Guzi, M., Kahancová, M. et al., (2023b) *Skills shortages and structural changes in the labour market during COVID 19 and in the context of the digital and green transitions – Thematic review 2023 – Synthesis report*. Publications Office of the European Union, 2023, <https://data.europa.eu/doi/10.2767/807269>.
- European Commission (2023c). *Industry 5.0 and the Future of Work: making Europe the centre of gravity for future good-quality jobs*. ESIR Focus Paper.
- Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. *International journal of production economics*, 210, 15-26.
- George, A. S., & George, A. H. (2023). Revolutionizing Manufacturing: Exploring the Promises and Challenges of Industry 5.0. *Partners Universal International Innovation Journal*, 1(2), 22-38.
- Ghobakhloo, M., Iranmanesh, M., Foroughi, B., Tirkolaee, E. B., Asadi, S., & Amran, A. (2023). Industry 5.0 implications for inclusive sustainable manufacturing: An evidence-knowledge-based strategic roadmap. *Journal of Cleaner Production*, 417, 138023.
- Gronau, N., Ullrich, A., & Teichmann, M. (2017). Development of the industrial IoT competences in the areas of organization, process, and interaction based on the learning factory concept. *Procedia Manufacturing*, 9, 254-261.
- Havey, M. (2005). *Essential business process modeling*. " O'Reilly Media, Inc."
- Hecklau, F., Galeitzke, M., Flachs, S., & Kohl, H. (2016). Holistic approach for human resource management in Industry 4.0. *Procedia Cirp*, 54, 1–6. <https://doi.org/10.1016/j.procir.2016.05.102>
- Hosseini, Z., Nyholm, S., Leblanc, P., Preenen, P. T. Y., & Demerouti, E. (2023). Assessing the artificially intelligent workplace: An ethical framework for evaluating experimental technologies in workplace settings. *AI and Ethics*. Advance online publication. <https://link.springer.com/article/10.1007/s43681-023-00265-w>
- Hirsch-Kreinsen, H. (2016). Digitization of industrial work: development paths and prospects. *Journal for Labour Market Research*, 49(1), 1-14.
- Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: a meta-analytic summary and theoretical extension of the work design literature. *Journal of applied psychology*, 92(5), 1332.
- Islam, M. A. (2022). Industry 4.0: Skill set for employability. *Social Sciences and Humanities Open*, 6(1),

100280. <https://doi.org/10.1016/j.ssaho.2022.100280>

- Janis, I., & Alias, M. (2018). *AIMC 2017 Asia International Multidisciplinary Conference A SYSTEMATIC LITERATURE REVIEW: HUMAN ROLES, COMPETENCIES AND SKILLS IN INDUSTRY 4.0*. <http://dx.doi.org/10.15405/epsbs.2018.05.84>
- Jerman, A., Pejić Bach, M., & Aleksić, A. (2020). Transformation towards smart factory system: Examining new job profiles and competencies. *Systems Research and Behavioral Science*, 37(2), 388-402.
- Karacay, G. (2018). Talent Development for Industry 4.0. In *Industry 4.0: Managing the digital transformation*, pp. 123–136.
- Kleineberg, T., Eichelberg, M., & Hinrichsen, S. (2017, September). Participative development of an implementation process for worker assistance systems. In *Proceedings of 7th International conference on Production Engineering and Management* (pp. 27-29).
- Koen, J., Klehe, U.C. & van Vianen, A.E.M. (2013). Employability among the long-term unemployed: a futile quest of worth the effort? *Journal of Vocational Behavior*, 82(1), 37-48. doi.org/10.1016/j.jvb.2012.11.001
- Kohlgrüber, M., Behrend, C. R., Götting, A., Cuypers, M., Warhust, C., & Wright, S. (2021). *Understanding future skills and enriching the skills debate* (Issue Second report-final). [http://129.217.131.68:8080/bitstream/2003/41410/1/Kohlgrüber Behrend et al 2021 - BEYOND 4.0 D6.1 2nd report.pdf](http://129.217.131.68:8080/bitstream/2003/41410/1/Kohlgrüber%20Behrend%20et%20al%202021%20-%20BEYOND%204.0%20D6.1%202nd%20report.pdf)
- Kopp, R., Dhondt, S., Hirsch-Kreinsen, H., Kohlgrüber, M., & Preenen, P. T. Y. (2019). Sociotechnical perspectives on digitalisation and Industry 4.0. *International Journal of Technology Transfer and Commercialisation*, 16(3), 290-309.
- Kwiatkowska, A., & Gębczyńska, M. (2022). Job satisfaction and work characteristics combinations in Industry 4.0 environment—Insight from the Polish SMEs in the Post-Pandemic era. *Sustainability*, 14(20), 12978.
- Lagorio, A., Cimini, C., & Gaiardelli, P. (2021). *Reshaping the Concepts of Job Enrichment and Job Enlargement: The Impacts of Lean and Industry 4.0 BT - Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems* (A. Dolgui, A. Bernard, D. Lemoine, G. von Cieminski, & D. Romero (eds.); pp. 721–729). Springer International Publishing.
- Leesakul, N., Oostveen, A. M., Eimontaite, I., Wilson, M. L., & Hyde, R. (2022). Workplace 4.0: Exploring the implications of technology adoption in digital manufacturing on a sustainable workforce. *Sustainability*, 14(6), 3311.
- Leitão, P., Pires, F., Karnouskos, S., & Colombo, A. W. (2020). Quo vadis industry 4.0? Position, trends, and challenges. *IEEE Open Journal of the Industrial Electronics Society*, 1, 298-310.
- Leng, J., Sha, W., Wang, B., Zheng, P., Zhuang, C., Liu, Q., ... & Wang, L. (2022). Industry 5.0: Prospect and retrospect. *Journal of Manufacturing Systems*, 65, 279-295.
- Lewandowska, A., Berniak-Woźny, J., & Ahmad, N. (2023). Competitiveness and innovation of small and medium enterprises under Industry 4.0 and 5.0 challenges: A comprehensive bibliometric analysis. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 18(4), 1045–1074. [doi: 10.24136/eq.2023.033](https://doi.org/10.24136/eq.2023.033)
- Liu, Q., Liu, Z., Xu, W., Tang, Q., Zhou, Z., & Pham, D. T. (2019). Human-robot collaboration in disassembly for sustainable manufacturing. *International Journal of Production Research*, 57(12), 4027-4044.
- Maddikunta, P. K. R., Pham, Q. V., Prabadevi, B., Deepa, N., Dev, K., Gadekallu, T. R., ... & Liyanage, M.

- (2022). Industry 5.0: A survey on enabling technologies and potential applications. *Journal of Industrial Information Integration*, 26, 100257.
- Maisiri, W., Darwish, H., & van Dyk, L. (2019). An investigation of industry 4.0 skills requirements. *South African Journal of Industrial Engineering*, 30(3), 90–105. <https://doi.org/10.7166/30-3-2230>
- Mark, B. G., Rauch, E., & Matt, D. T. (2021). The application of digital worker assistance systems to support workers with disabilities in assembly processes. *Procedia CIRP*, 103, 243-249.
- Mark, B. G., Rauch, E., & Matt, D. T. (2021). Worker assistance systems in manufacturing: A review of the state of the art and future directions. *Journal of Manufacturing Systems*, 59, 228-250.
- Mark, B. G., Rauch, E., & Matt, D. T. (2022). Systematic selection methodology for worker assistance systems in manufacturing. *Computers & Industrial Engineering*, 166, 107982.
- Mavrikios, D., Georgoulas, K., & Chryssolouris, G. (2018). The Teaching Factory Paradigm: Developments and Outlook. *Procedia Manufacturing*, 23(2017), 1–6. <https://doi.org/10.1016/j.promfg.2018.04.029>
- Meindl, B., Ayala, N. F., Mendonça, J., & Frank, A. G. (2021). The four smarts of Industry 4.0: Evolution of ten years of research and future perspectives. *Technological Forecasting and Social Change*, 168, 120784.
- Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2019). Smart manufacturing: Characteristics, technologies and enabling factors. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 233(5), 1342-1361.
- Morgenson, F.P., & Humphrey, S.E. (2006). The Work Design Questionnaire (WDQ): developing and validating a comprehensive measure for assessing Job Design and the nature of work. *Journal of Applied Psychology*, 91(6), 1321.
- Mudzar, B. M., Muzdalifah, N., & Chew, K. W. (2022). Change in Labour Force Skillset for the Fourth Industrial Revolution: A Literature Review. *International Journal of Technology*, 13(5).
- Mukherjee, A. A., Raj, A., & Aggarwal, S. (2023). Identification of barriers and their mitigation strategies for industry 5.0 implementation in emerging economies. *International Journal of Production Economics*, 257, 108770.
- Mueller-Frommeyer, L. C., Aymans, S. C., Bargmann, C., Kauffeld, S., & Herrmann, C. (2017). Introducing competency models as a tool for holistic competency development in learning factories: Challenges, example and future application. *Procedia Manufacturing*, 9, 307-314.
- Müller, J. (2021). Enabling Technologies for Industry 5.0-Results of a workshop with Europe's technology leaders (2020). URL: <https://op.europa.eu/en/publication-detail/-/publication/8e5de100-2a1c-11eb-9d7e-01aa75ed71a1/language-en>.
- Nair, A., Pillai, S. V., & Senthil Kumar, S. A. (2024). Towards emerging Industry 5.0—a review-based framework. *Journal of Strategy and Management*.
- Noghabaei, M., Heydarian, A., Balali, V., & Han, K. (2020). Trend analysis on adoption of virtual and augmented reality in the architecture, engineering, and construction industry. *Data*, 5(1), 26.
- Oeij, P., Rus, D., & Pot, F. D. (Eds.). (2017). *Workplace innovation: Theory, research and practice*. Springer.

- Oeij, P. R. A., Dhondt, S., & McMurray, A. (2021). Workplace innovation literature review: a converging or diverging research field? A preparatory study for a research agenda.
- Oeij, P. R. A., Dhondt, S., & McMurray, A. J. (Eds.). (2023). A research agenda for workplace innovation: The challenge of disruptive transitions.
- Oeij, P. R. A., Lenaerts, K., Dhondt, S., Van Dijk, W., Scharinger, D., Sorko, S.R., Warhurst, C., (2024). A Conceptual Framework for Workforce Skills for Industry 5.0: Implications for Research, Policy and Practice, *Journal of Innovation Management*, 12(1), 205-233.; DOI: https://doi.org/10.24840/2183-0606_012.001_00010
- Oeij, P. R. A., Preenen, P. T. Y., & Dhondt, S. (2021). Workplace Innovation as a process: Examples from Europe. In McMurray, A., Muenjohn, N., & Weerakoon, C. (Eds.), *The Palgrave Handbook of Workplace Innovation* (pp. 199-221). Cham (Switzerland): Palgrave Macmillan.
- Oeij, P. R. A., Preenen, P. T. Y., van der Torre, W., F., Van der Meer, L., & Eerenbeemt, J. (2019). Technological choice and workplace innovation: Towards efficient and humanised work. *European Public and Social Innovation Review*, 4(1), 15-26.
- Oestreich, H., Wrede, S., & Wrede, B. (2020, June). Learning and performing assembly processes: an overview of learning and adaptivity in digital assistance systems for manufacturing. In *Proceedings of the 13th ACM international conference on Pervasive technologies related to assistive environments* (pp. 1-8).
- OPOCE. (n.d.). *EUR-LEX* - 32003H0361 - NL. <https://eur-lex.europa.eu/legal-content/NL/TXT/HTML/?uri=CELEX%3A32003H0361>
- Pacaux-Lemoine, M. P., Berdal, Q., Guérin, C., Rauffet, P., Chauvin, C., & Trentesaux, D. (2022). Designing human-system cooperation in industry 4.0 with cognitive work analysis: a first evaluation. *Cognition, Technology & Work*, 24(1), 93-111.
- Parker, S. K., & Knight, C. (2024). The SMART model of work design: A higher order structure to help see the wood from the trees. *Human Resource Management*, 63(2), 265-291.
- Parker, S. K., Morgeson, F. P., & Johns, G. (2017). One hundred years of work design research: Looking back and looking forward. *Journal of Applied Psychology*, 102(3), 403-420. <https://doi.org/10.1037/apl0000106>
- Pejic-Bach, M., Bertoncel, T., Meško, M., & Krstić, Ž. (2020). Text mining of industry 4.0 job advertisements. *International Journal of Information Management*, 50(December 2018), 416-431. <https://doi.org/10.1016/j.ijinfomgt.2019.07.014>
- Peterson, T. O., & Van Fleet, D. D. (2004). The ongoing legacy of RL Katz: An updated typology of management skills. *Management decision*, 42(10), 1297-1308.
- Pinzone, M., Fantini, P., Perini, S., Garavaglia, S., Taisch, M., & Miragliotta, G. (2017). Jobs and skills in industry 4.0: An exploratory research. *IFIP Advances in Information and Communication Technology*, 513, 282-288. https://doi.org/10.1007/978-3-319-66923-6_33
- Pontes, J., Geraldes, C. A., Fernandes, F. P., Sakurada, L., Rasmussen, A. L., Christiansen, L., ... & Leitão, P. (2021, March). Relationship between trends, job profiles, skills and training programs in the factory of the future. In *2021 22nd IEEE International Conference on Industrial Technology (ICIT)* (Vol. 1, pp. 1240-1245). IEEE.

- Praj, F., Horváthová, M., & Čambál, M. (2022, October). Employee competencies in line with Industry 4.0. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1256, No. 1, p. 012033). IOP Publishing.
- Preenen, P. T. Y., Verbiest, S., Van Vianen, A. E. M., & Van Wijk, E. (2015). Informal learning of temporary agency workers in low-skill jobs: The role of self-promotion, career planning, and job challenge. *Career Development International*, 20(4), 339-362. doi.org/10.1108/CDI-12-2013-0158
- Prifti, L., Knigge, M., Kienegger, H., & Krcmar, H. (2017). A Competency Model for. *Wirtschaftsinformatik Und Angewandte Informatik*, 46-60. <http://aisel.aisnet.org/wi2017/track01/paper/4>
- Probst, L., Pedersen, B., & Wenger, J. (2019). *Skills for smart industrial specialisation and digital transformation: final report* (Issue November).
- Prus, I., Nacamulli, R. C., & Lazazzara, A. (2017). Disentangling workplace innovation: a systematic literature review. *Personnel Review*, 46(7), 1254-1279.
- Putnik, K., Oeij, P., Dhondt, S., van der Torre, W., de Vroome, E., Preenen, P. T. Y. (2019). Innovation adoption of employees in the logistics sector in the Netherlands: The role of workplace innovation. *European Journal of Workplace Innovation*, 4(2), 176-192.
- Rampelt, F., Orr, D., & Knoth, A. (2019). Bologna Digital 2020: White Paper on Digitalisation in the European Higher Education Area. Berlin. Retrieved from https://hochschulforumdigitalisierung.de/sites/default/files/dateien/2019-05_White_Paper_Bologna_Digital_2020.pdf
- Romero, D., Stahre, J., & Taisch, M. (2020). The Operator 4.0: Towards socially sustainable factories of the future. *Computers & Industrial Engineering*, 139, 106128.
- Romero, D., Stahre, J., Wuest, T., Noran, O., Bernus, P., Fast-Berglund, Å., & Gorecky, D. (2016, October). Towards an operator 4.0 typology: a human-centric perspective on the fourth industrial revolution technologies. In *proceedings of the international conference on computers and industrial engineering (CIE46), Tianjin, China* (pp. 29-31).
- Rus, D., Oeij, P. R., Pot, F. D., & Totterdill, P. (2019). Workplace innovation: a review and potential future avenues. *International Journal of Technology Transfer and Commercialisation*, 16(3), 208-227.
- Schipper, T. M., Mennens, K., Preenen, P., Vos, M., van den Tooren, M., & Hofstra, N. (2023). Interorganizational Learning: A Conceptualization of Public-Private Learning Communities. *Human Resource Development Review*, 22(4), 494-523.
- Schröder, A. J., Cuypers, M., & Götting, A. (2024). From Industry 4.0 to Industry 5.0: The Triple Transition Digital, Green and Social. In *Industry 4.0 and the Road to Sustainable Steelmaking in Europe: Recasting the Future* (pp. 35-51). Cham: Springer International Publishing.
- Schumacher, A., Erol, S., & Sihn, W. (2016). A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia Cirp*, 52, 161-166.
- Sengupta*, K., & Jacobs, F. R. (2004). Impact of work teams: a comparison study of assembly cells and assembly line for a variety of operating environments. *International Journal of Production Research*, 42(19), 4173-4193.
- Shaba, E., Guerici, M., Gilardi, S., & Bartezzaghi, E. (2019). Industry 4.0 technologies and organizational design—Evidence from 15 Italian cases. In *MCIS 2019 Proceedings" Digital transformation and social innovation: Organizing, managing and controlling in the information age"*. (pp. 1-30).

- Spencer, D. A. (2018). Fear and hope in an age of mass automation: debating the future of work. *New Technology, Work and Employment*, 33(1), 1–12. <https://doi.org/10.1111/ntwe.12105>
- Trist, E. (1980). The environment and system-response capability. *Futures*, 12(2), 113-127.
- van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, 72, 577–588. <https://doi.org/10.1016/j.chb.2017.03.010>
- van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2020). Determinants of 21st-Century Skills and 21st-Century Digital Skills for Workers: A Systematic Literature Review. *SAGE Open*, 10(1). <https://doi.org/10.1177/2158244019900176>
- Vukicevic, A. M., Djapan, M., Todorovic, P., Erić, M., Stefanovic, M., & Macuzic, I. (2019). Decision support system for dimensional inspection of extruded rubber profiles. *IEEE Access*, 7, 112605-112616.
- Waheed, A., Alharthi, M., Khan, S. Z., & Usman, M. (2022). Role of industry 5.0 in leveraging the business performance: investigating impact of shared-economy on firms' performance with intervening role of i5. 0 technologies. *Sage Open*, 12(2), 21582440221094608.
- Waschull, S., Bokhorst, J. A., Wortmann, J. C., & Molleman, E. (2022). The redesign of blue-and white-collar work triggered by digitalization: collar matters. *Computers & Industrial Engineering*, 165, 107910.
- Waschull, S., Wortmann, J. C., & Bokhorst, J. A. (2019). Identifying the role of manufacturing execution systems in the IS landscape: a convergence of multiple types of application functionalities. In *Advances in Production Management Systems. Towards Smart Production Management Systems: IFIP WG 5.7 International Conference, APMS 2019, Austin, TX, USA, September 1–5, 2019, Proceedings, Part II* (pp. 502-510). Springer International Publishing.
- Wilson, H., Daugherty, P., & Bianzino, N. (2017). *The jobs that artificial intelligence will create*. Summer: MIT Sloan Management Review.
- World Economic Forum. (2017). Realizing human potential in the Fourth Industrial Revolution: An agenda for leaders to shape the future of education, gender and work. World Economic Forum, Geneva.
- World Economic Forum. (2020). The Future of Jobs Report 2020. Available online at https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf, Accessed on August 19, 2022.
- World Economic Forum. (2023). The Future of Jobs Report 2020. Available online at https://www3.weforum.org/docs/WEF_Future_of_Jobs_2023.pdf, Accessed on June 11, 2024.
- Wotschack, P., Vladova, G., de Paiva Lareiro, P., & Thim, C. (2023). Learning via assistance systems in industrial manufacturing. An experimental study in an Industry 4.0 environment. *Journal of Workplace Learning*, 35(9), 235-258.
- Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of manufacturing systems*, 61, 530-535.
- Zhang, D., Mishra, S., Brynjolfsson, E., Etchemendy, J., Ganguli, D., Grosz, B., ... & Perrault, R. (2021). The ai index 2021 annual report. *arXiv preprint arXiv:2103.06312*.

Zizic, M. C., Mladineo, M., Gjeldum, N., & Celent, L. (2022). From industry 4.0 towards industry 5.0: A review and analysis of paradigm shift for the people, organization and technology. *Energies*, 15(14), 5221.

Appendix 1: Overview of main skills literature associated with smart technologies

Author	Title	Skills area (or category)
Acatech (2016)	Kompetenzentwicklungsstudie Industrie 4.0	• Technical skills (e.g., data analysis); • Process skills (e.g., process management); • Organizational skills (e.g., leadership, autonomy, decision making).
Behrend et al. (2022)	Understanding future skills and enriching the skills debate	• Digital; • Social; • Methodological; • Personal; • Job-specific.
Bouwman et al. (2024)	Developing the digital transformation skills framework: A systematic literature review approach	• Digital working; • Communication; • Adaptation; • Collaboration; • Evidence based working; • Entrepreneurial.
Büth et al. (2017)	Bridging the qualification gap between academia and industry	• Professional (e.g., specific technical skills); • Methodological (e.g., problem solving); • Social (e.g., communication); • Personal (e.g., self-discipline).
Corporaal et al. (2018)	Werken in de nieuwe industriële revolutie	• Analytical capabilities; • Reflecting and accurate working; • Communication; • Collaboration; • Creativity / innovativeness; • Commercial skills.
Gronau et al. (2017)	Development of the Industrial IoT Competences in the Areas of Organization, Process, and Interaction based on the Learning Factory Concept	• Professional; • Personal; • Cultural; • Methodological; • Leadership; • Social; • Process; • Organization; • Interaction.
Hecklau et al. (2016)	Holistic approach for human resource management in Industry 4.0	• Technical; • Methodological; • Social; • Personal.
Islam (2022)	Industry 4.0: Skill set for employability	• Business Skills; • Technical Skills.
Janis and Alias (2018)	A systematic literature review: human roles, competencies and skills in industry 4.0	• Technical skills (knowledge, manufacturing, IT, computer science, Robotics, Automation); • Non-technical skills (personal, social, professional, methodological).
Kohlgrüber (2021)	Beyond 4.0	• Digital; • Personal; • Social; • Methodological; • Professional.

Maisiri (2021)	Industry 4.0 skills: A perspective of the South African manufacturing industry.	• Digital Skills (e.g., advanced Robotics); • Soft Skills (e.g., social); • Domain Skills.
Mudzar et al. (2022)	Change in Labour Force Skillset for the Fourth Industrial Revolution: A Literature Review	• High-level technical skills (e.g., data analysis); • Higher-order cognitive skills (e.g., problem solving); • Human or interpersonal skills (e.g., leadership).
Müller-Frommeyer et al. (2017)	Introducing competency models as a tool for holistic competency development in learning factories: Challenges, example and future application	• Professional & Methodological Skills (e.g., presentation skills, analytical skills); • Social skills (e.g., teamwork, communication); • Personal Skills (e.g., motivation, openness).
Pinzone et al. (2017)	Jobs and skills in Industry 4.0: an exploratory research	• Technical skills associated with: Operations Management (e.g., Simulation modeling), Supply chain (e.g., virtual design), Product-Service Innovation Management (e.g., smart product design), Data Science Management (e.g., big data analysis), IT-OT Integration Management (e.g., integration of embedded devices).
Prift et al. (2017)	A Competency Model for "Industrie 4.0" Employees	• Leading & Deciding; • Supporting and cooperating; • Interacting and presenting; • Analysing & interpreting; • Creating and conceptualizing; • Organizing and executing; • Adapting and coping; • Enterprising and Performing.
Probst et al. (2019)	Skills for smart industrial specialisation and digital transformation	• Technical; • Quality, Risk and Safety; • Management, leadership & entrepreneurship; • Communication; • Innovation; • Emotional Intelligence; • Ethics.
Schröder et al. (2014)	From Industry 4.0 to Industry 5.0: The Triple Transition Digital, Green and Social	• Digital; • Green; • Social; • Individual; • Personal; • Methodological; • Technical (subject specific)
Van Laar et al. (2017)	The relation between 21 -century skills and digital skills or literacy: A systematic literature review	• Core skills (technical, information management, communication, collaboration, creativity, critical thinking, problem solving); • Contextual skills (ethical and cultural awareness, flexibility, self-direction, lifelong learning).

Van Laar et al. (2020)	Determinants of 21st-Century Skills and 21st-Century Digital Skills for Workers: A Systematic Literature Review	• Technical; • Information; • Communication; • Collaboration; • Critical thinking; • Creativity; • Problem-solving skills.
------------------------	---	--

About the authors

Koen Nijland is a researcher at the Employability Transition research group of Saxion University of Applied Sciences and a PhD candidate at the Manufacturing Systems chair of the University of Twente. His research combines the fields of organisational design, work design, and human-centred technology to design human-centred manufacturing systems.

Dr. Dennis Trotta is a Senior Lecturer and Researcher at Saxion University of Applied Sciences in Enschede, Netherlands. His work focuses on Strategic Human Resource Management, with particular emphasis on Smart Skills, Workplace Innovation, and Industry 5.0. Dr. Trotta's research interests span organisational behaviour, the impact of technology on management and employees and innovation resistance. He is actively involved in international collaborations, including Erasmus+ projects across Europe, contributing to the advancement and dissemination of knowledge in HRM practices.

Dr. Paul Preenen is a senior researcher at TNO, Sustainable Productivity and Employability, and a Professor of Applied Sciences in Human Capital at Saxion University of Applied Sciences. His research focuses on organisational behaviour and the consequences of technology for organizations, management, and employees.

Prof. Dr.-Ing. Sebastian Thiede is a full professor of Manufacturing Systems at the University of Twente (Netherlands) within the faculty Engineering Technology. Prof. Thiede is interested in innovative technologies, methods and tools for the planning and operation of manufacturing systems and whole factories.

Acknowledgements

This research has been supported by the Sharehouse, Skills in Smart Industry, and Smart Skills @ Scale projects. The Sharehouse project is co-financed and supported by the Dutch Research Council NWO, the Dutch Ministry of I&W, Taskforce for Applied Research SIA, the Dutch Topsector Logistics, and TKI Dinalog (project number 439.18.452). The Skills in Smart Industry and Smart Skills @ Scale projects are co-financed and supported by the Dutch Research Council NWO (project numbers 1418.22.020 and 1518.22.055).