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REVIEW

The Operator Side of Industry 5.0: A Scoping Review of Learning and Skill Development Conditions in the Era of Digital and Green Transitions

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Abstract
The fifth industrial revolution, Industry 5.0, is initiating a paradigm shift in manufacturing and challenging the techno-centric orientation of production seen in Industry 4.0. Industry 5.0 places operators at the centre of the production together with technological development and sustainability, marking a shift that positions them as key drivers of the industry's digital and green transitions. This study addresses this under-researched topic by examining existing literature on Industry 5.0 with a focus on workplace conditions that support operators' learning and skills development for digital and green transitions of Industry 5.0. Using a scoping review technique, the search was conducted in the Scopus and Web of Science databases between 2020 and 2025. After applying the inclusion criteria, 43 papers were analysed using descriptive and thematic methods. The thematic analysis identified five conditions facilitating operator learning: redesign work for operator-robot collaboration; immersive technologies as training tools; supportive leadership and management; encourage operators to try new technologies and roles; and collaboration in partnerships to support skill development. By analysing these conditions through a workplace learning perspective, this review concludes that Industry 5.0 is not merely a technological or environmental revolution but a learning-centred paradigm shift. Realising its operator-centric vision requires embedding learning into everyday work. It calls for changes in workplaces such as redesigning work for operator–robot collaboration, adopting innovative training strategies in immersive learning environments, and developing leadership support for transitions to digital and green production.

Keywords Industry 5.0 · Digital and green transitions · Twin transition · Workplace learning · Learning environment · Manufacturing industry

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Introduction

The manufacturing industry is in a process of transformation, transitioning from the fourth industrial revolution, Industry 4.0 (I4.0) to the fifth industrial revolution, known as Industry 5.0 (I5.0). While I4.0 technologies such as digitalisation, robotics and artificial intelligence (AI) brought significant benefits to the manufacturing industry (Oztemel & Gursev, 2020), I4.0 has also been criticised for neglecting the human dimension of production and failing to sufficiently integrate sustainability (Grabowska et al., 2022). In contrast, I5.0 places the operator at the centre of production (Breque et al., 2021; Narkhede et al., 2024) and uses I4.0 technologies to enable the transition to greener industry (Enang et al., 2023). Because of the importance of digitalisation as a driver for the green transition, the manufacturing industry is obliged to deal with two concurrent transformational trends, the digital and the green, or what is called the 'twin transitions' (European Commission, 2022; Kovacic et al., 2024; Muench, et al., 2022). While 'twinning' means that the green and digital transitions run in parallel and are mutually reinforcing, it does not mean that the two processes are always aligned. Each one faces different challenges and progresses at different paces (Kovacic et al., 2024; Muench, et al., 2022). As digital technology evolves rapidly, it can be challenging to enhance environmental sustainability in product design and large-scale production at the same pace (Quimba et al., 2023).

The digital and green transitions have created a growing need for upskilling and reskilling operators – industrial workers – so that they are prepared to handle more technical and digital innovations (Alves et al., 2023; Cunha et al., 2022), green innovations (Awwad Al-Shammari et al., 2022) and organisational innovations (Cecere & Mazzanti, 2017) within contemporary manufacturing environments. Accommodating these innovations challenges traditional assumptions about the operator role and reinforces the need for a new type of industrial operator. It is no longer sufficient for operators to operate a machine. Instead, their role is expected to shift from primarily operating machines to being flexible, proactive and integrated into technological and digital manufacturing processes to contribute to a more sustainable and greener production (Hattinger & Stylidis, 2023). This expanded role requires operators to "learn how to learn" and be able to enhance their self-learning skills so that they can better solve problems and collaborate effectively with technology (Kaasinen et al., 2020; Rassameethes et al., 2021; Romero et al., 2016). Therefore, it is important to reimagine the operator role and recognise the value of the learning and skills that operators bring to the workplace. Emphasising the value added of operators' learning is particularly important in an era where technology is often seen as having the potential to function entirely by itself without human expertise (Cunha et al., 2022). Although the literature widely recognises the importance of developing operator skills for technology adoption, there is still a long way to go to develop their skills for the green and digital requirements of I5.0 (Oeij et al., 2024). Humanising technology, by placing operator learning and skill development at the core of production, requires an approach to learning that goes beyond the mere technical.

This article adopts a workplace learning perspective that defines learning as a social process through which human capacities are expanded in and through everyday work (Billett et al., 2023). The opportunity for learning increases when the unfamiliar makes it necessary to learn “something that is not yet there” (Engeström & Sannino, 2010, 2). This type of expansive learning expands the boundaries of what can be learned. It enables learning from the unexpected and learning when no one knows exactly what needs to be learned (Engeström, 2001). Although uncertainty remains about the skills required to drive the digital and green transitions of I5.0, the workplace is an important environment for learning. The question has then become what workplace conditions are necessary to facilitate learning and innovation in everyday work (Billett et al., 2023; Evans et al., 2006). This implies that workplace conditions can serve as a catalyst for operators’ learning and skill development during digital and green transitions. However, the conditions which can shape the workplace as a learning environment can differ considerably. Some environments are expansive and offer abundant and diverse conditions for learning and skill development while others are more restrictive and offer limited support for learning (Fuller & Unwin, 2004).

To our knowledge, there is currently no overview of the workplace conditions that are thought to be necessary for developing the learning and skills operators need to implement digital and green transitions of I5.0. This study aims to address this knowledge gap by examining existing literature on I5.0 with a focus on workplace conditions that support operators’ learning and skill development for digital and green transitions of I5.0. By applying a workplace learning perspective, we argue that the realisation of I5.0’s digital and green transitions is dependent on the presence of conditions that support operators’ learning and skill development in the workplace. The following section presents the scoping review method. After that, the findings of the scoping review are presented. A discussion then follows which synthesises and analyses the findings from a workplace learning perspective. Finally, some conclusions are drawn and contributions for future research are presented.

Scoping Review Method

This study used a scoping review to gain an overview of the complex field of I5.0 research, various evidence and primary sources was identified (Arksey & O’Malley, 2005), and its findings were synthesised (Anderson et al., 2008). With inspiration from Arksey and O’Malley’s (2005), this scoping review was conducted according to their five steps: (1) Identifying the research question; (2) Identifying relevant studies; (3) Selecting studies; (4) Mapping out the selected studies; and (5) Collecting, summarising, and reporting the results. In the initial step, a scoping review does not require a clearly defined research question (Arksey & O’Malley, 2005). Instead, an aim was formulated which helped to define the scope and focus of the review. Setting a clear aim and following the steps of the scoping review enabled us to capture a broad range of concepts and evidence to understand how I5.0 is portrayed in the existing research literature, as well as the workplace conditions that the research suggests will facilitate the learning and skill development which operators need for I5.0 and its digital and green transitions.

Identifying Review Scope and Boundaries

The authors initiated the search process by identifying keywords portrayed in the existing literature on I5.0, while two librarians simultaneously assisted us with developing a search string through the construction of different blocks of keywords and different combinations of keyword blocks. Using this master search string as a base, different modifications were tested, evaluated and refined until a satisfactory version was found. This process proved to be quite time-consuming, because many of the identified studies turned out to be irrelevant for the review's scope. For instance, some studies focused only on technology, such as machine learning or machine training, and lacked a human dimension. The result of these adjustments is the search string (blocks and keywords in the blocks) presented in Table 1.

Searching, Screening, and Selecting Relevant Studies

The search string (Table 1) was employed in the databases Scopus and Web of Science with the inclusion criteria of articles published in journals, conference proceedings or literature reviews written in English and published between January 2020 and 1 September 2025. This time period was selected because a significant increase in research falling within the scope of this literature review was noted, with a steady upward trend that began in 2019 and has continued since then. Books, book chapters, and editorials were excluded. Using the inclusion and exclusion criteria, a total of 481 papers were found (Fig. 1).

The first author imported all of the papers into an Excel spreadsheet for further processing (Callahan, 2014) and then uploaded them to the software Rayyan Systems (n.d.). After the removal of 55 duplicates in Rayyan, the first round of screening, where 426 abstracts were reviewed by the authors of the paper and two other researchers. In Rayyan, it is possible to carry out a blind abstract screening using the yes, no and maybe functions. Each of the four participating researchers used this function to review titles, abstracts, and keywords of the papers in order to determine their relevance to the scope of the review. After the researchers had completed their individual screening, the blind screening function was removed. The researchers then compared their results and discussed which papers should advance to the second round. Ultimately, 161 papers were selected for full-text reading. At this point two of the researchers left the project. As the two remaining researchers (the authors of the article) we then divided the 161 papers between ourselves, read our allocated set of papers thoroughly and created summaries for each paper. The summaries included details such as authorship, publication year, purpose, method, findings and conclusions relevant for the review's scope. After completing our summaries, we met again to compare and discuss the papers. Although we aimed to handle all of the papers uniformly, Arksey and O'Malley (2005) note that this process can be challenging because papers present its data in widely differing ways. While comparing the papers, our discussions allowed us to familiarise ourselves with the data and assess the relevance of each paper to the scope of the review. These discussions ultimately lead to the exclusion of 118 papers, thus leaving 43 papers for analysis (Fig. 1).

Table 1 The Search String: Blocks (A-D) and The Keywords in The Blocks

Search string: blocks and keywords in the blocks			
A. Context	**B. Support measures for learning and skill development**	**C. Operator, green and digital**	**D. AND NOT**
(("Industry 5.0" OR "I5.0")) AND	(("Skill* transform*" OR "skill* development" OR reskill* OR upskill* OR up-skill* OR re-skill* OR "competence development" OR "workforce skill*" OR "workforce development" OR "vocational training" OR train* OR "vocational learning" OR "personalized training" OR "personalised training") OR ("vocational education*" OR VET OR "technical education" OR "ecosystem*")) AND	((human-cent* OR operator-cent* OR "operator development" OR "human–robot collab*" OR "human–machine collab*" OR "worker-robot collab*" OR "virtual realit*" OR "augment* realit*") OR ("green transition*" OR "twin transition*" OR "sustainable transition*" OR "green transformation*" OR "Green Human Resource Management" OR GHRM OR "green leadership*" OR "green jobs" OR "green skill*" OR "green behaviour" OR "green behavior*" OR "green innovat*" OR "green*"OR "green future") OR ("digital transition*" OR digitalization OR digitalisation OR digital* OR "artificial intelligence" OR AI OR robot* OR automat*))	("machine learning" OR "machine training")

Analysis and Synthesis of the Results

The analysis of the 43 papers was conducted in two steps: a descriptive analysis followed by a thematic analysis. In the descriptive analysis, Rayyan was used to compare the papers based on a descriptive analytical approach (Arksey & O'Malley, 2005). The results are displayed in Appendix A. In the next step, an inductively driven thematic analysis inspired by Braun and Clarke (2006) was carried out, with the aim of identifying, distinguishing and analysing recurrent patterns and contents which constitute different themes. The summaries of the papers that had been created earlier were now read again. From their content, the papers were sorted into

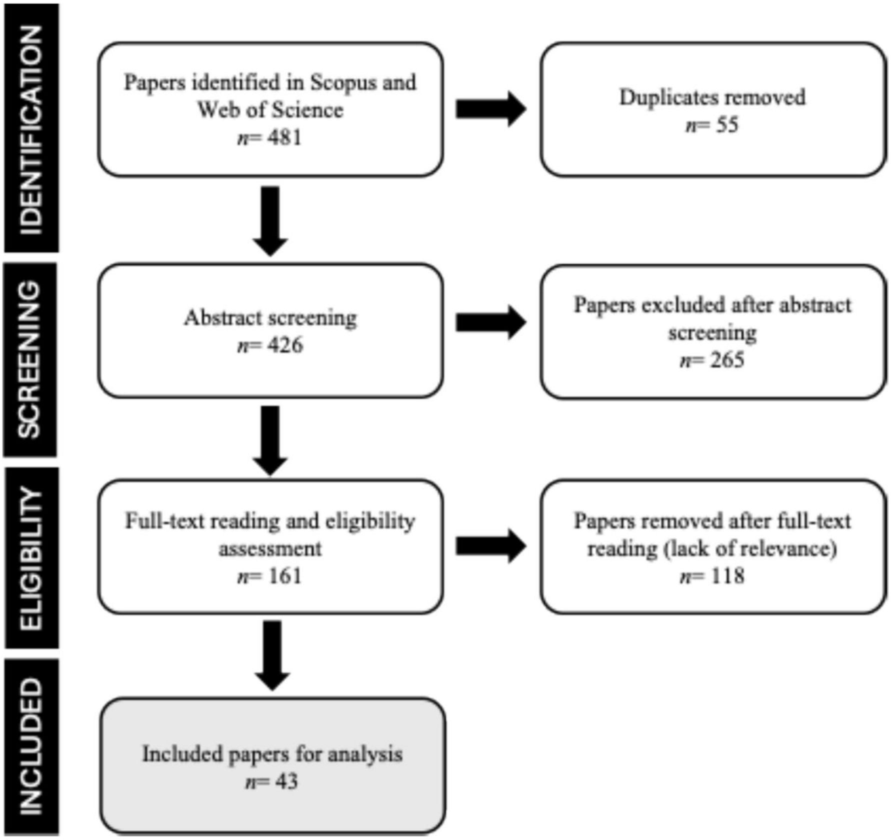

Fig. 1 Flowchart Over The Publication Selection, Screening and Assessment Process

cross-cutting recurrent patterns (themes) which illustrated any identified workplace conditions that facilitated operators' learning and skill development for I5.0's green and digital transitions. These conditions were then categorised into the following five themes: (1) redesign work for operator-robot collaboration; (2) immersive technologies as training tools; (3) supportive leadership and management; (4) encourage operators to try new technologies and roles; and (5) collaboration in partnerships to support skill development. Arksey and O'Malley's (2005) argue that a scoping review typically uses a thematic analytical framework that provides a description of the current literature. It does not attempt to synthesise the thematic content of the different studies. However, some scoping reviews include a synthesis element. Munn et al. (2022), for example, argue that synthesis is a process of systematically depicting the full breadth of available key concepts and evidence about a topic within a certain area, such as Industry 5.0. Using a workplace learning perspective and synthesising the thematic content from this study helped us to identify the conditions that support operator learning and skill development for green and digital transitions in the existing research on I5.0.

Findings

This section presents the findings of the thematic analysis of workplace conditions that support operators' learning and skills development for digital and green transitions in the existing literature on I5.0.

Redesign Work for Operator-Robot Collaboration

Automation technology is reshaping operator work and roles by eliminating routine manual tasks and increasing the demand for advanced supervisory skills (Lagorio et al., 2023). This job transformation calls for work redesign strategies such as job enlargement and job enrichment. Job enlargement expands operators' responsibilities by upskilling and reskilling through targeted training (Lagorio et al., 2023). By introducing a wider range of responsibilities encourages learning beyond regular duties and supports a more resilient and sustainable production (Trkawi & Ettehad, 2022). Job enrichment equips operators to work more independently and take on greater responsibility by learning adjacent work areas or deepening their existing expertise (Lagorio et al., 2023).

This shift in operator expertise is closely tied to the impact of digital technologies on production. As robots are increasingly being integrated into workplaces, operators are expected to work in collaboration with robots (Panagou et al., 2024a, 2024b). However, robots can vary in complexity. They can range from the traditional industrial robot to the collaborative robot, or 'cobot ', designed for close human collaboration (Schnell & Holm, 2022). Given that cobots can function more autonomously, the distinction between operator and cobot roles is becoming less clear (Panagou et al., 2024a, 2024b). This synergy utilises human strengths, such as adaptability and problem-solving skills, alongside the robot's precision and speed (Moya et al., 2023). However, knowledge of human–robot collaboration is still limited, and little is known about how humans adapt and interact with cobots (Callari et al., 2025; Schnell & Holm, 2022). Therefore, there is a growing need to explore not only the skills required to operate this technology, but also the impact human–robot collaboration can have on operators (Emma-Ikata & Doyle-Kent, 2022). Research suggests that it will be a challenge to create the conditions necessary for seamless collaboration with cobots and to define how tasks will be shared between operators and cobots (Schnell & Holm, 2022). Therefore, operators and managers must jointly identify and select tasks that are suitable for operator-robot collaboration (Callari et al., 2025; Schnell & Holm, 2022). It is argued that transparency and early operator involvement enable operators to test, learn, and train with cobots (Schnell & Holm, 2022). This in turn will refine work processes, facilitate robot collaboration, and assist operators with understanding the technology's functionalities. Training builds trust which in turn ensures a safer working environment (Schnell & Holm, 2022), but gaining operator acceptance is also critical when implementing cobots (La Fata et al., 2025).

Some studies argue that, despite increasing automation, the operator role will remain important. Operators will require advanced technical and critical thinking skills (Emma-Ikata & Doyle-Kent, 2022). In one case study, Dornelles et al. (2023) examined the influence human-cobot interaction had on operators' skills across different manufacturing tasks. The impact varied by collaboration level: simple coexistence (with cobots replacing repetitive tasks) often led to operator deskilling or reskilling while close collaboration around advanced tasks like robot supervision promoted upskilling. These types of collaboration enhanced operator decision-making, creativity, and process improvement. However, Dornelles et al. (2023) also showed that smaller firms tend to use cobots for task substitution to increase productivity whereas larger companies use cobots to improve working conditions, by including and retraining operators. Despite the emphasis within I5.0 on flexible, collaborative production, close collaboration between operators and cobots remains rare. Therefore, Dornelles et al. (2023) conclude that companies and leaders must understand the use of cobots as a means to empower operators, enhance skills, and create collaborative environments.

Immersive Technologies as Training Tools

One condition that was frequently suggested to support operators' learning and skills development is the use of a wide variety of immersive technologies as training tools, such as Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR), Extended Reality (XR), Digital Twins (DT), and Metaverse as training tools (Ariansyah et al., 2024; Brunzini et al., 2024; Isik et al., 2024; Moser et al., 2024; Mourtzis & Angelopoulos, 2023; Rega et al., 2025). Using both real and virtual environments, these technologies create immersive platforms for operator learning and interaction with machines and colleagues via digital tools and wearables (Isik et al., 2024; Konstantinidis et al., 2022). VR fully immerses users in a digital world, AR overlays digital elements onto the physical environment, and MR enables interaction with both physical and digital objects in a blended, hybrid environment (Brunzini et al., 2024; Mourtzis & Angelopoulos, 2023). Metaverse combines technologies such as AR and Digital Twins to create 3D virtual environments for location-independent collaboration (Agarwal & Alathur, 2023; Kaigom, 2024). These technologies create realistic, interactive environments that enable scenario-based training to support operator–robot collaboration (Kaigom, 2024) and develop human–machine innovations (Martínez-Gutiérrez et al., 2024). They are designed to facilitate the operators' hands-on training, enhance their problem-solving skills, and support their knowledge preparation to handle new and complex industrial tasks and strengthen their task comprehension (Ariansyah et al., 2024; Mourtzis et al., 2023; Rojas et al., 2024).

Using immersive technologies in training can improve operators' learnability by facilitating knowledge acquisition and its reuse in new situations (Ariansyah et al., 2024). The advantage of these technologies is their ability to deliver personalised training tailored to an operator's specific needs (Mourtzis et al., 2023). They can enable 'just-in-time learning' (Moser et al., 2024) and flexible, 'on-demand training' that provides access to learning directly on the shop floor (Brunzini et al., 2024). Training with immersive technologies is a cost-saving and time-efficient way to improve operator skills (Passalacqua et al., 2024; Shchepkina et al., 2024). It reduces the frequency of errors, forgetfulness, and mental effort while improving operator performance and procedural safety (Brunzini et al., 2024; Mourtzis et al., 2023; Valentini et al., 2025). By making training more understandable, easier and engaging, these technologies offer high usability that shorten the time spent on tasks (Brunzini et al. (2024). For example, Brunzini et al. (2024) found that MR training enabled operators without advanced programming skills to quickly learn and master wire harness tasks. When compared to paper-based training methods, MR training resulted in fewer operator errors and faster execution times. Similarly, Alfaro-Viquez et al. (2025) showed that operators who took part in a VR-based welding training improved their welding technique, had faster learning trajectories, and increased their task uniformity.

While personalised training can improve resource efficiency and accelerate skill growth, designing such training requires the collection of a large amount of technical data. Some of the papers in this scoping review sought to address this problem by developing predictive frameworks, models and methods that can anticipate future operator skill needs. For example, Fraile et al. (2023) proposed a seven-stage framework to assess operator skills by using large language models and human-centric principles as the bases for qualification tests. The test results could be compared with the company's future requirements and then used to design training tailored for each operator to close identified skill gaps. Tusquellas et al. (2025) proposed an AI-driven model to analyse staff data and thereafter to create profiles, identify skill gaps and future learning needs. This model could use its data to recommend courses, customise learning paths, and help companies to map their existing talent base. In a third example, Becattini et al. (2025) proposed a method to assess training needs by using an XR environment's data output to design training pathways. By leveraging AI-powered data produced in the XR environment, this method can tailor its content and pace to operators' experience levels, skill needs, and learning preferences. This enables self-paced, on-the-job training that adapts to the organisation's technology changes. Although these proposals offer encouraging evidence for the prediction of future operator skills, the literature also notes that accurate forecasting remains difficult (Fraile et al., 2023; Tusquellas et al., 2025). It can be difficult to assess operators' current skill needs and align them with long-term industrial goals when skill requirements change rapidly and are often poorly defined.

Of the experimental studies examined in this review, their focus was on testing immersive training applications. Their conclusions emphasised the need for training designs that improve technical skills while promoting collaboration, autonomy, and inclusion. Shchepkina et al. (2024) showed that structured human-centric AI training programmes increased skill development by nearly 30 per cent. This prepared operators to collaborate more effectively with AI systems and created more productive, rewarding, and economically resilient workplaces. Passalacqua et al. (2024) identified the importance of making room for decision-making in AI training. They found that workers with control over their decisions felt more autonomous which helped them to develop technical skills for managing AI-related errors. Training that blends AI with human judgment fosters skilled operators and reinforces the argument that technology works best when it augments rather than replaces human expertise. For example, Mourtzis and Angelopoulos (2023) found that an XR platform for training future Operator 5.0 roles facilitated remote collaborative product development, virtual prototype interaction, and real-time communication with customers and engineers. Supporting informed decisions and knowledge exchange, the platform served as a shared learning space for skill development. These findings indicate the important role immersive technologies play in supporting collaborative learning and preserving human agency in AI-supported training.

As the research shows, these immersive technologies can empower operators, by providing them with training and improving their decision-making and problem-solving skills (Passalacqua et al. (2024), foster lifelong learning (Ariansyah et al., 2024), support career advancement (Tusquellas et al., 2025), and even increase creativity and productivity in industrial processes (Shchepkina et al., 2024). Scholars agree that using immersive technologies in training can empower operators and improve their ability to learn the skills they need to adapt to changes technology is continually making to their work and workplaces. However, these benefits have also been critically examined. As several studies point out, much of the current research lacks a solid evidence base (Tusquellas et al., 2025) and the impact of human-centred training strategies and practices on skills development is still not fully understood (Konstantinidis et al., 2022). There has been an insufficient examination of operators' user experiences (Brunzini et al., 2024). Instead, much of the focus has been on the robustness of the technology and its user friendliness (Konstantinidis et al., 2022) and the technology's long-term effects on learning remain uncertain (Moser et al., 2024). Moser et al. (2024) note that the current research is largely experimental, prioritises usability over learning, and offers little practical guidance for implementing training that merges technological design with personalised learning needs. Most of the research on immersive technologies in operator training has been theoretical or conducted in controlled environments, with little empirical validation in real industrial settings (Rega et al., 2025; Valentini et al., 2025), which may currently limit their practical use for skill development in workplaces (Rega et al., 2025).

Supportive Leadership and Management

Leadership and management support are recognised within the literature as an essential condition for supporting operators' learning and skills development towards I5.0. Marcon et al. (2025) identified top management support, such as strategic projects, targeted investments, clear communication, and organisation-wide funding efforts, as an important condition. In their study, managers had been trained and incentivised to increase I4.0 technology adoption. This training had prepared them for upcoming changes in their leadership responsibilities and had positioned them in the technology implementation phase as knowledge providers and improvers. The technical expertise and open-innovative leadership these managers demonstrated had inspired operators in turn to adopt technological solutions, with the result that operator engagement increased as well as their acceptance of the technology. Another study found that a clear leadership vision was necessary to keep pace with rapid technological advancements (Kuwar et al., 2025). This leadership vision extended beyond investing in technology as it also required strategic leadership, organisational restructuring, a culture of continuous learning and adaptability to technological change. The study by Moreno-Marcial et al. (2024) showed that empowering leadership is positively related to employees' proactive behaviours, such as developing autonomy and readiness for change towards I5.0. When managers trusted their employees' willingness to take the initiative and their ability to do so, it encouraged the employees to learn and develop new skills. This mutual trust fostered knowledge exchange between managers and employees. With ideas, information, and tasks being shared, decision-making became collaborative and managers started to recognise the importance of team contributions. Given their central role in implementing I5.0, managers need to be open to digitalisation, display the qualities of analytical and creative thinking, and have the ability to integrate technical expertise with managerial skills (Saniuk & Grabowska, 2023).

In their literature review, Alshaibani et al. (2025) explored the leadership behaviours necessary for AI-driven I5.0 environments and they emphasised the need for transformational, adaptive, and servant leadership behaviours. These leadership behaviours help create environments where employees feel safe, engaged, and motivated to embrace change, learn, and innovate, all of which are important conditions for I5.0. The researchers also found that leadership is a mediating factor between organisational conditions (such as psychological safety, team cohesion, and a learning culture), and employee performance and learning. Understanding and optimising organisational conditions can significantly enhance managers' influence on employee learning towards I5.0. However, as Zare et al. (2025) show, a major barrier managers face in implementing an I5.0 strategy is employees' fear of being replaced by machines, a concern rooted in the widespread belief that more technology leads to job losses. In their study, this employee anxiety undermined skill development and risked creating employer–employee tensions, which could lead to employee resistance, boycotts, or even deliberate equipment sabotage. As Dcruz et al. (2023) note, managers must not only implement new technologies. They also need to lead their operators and engage with them to ensure their acceptance of new machinery and their effective use of it. With workplaces increasingly implementing spaces for human–machine collaboration and where intelligent machines (cobots) are seen as co-workers rather than tools, leadership in I5.0 must change to adapt to the new reality of leading both human operators and machines. According to Dcruz et al. (2023) traditional leadership models are no longer sufficient because they exclude machines as subordinates. Addressing the new 'Leadership 5.0' paradigm, therefore, requires a leadership that guides collaborative operator-machine teams.

Encourage Operator to Try New Technologies and Roles

The implementation of immersive technologies in the workplace requires learning environments that account for the diverse ways individual operators experience and react to technological change. Differences in experience, motivation, and learning attitudes can affect how operators adapt to new technologies, and the extent to which they can access training and learning opportunities (Morandini et al., 2023). Operators on the shop floor need to be skilled; they are often the first to use new technology to assemble products (Mourtzis et al., 2022). Operators are not only early users of emerging technologies; their skills and initial experiences can also shape the way technology is applied. In I5.0 the operator's role is redefined. It has been expanded beyond its traditional boundaries to a more dynamic operator who can combine human creativity with advanced technologies, data-driven decision-making, and sustainable manufacturing practices (Mourtzis et al., 2022). The ‘Resilient Operator 5.0’ demonstrates adaptability and ingenuity through the use of digital tools and information systems to tackle complex, unforeseen challenges. To fulfil this role, operators need a broad skill set and the training it requires, such as technical and communication skills and an openness to constant change (Mourtzis et al., 2022). As the literature suggests, operator roles are evolving towards new job profiles, with job titles such as robot assistant, mobile robot manager, machine programmer, device linker, AI operator, and virtual operator (Grabowska et al., 2022). These emerging roles require targeted skill development while production systems also need to be open to operator feedback in order to improve (Crnobrnja et al., 2024).

Collaboration in Partnerships to Support Skills Development

Developing operator skills cannot be managed solely by manufacturing companies; it requires collaboration with educational institutions and other external partners to close the industry’s emerging skills gap (Braun et al., 2024). As the literature points out, establishing collaborative partnerships enables educational providers to support manufacturers in identifying emerging skill requirements and delivering hands-on training that is aligned with an operator’s real work context and tailored to a company’s needs. Ensuring that this training is relevant remains a considerable challenge (Braun et al., 2024). In one pilot project, Aslam et al. (2022) examined how universities and companies collaborated to create flexible, industry-relevant education for employees. The researchers found that employees’ learning needs often differed from traditional students. They lacked academic credentials and had a greater task in balancing work duties with training. To be relevant, therefore, courses needed to be practical, accessible, and use digital tools to support participation. Offering courses across a range of levels, from the introductory to the advanced, as well as incorporating in their content the latest technologies and methods, helped employees to learn the skills required for their jobs. Some of the research showed that, aligned with I5.0 skill needs, companies are placing growing emphasis on engineering skills for their digital technology development as well strengthening the soft skills operators are expected to have for effective technology use (da Silva et al., 2022).

The literature indicates that collaborative efforts to address the skills gap within manufacturing companies must be shared with other stakeholders, not just educational providers. According to Braun et al. (2024), researchers can play a key role in analysing skills gaps, identifying strategies to bridge them, and connecting stakeholders and companies to share best practices and benchmark solutions. Policymakers are equally important for creating incentives that help manufacturing companies proactively identify skill needs and implement workforce development strategies. Industry stakeholders must also be part of the response to skills gaps; digital and green transitions will have an impact on their operations and will likely require learning new skills and role adaptation (Braun et al., 2024). Collaborative partnerships between these and other actors can also bring with them other benefits. As Hafeez et al. (2025) have noted, working together enables manufacturing, especially small and medium-sized enterprises (SMEs) with limited internal resources, access to the external expertise necessary to improve their technological knowledge and digital readiness. Firms like these rely on cross-boundary collaborative partnerships with suppliers, technology providers, intermediaries, government bodies, and customers to explore opportunities and adopt emerging technologies. SMEs that prioritise participation in collaborative partnerships are often characterised by strong leadership, a skilled employee base, robust operations, and the ability to align their knowledge management strategies with their business goals. During processes of digital transformation, they are able to encourage operator learning through structured value-chain networks, ecosystems and innovation platforms to enable rapid and flexible adaptation to changing conditions (Hafeez et al., 2025).

Discussion

This scoping review has revealed a rapidly growing research field. So far forty-three papers have been published on conditions that support operators' learning and skills development to meet changes in the workplace brought about by the digital and green transitions of I5.0. The papers are predominantly literature reviews and experimental studies and conducted across multiple countries. The research was mainly published in technically oriented journals and conference proceedings (see Appendix A for a full list) and predominantly focused on technological integration and efficiency. While none of the examined papers explicitly addressed the green transition, they were implicit in their assumption that digital and green transitions are integral to the I5.0 concept and that the role of the operator will change. Analysing I5.0 from a workplace learning perspective, therefore, is not only relevant; it is critical for understanding the human-centric goals that I5.0 promotes. The argument here is that the realisation of I5.0 and its digital and green transitions is dependent on the presence of conditions in everyday work that support operator learning and skill development. This means that the transitions required by I5.0 are not merely technological (digital) or environmental (green) changes; there also needs to be a profound adjustment in the way work is organised. Workplaces need to be set up so that operators can continuously learn, innovate, and engage with complex production systems (Billett et al., 2023).

Our synthesis of the existing literature has enabled us to identify the conditions that support operator learning and skill development and analyse them from a workplace learning perspective. As the scoping review has shown, redesigning work can serve as a condition to support operators' learning and skill development. As automation and digitalisation replace routine manual tasks, operators are increasingly required to learn and perform advanced supervisory, analytical, and decision-making skills. This change introduces job enlargement and job enrichment that prompts learning in broader or deeper areas. Both strategies facilitate learning by exposing operators to new challenges and responsibilities but also by creating a need to learn the 'unknown' when faced with unexpected tasks and technologies (Engeström & Sannino, 2010). The integration of collaborative robots (cobots) introduces a new dimension to workplace learning. Unlike traditional industrial robots, cobots are designed to work alongside humans. This collaboration blurs the boundaries between operator and machine roles, creating opportunities for co-learning and shared task execution. However, operators must learn to understand cobots' functionalities, anticipate their actions, and coordinate tasks effectively. This necessitates expansive learning (Engeström, 2001), where operators can test, adapt, and refine their collaborations with cobots.

As the scoping review has shown, operator learning and training is expected to be facilitated by immersive technologies such as Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR), Extended Reality (XR), Digital Twins, and the Metaverse. The introduction of these technologies in industrial training marks a significant shift in workplace learning. They are changing how operators learn on the job and are becoming important conditions for skill development. Immersive technologies do not merely function as tools: they also create learning environments (Fuller & Unwin, 2004) that provide interactive, realistic training that bridging the physical and digital worlds and enabling operators to engage in training without incurring the risks associated with real-world operations. Studies referenced in this literature review demonstrate, for example, how VR-based welding training and MR-based wire harness assembly can create immersive learning environments in which operators can experiment, commit errors without adverse consequences, solve problems and iteratively refine their skills through repeated practice. The opportunity to perform procedures multiple times and receive immediate feedback supports skill development, mitigates error rates, and equips operators to manage complex tasks in unknown situations (Engeström & Sannino, 2010). These technologies enable operators to interact with virtual prototypes, simulate complex tasks, and collaborate remotely, all within controlled settings that encourage learning and iterative skill refinement. By using immersive technologies, training can be tailored to individual operators' skill levels, learning preferences, and future skill needs. Personalisation facilitates just-in-time learning and on-demand training, enabling operators right on the shop floor to access learning tailored to their individual skill levels.

Although these technologies are suggested to provide promising conditions for operator learning, their usefulness still depends on their thoughtful integration into operator training. The literature reviewed here shows that the creation of immersive learning environments must go beyond technical robustness to incorporate human-centred design principles. Preserving operator autonomy and decision-making within immersive technology-supported training can facilitate operator engagement and motivation, ensuring that technology augments rather than replaces operator expertise. Maintaining this autonomy is particularly important because immersive technologies, while offering training opportunities, must be implemented in ways that respect how individual operators experience and adapt to technological change. This requires a consideration of operators' different levels of engagement with learning and motivation to learn, which can often be dependent on their experiences of and attitudes toward technological change. Operators must perceive technological change as an opportunity rather than a threat and be actively involved in using innovations to shape future production systems. Integrating operator feedback into technology design and implementation supports technology acceptance and reduces resistance, creating a learning environment where learning becomes a shared responsibility in everyday work.

Operator engagement, however, is not enough. As the scoping review shows, leadership plays a central role in shaping the conditions under which operators learn and adapt to technological change. From a workplace learning perspective, the transition to I5.0 is not merely a technical upgrade. It is a profound transformation in the workplace that requires managers to act as facilitators of operator learning. As operator-robot collaboration becomes increasingly central, leadership will be expected to evolve towards Leadership 5.0. This means that the role of managers is likely to be redefined, as they are now expected to lead hybrid teams consisting of humans and intelligent machines. This evolution demands that managers, in order to create conditions where operators feel safe, engaged, and motivated to learn, combine technical expertise with managerial skills. Empowering and visionary leadership will be that which facilitates autonomy and proactive behaviours among operators which are essential for developing readiness for technology change. When managers trust operators and involve them in decision-making, knowledge exchange becomes collaborative. This mutual trust supports a bottom-up engagement that strengthens operators' learning and transforms technological change into a learning opportunity rather than a source of job insecurity.

This scoping review indicates that the rapid transformation of manufacturing under I5.0 has driven an increased demand for advanced operator skills. Relying solely on company-led training is insufficient to meet these skill requirements. Companies must therefore look beyond internal training resources to upskill and reskill their operators. To address these skill gaps companies can establish multi-stakeholder partnerships with universities and other educational providers. Such collaboration can help companies anticipate future skill needs and deliver industry-relevant training that is tailored to operators' learning requirements. However, ensuring that such training remains accessible poses a challenge, particularly for operators who must balance work responsibilities with training in everyday work. Flexible course design supported by digital tools and offerings at varying levels of complexity can enable operators to develop skills aligned with I5.0 demands at their own level and pace. Beyond educational providers, researchers, policymakers, and industry stakeholders can share the responsibility for bridging skills gaps by creating incentives, disseminating best practice, and establishing learning and skill development ecosystems.

Limitations and Strengths

This scoping review has some limitations. First, the selection of papers was limited to English-language publications, which may have excluded relevant research in other languages. Despite using a broad range of search terms, the rapidly expanding and highly diverse nature of I5.0 research made it challenging to identify all of the possibly relevant research, which means that some relevant studies may have been missed. Second, most of the reviewed papers had a technical and engineering perspective which prioritised technological aspects of I5.0 instead of operator learning and skill development for I5.0. Although we identified within this literature the conditions that shaped operators' learning and skills development, these conditions were not always clearly articulated and at times this challenged us to assess the relevance of certain papers. However, to ensure the reliability of the thematic analysis process, we applied a thorough review process and conducted systematic discussions to identify the conditions that support operator learning and skill development. Despite its limitations, this scoping review makes a valuable contribution to the growing body of I5.0 research. By analysing the existing literature on I5.0 through a workplace learning perspective, the review provides insight into conditions that support operator learning and skill development under the changed workplace conditions brought about by the digital and green transitions of I5.0.

Conclusion and Further Research

This scoping review serves as an initial step in exploring the conditions that support operators' learning and skill development for digital and green transitions of I5.0. This research suggests that I5.0 is changing the learning landscape in industrial workplaces, necessitating a rethink of current conditions and a redirection of attention to new ones that support operator learning and skill development. The conclusion is that, while previous research has identified many conditions necessary for operator learning and skill development (Billett et al., 2023; Evans et al., 2006), I5.0 introduces a profound paradigm shift in workplaces. Technological advancements and sustainability imperatives are redefining workplace conditions and creating new ones, which fundamentally changing what learning at work entails. This means that the digital and green transitions of I5.0 are not only beginning to reshape the processes of production, but they are also transforming operators' learning environments (Fuller & Unwin, 2004) to prepare them to face the unknown future of work in industry (Engeström & Sannino, 2010).

Another conclusion to be drawn from this review is that the operator's role in I5.0 is no longer peripheral but foundational to the success of digital and green transitions. Operators are not merely executors of predefined tasks; they have become problem-solvers, decision-makers, and learners in environments characterised by complexity and rapid change. This change in the operator's role, "Operator 5.0", envisions an operator who is smart, skilled, and future-oriented, capable of bridging advanced technologies with sustainable production solutions. However, achieving this vision requires more than rhetoric; it calls for changes in workplaces, such as redesigning work for operator-robot collaboration, adopting innovative training strategies in immersive learning environments, and developing leadership support for the transition to digital and green production. This means that learning must be embedded into everyday work and supported by conditions that align with operators' needs and the pace of industrial change. Ultimately, I5.0 is not just a technological or environmental revolution; it is a learning-centred paradigm shift. Its success hinges on recognising operators' learning as an asset and investing in their skill development. This scoping review suggests a future direction for I5.0, but many challenges remain. Much of the current research on I5.0 is largely conceptual and experimental and often conducted in controlled settings with limited empirical validation in real industrial contexts. Addressing this knowledge gap calls for further empirical research to investigate how I5.0-driven changes are provoking new learning requirements and conditions for operators' learning and skills development within the industry.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Ethics Approval and Consent to Participate Not applicable.

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