Print ISSN: 1738-3110 / Online ISSN 2093-7717
JDS website: http://accesson.kr/jds
http://doi.org/10.15722/jds.23.12.202512.91

Digital Skills in the AI Age: A Comparative Perspective from Construction, Manufacturing, and Information Technology

Thi Thanh Van NGUYEN[1], Thi Thanh Thuy NGUYEN[2]

Received: August 01, 2025. Revised: September 04, 2025. Accepted: December 05, 2025.

Abstract

Purpose: This study seeks to identify the core digital skills that are indispensable for organizational success in the era of AI-driven digital transformation. By focusing on three pivotal sectors—construction, manufacturing, and information technology—it explores how firms can strategically leverage human capital to meet evolving technological demands. In doing so, the study highlights how these digital capabilities extend beyond internal organizational benefits to reinforce distribution efficiency and trade competitiveness across interconnected industries. **Research design, data and methodology:** Using the Delphi method, this study constructs a structured framework of digital skills tailored to employees across the three industries. Experts from each sector participated in two rounds of consensus-building to determine the most relevant digital skills. **Results:** The findings identify a portfolio of digital skills that are both cross-sectoral and sector-specific, highlighting the heterogeneous nature of skills demanded across distinct operational contexts. These results reaffirm the pivotal role of digital skills in sustaining competitiveness and efficiency across industries that collectively shape the value chain of economic distribution. **Conclusions:** These insights offer meaningful theoretical contributions to the digital skills literature and practical guidance for firms seeking to align training and recruitment strategies with digital demands. By clarifying essential skill priorities, the study supports more informed decision-making in workforce development amid the growing influence of AI in the digital economy.

Keywords : Digital Skills, AI, Construction, Manufacturing, IT, Distribution, CRM

JEL Classification Code: M12, M53, M54

1. Introduction[1,2]

In the AI Age, generative artificial intelligence (GenAI) has emerged as one of the most compelling and transformative frontier technologies for business applications (Wu et al., 2023). GenAI not only enhances operational efficiency and decision-making but also drives innovation by autonomously producing new content—ranging from text and code to images and designs—based on learned patterns from vast datasets (Oran et al., 2023; Şahin & Karayel, 2024). This capacity for content generation enables organizations to redesign their

1 First Author. Lecturer, Business Administration Department, Faculty of Economics, Ho Chi Minh City University of Technology and Education, Vietnam. Email: vanntt@hcmute.edu.vn
2 Corresponding Author. Lecturer, Business Administration Department, Faculty of Economics, Ho Chi Minh City University of Technology and Education, Vietnam. Email: thuynguyen@hcmute.edu.vn

workflows, tailor user experiences on a large scale, and create new business models that emphasize creativity and flexibility (Khan et al., 2025).

By leveraging GenAI's ability to synthesize information, identify emerging trends, and simulate scenarios, enterprises can achieve a higher degree of strategic foresight and innovation agility (Liu & Wang, 2024; Ramirez et al., 2024). According to McKinsey & Company, GenAI has the potential to automate 60~70% of the tasks workers currently spend their time on, depending on the industry and job function (McKinsey & Company, 2023). For example, smart chatbots are gradually replacing traditional customer service systems and supporting employees with everyday tasks (Yue et al., 2024). The World Economic Forum (WEF) reports that digital trends - especially AI and data-processing technologies - are expected to reshape jobs and responsibilities across all industries. In fact, 60% of employers believe that digital adoption will fundamentally change their businesses by 2030 (World Economic Forum, 2025). However, this rapid shift presents a significant challenge, as some workers may lose their jobs or be replaced by emerging technologies. According to the WEF (2025), 39% of the skills currently used in the workforce are expected to change or become obsolete between 2025 and 2030. Therefore, Kanbach et al. (2024, p. 1203) propose that "GenAI redefines the skill set required to generate content as many job roles transform from creators to editors—human amplification and not complete substitution".

The International Yearbook of Industrial Statistics 2023 (United Nations Industrial Development Organization, 2023) emphasizes the critical role of rapidly growing high-technology industries in contributing significantly to national GDP. In General Statistics Office of Vietnam, the construction and manufacturing sectors alone accounted for 44.28% of GDP in the first half of 2024. Additionally, the information technology (IT) sector—classified as part of the service industry—made a substantial contribution to the service sector's share of 49.76% in GDP during the same period. Given their considerable influence on Vietnam's economic performance, this study aims to redefine the skill set required for these key sectors (i.e., construction, manufacturing, and IT).

The OECD (2016) emphasizes the importance of training programs that enable workers to adapt to evolving skill requirements, identifying this as a critical factor for future success. These emerging requirements are closely tied to digital skills (Sousa & Rocha, 2019). While digital skills are increasingly essential across all industries, the impact of AI varies by sector. For instance, in construction, workers primarily depend on practical, on-site experience; in manufacturing, automation has long been integrated into production processes; whereas the IT sector is primarily concerned with advancing digital innovation. Responding to these sector-specific dynamics, Bouwmans et al. (2024) call for a research that addresses the distinct skill demands of specific professions. Accordingly, this study aims to develop a digital skills framework tailored to three key sectors in developing countries: construction, manufacturing, and information technology.

Digital competencies extend beyond internal operations of individual industries and exert influence on broader domains such as sharing logistics and sustainable distribution networks. In the construction sector, the adoption of BIM, IoT integration, and data analytics facilitates synchronization between project schedules and material flows, thereby enhancing supply chain visibility and minimizing procurement or transportation bottlenecks. These capabilities further strengthen supply chain resilience through early risk prediction and optimized coordination with suppliers (Ekanayake et al., 2021). In manufacturing, expertise in robotics, cybersecurity, and cloud infrastructure constitutes the foundation of Logistics 4.0, enabling the operation of smart warehouses, predictive maintenance of logistics equipment, and real-time inventory control, which ensures distribution continuity and improves production efficiency (Wassan & Kalwar, 2025). Within the information technology domain, proficiency in artificial intelligence, blockchain, and cloud computing strongly supports omnichannel distribution strategies. These skills allow firms to integrate ERP and CRM systems, safeguard customer data across platforms, and deliver seamless service experiences across online and offline channels. Collectively, such competencies demonstrate that digital skills not only determine sectoral productivity but also foster supply chain digitalization, collaborative logistics models, and sustainable distribution networks, thereby reinforcing the relevance of this research to contemporary distribution science.

2. Literature Review

2.1. Digital competence and digital skills

According to Vuorikari et al. (2016), digital competence refers to the confident, critical, and responsible use of digital technologies in learning, work, and participation in society. It is recognized as one of the eight key competences for lifelong learning. Competence is typically expressed through a combination of knowledge, skills, and attitudes. Digital skills are considered a component of digital competence (Palanimally et al., 2024). They refer to specific technical abilities such as using software, digital devices, and online tools. Digital skills combine information, communication, and technical abilities with cognitive skills for learning and innovation, as well as social-emotional aspects of life and work (OECD, 2021). Developing digital skills is viewed as the starting point for building digital competence.

In the context of widespread digital transformation, many industries are undergoing significant restructuring in terms of workforce competencies, especially digital skills (Kasmono et al., 2025). The construction sector is evolving under the influence of technologies such as digital project management, Building Information Modeling (BIM), and online collaboration platforms. According to Succar (2009), mastering BIM not only improves design and construction processes but also helps reduce errors, control costs, and enhance transparency in project management. Workers in this field need to collaborate across multiple stakeholders using real-time data sharing and be proficient in simulation tools for scheduling and risk analysis. Driven by advanced digitalization in manufacturing environments (Majeed & Sharif, 2024), the integration of Internet-based systems with emerging smart technologies - such as intelligent machines and products - is leading to a fundamental shift in the principles of industrial production (Lasi et al., 2014). In this environment, digital skills go beyond technical operations to include the ability to analyze production data, monitor equipment status, and respond to issues in real time. In the information technology sector, digital skills are not just supportive tools but foundational capabilities. Van Laar et al. (2017) identify software development, data system management, and cloud computing as core skills for the modern IT workforce. Additionally, self-directed learning, critical thinking, and cross-platform communication are essential for adapting to rapid technological changes. Innovation and artificial intelligence application skills as strategic advantages in digital environments. Digital skills requirements are increasingly specialized across different industries. The growing specialization of digital skills across sectors underscores the need for targeted skill development strategies. Generic digital training programs may fall short in addressing the requirements of specific industries. The distinct nature of digital competencies in each sector makes it necessary to study specific skill groups relevant to workers in construction, manufacturing, and IT. Many scholars have emphasized the need to expand research on digital skills to better reflect the realities of rapid digital transformation. Siddiqui et al. (2023) argue that industries require not only specialized skills such as BIM, but also a broader set of digital competencies to adapt to increasingly complex and connected work environments. Ginigaddara et al. (2019) highlight that forecasting future skill demands is a critical research direction in the context of Industry 4.0, where smart technologies are significantly reshaping job structures. In addition, Li et al. (2021) recommend extending the analysis to emerging job roles and conducting cross-country comparisons to capture global labor market trends. (10 point blank line)

2.2. Digital Skills Framework

Identifying the digital skills required in the age of artificial intelligence remains a complex and unresolved issue (Bouwmans et al., 2024). Various studies have proposed Digital Skills Frameworks or Digital Competence Frameworks, with notable contributions from organizations such as the European Commission, the National Centre for Vocational Education Research (NCVER), and McKinsey & Company.

DigComp 2.2, developed by the Joint Research Centre of the European Commission, is the most recent version of the Digital Competence Framework for Citizens, published in 2022. It provides a comprehensive structure to describe the digital competences needed for learning, work, and participation in a digital society. The framework consists of five core competence areas: Information and data literacy; Communication and collaboration; Digital content creation; Safety; and Problem solving. These areas are further divided into 21 sub-skills (Vuorikari et al., 2022).

The Australian Workforce Digital Skills Framework, developed by the National Centre for Vocational Education Research (NCVER), addresses the urgent need for digital skills in the Australian workforce. This need arises from the increasing influence of technologies such as artificial intelligence, robotics, and automation. The framework is organized into three main skill categories: Digital tools for working, which includes the use of digital devices, industry-specific software, and emerging technologies for communication and information processing; Digital ways of thinking, which focuses on creativity, problem-solving, and innovation in digital environments; and Living in the digital age, which covers digital safety, ethical technology use, and social responsibility. These categories are associated with nine sub-skills (Gekara et. al, 2019).

The report of McKinsey & Company "Defining the skills citizens will need in the future world of work" by Dondi et al. (2021) presents a global study aimed at identifying foundational skills for adapting to a rapidly changing labor market shaped by digitalization, automation, and artificial intelligence. The study outlines 56 foundational skills, referred to as DELTAs (Distinct Elements of Talent), grouped into four categories: Cognitive skills such as critical thinking, flexibility, communication, and planning; Interpersonal skills including relationship building, teamwork, and system mobilization; Self-leadership skills such as self-awareness, self-management, goal orientation, and entrepreneurial mindset; and Digital skills involving technological literacy, software use, algorithmic thinking, and cybersecurity awareness.

Bouwmans et al. (2024) introduced a new competency model called the Digital Transformation Skills Framework (DTSF). This framework aims to identify the essential skills needed for digital transformation in modern organizations. The authors used a systematic literature review based on the PRISMA method. They selected 36 relevant studies and applied thematic analysis to develop the framework. The DTSF includes six main skillsets: digital working skills, entrepreneurial skills, evidence-based working skills, collaboration skills, adaptation skills, and communication skills. Each skillset is further divided into sub-groups, resulting in a total of 44 sub-skills.

Table 1 presents a correlation matrix of sub-skills, illustrating the extent of alignment and divergence across the theoretical frameworks. The comparison of prominent digital skills frameworks shows that the Digital Transformation Skills Framework (DTSF) developed by Bouwmans et al. (2024) addresses a gap in the academic literature on digital transformation competencies. The DTSF offers a broad and detailed structure of sub-skills, which can serve as a foundation for designing training, reskilling, and capacity-building programs within organizations. The DTSF integrates technical, organizational, data-driven decision-making, and innovation skills in digital environments. With six main skillsets, multiple sub-groups, and 44 sub-skills, DTSF provides a solid theoretical foundation for classifying, assessing, and comparing digital competencies across construction, manufacturing, and IT sectors. Accordingly, this study employs the Digital Transformation Skills Framework (DTSF) proposed by Bouwmans et al. (2024) to guide its structured analysis.

A notable aspect of Bouwmans et al. framework is the detailed subdivision within each skillset, which illustrates the developmental trajectory of digital skills. This granularity enables both employees and managers to identify specific areas for training and upskilling, aligned with the practical demands of their roles. Importantly, these skill sets should not be viewed in isolation but as an integrated constellation of competencies that employees must collectively acquire. Sectors such as construction, manufacturing, and IT all contribute to the broader economic distribution chain, thereby requiring a shared foundation of common skills. For instance, value creation competencies entail the ability to plan for distribution activities, accept and manage risks inherent in distribution processes, and actively contribute to the strategic orientation and decision-making of distribution channels. Nevertheless, each sector also demands distinctive, domain-specific skills—for example, advanced programming expertise in IT or project management in construction. Yet, scholarly research has thus far paid limited attention to systematically identifying and theorizing these cross-sectoral differences in digital skill requirements.

The theoretical section has outlined a comprehensive picture of the digital competencies required in AI age. However, most existing studies still focus on individual sectors or approach the topic at a general level, without clearly addressing the differences in digital skill requirements across industries with distinct technical and organizational characteristics. As a result, cross-sector comparisons—especially among fields such as construction, manufacturing, and information technology—remain a significant gap in current research.

Accordingly, the present study is guided by the following research question:

RQ1: In the context of widespread digital transformation driven by AI, what digital skills are required in the construction, manufacturing, and information technology sectors?

RQ2: What are the similarities and differences in digital skill requirements across the construction, manufacturing, and information technology sectors?

3. Research Methodology

This study adopts the modified Delphi method, initially introduced by Dalkey and Helmer (1963) and later refined by Murry and Hammons (1995), to systematically identify essential digital transformation (DT) skills. The modified Delphi approach enhances procedural efficiency by utilizing a structured, pre-developed questionnaire (Nguyen et al., 2024).

Expert selection followed predefined criteria, requiring at least five years of professional experience in construction, manufacturing, or information technology, as well as managerial responsibility at the level of supervisor or higher. To ensure broader perspectives, two-thirds of the experts were drawn from multinational companies, thereby reducing the risk of local bias. All panel members committed to completing the Delphi rounds and providing candid, high-quality feedback. The panel size was determined in line with Delphi best practices, ensuring a sufficient number to reach consensus while keeping rounds manageable. The process included multiple iterations: an initial round to assess item necessity and propose suggestions, followed by subsequent rounds in which consolidated feedback was circulated to refine judgments and strengthen consensus. Purposive sampling and the anonymity of responses served as safeguards to minimize bias and prevent dominance by individual viewpoints.

The identification process comprised three main steps: (1) Development of the initial questionnaire, (2) First Delphi round, (3) Second Delphi round. The initial questionnaire was designed based on a literature review and semi-structured interviews with five experts (three academics and two HR managers from multinational firms). It included 11 skill groups encompassing 44 sub-skills.

In the first Delphi round, the questionnaire consisted of four sections: (1) screening questions to verify DT expertise, (2) importance ratings of skill items on a 5-point Likert scale, (3) open-ended prompts for suggesting additional skills, and (4) demographic information, including industry, position, and experience. Participants' emails were also collected for subsequent rounds. In this round, we surveyed 17 experts from the construction sector, 14 from the information technology sector, and 15 from the manufacturing sector.

The second Delphi round involved 32 experts: 11 from construction, 10 from information technology, and 11 from manufacturing (see Table 1). Retention of items followed the same dual-criteria approach as Round 1, with updated CVR thresholds based on reduced panel sizes: ≥ 0.59 (construction and manufacturing) and ≥ 0.62 (IT). Items that met both the mean score threshold (≥ 4.0) and the sector-specific CVR threshold were confirmed as essential DT skills.

Table 2: Number of Experts in Two Delphi Rounds.

	Construction sector	**Information technology sector**	**Manufacturing sector**
Round 1	17 (11 supervisors, 6 managers)	14 (9 supervisors, 5 managers)	15 (10 supervisors, 5 managers)
Round 2	11 (7 supervisors, 4 managers)	10 (7 supervisors, 3 managers)	11 (7 supervisors, 4 managers)

Table 1: Correlation Matrix between Theoretical Frameworks

DTSF (Bouwmans et al., 2024)		**DigComp 2.2 (Vuorikari et al., 2022)**	**Australian Workforce Digital Skills Framework (Gekara et. al., 2019)**	**DELTAs (Dondi et al., 2021)**
Sillsets	Sub-skill			
Fundamental Digital Working Skills	1.1 Handling hardware	✓	✓	
	1.2 Handling software	✓	✓	✓
	1.3 Handling social media and the internet	✓	✓	✓
	1.4 Sharing information and data	✓	✓	
	1.5 Solving basic digital problems	✓	✓	✓
Advanced Digital Working Skills	2.1 Programming			✓
	2.2 Digital content creation	✓	✓	✓
	2.3 Dealing with laws, copyrights and licenses	✓	✓	✓
	2.4 Digital safety	✓	✓	✓
Fundamental Evidence-Based Working Skills	3.1 Creativity and innovation	✓	✓	✓
	3.2 Problem solving	✓	✓	✓
Openness to Novelty	4.1 Spotting opportunities		✓	
	4.2 Sensemaking		✓	
Value Creation Skills	5.1 Taking initiative		✓	
	5.2 Strategic planning		✓	✓
	5.3 Decision making		✓	✓
	5.4 Anticipation		✓	
	5.5 Risk taking		✓	✓
	5.6 Risk management		✓	✓
	5.7 Leadership		✓	✓
Fundamental Evidence-Based Working Skills	6.1 Formulating research questions		✓	✓
	6.2 Critical thinking		✓	✓
Information Processing Skills	7.1 Searching and selecting information	✓	✓	✓
	7.2 Information interpretation and evaluation	✓	✓	✓
	7.3 Information management	✓	✓	

DTSF (Bouwmans et al., 2024)		DigComp 2.2 (Vuorikari et al., 2022)	Australian Workforce Digital Skills Framework (Gekara et. al., 2019)	DELTAs (Dondi et al., 2021)
Data Fluency Skills	8.1 Data collection	✓	✓	✓
	8.2 Data management	✓	✓	✓
	8.3 Data analysis	✓	✓	✓
	8.4 Data interpretation	✓	✓	✓
	8.5 Data application	✓	✓	✓
	8.6 Data ethics and security		✓	✓
Collaboration Skills	9.1 Negotiation			✓
	9.2 Multidisciplinary teamwork	✓	✓	✓
	9.3 Social intelligence	✓	✓	
	9.4 Cultural awareness	✓		
	9.5 Networking	✓	✓	✓
Adaptation Skills	10.1 Self-directed learning			✓
	10.2 Experiential learning			✓
	10.3 Training others			✓
	10.4 Resilience			
Communication Skills	11.1 Using appropriate ways to communicate	✓	✓	
	11.2 Storytelling			✓
	11.3 Netiquette	✓	✓	
	11.4 Digital identity management	✓	✓	

4. Results

4.1. Round 1

In the first Delphi round, experts evaluated 44 sub-skills across 11 skill groups in three sectors. Each item was assessed using a 5-point Likert scale (1 = Not important to 5 = Extremely important), and items were retained based on two criteria: Mean and Content Validity Ratio (CVR).

In the construction sector, a total of 17 experts were surveyed to evaluate 44 sub-skills categorized into 11 skill groups, with item retention determined by two criteria: a mean score of ≥ 4.0 and a CVR of ≥ 0.42. Out of the 44 sub-skills, 36 were accepted and 8 were rejected. The rejected items included: Handling hardware (Mean = 3.53; CVR = –0.06), Programming (3.71; 0.18), Strategic planning (3.71; 0.18), Risk taking (3.35; 0.06), Formulating research questions (3.71; 0.18), Multidisciplinary teamwork (3.88; 0.29), Training others (3.35; 0.06), Storytelling (3.65; 0.06). Most accepted skills fell into clusters such as digital fluency, problem solving, information processing, adaptability, and communication, reflecting strong consensus among experts regarding core competencies for digital transformation in the construction sector.

Table 3: The Results of the First Delphi round for Construction sector

No	Skills	Mean	CVR	Result
1	***Fundamental Digital Working Skills***			
1.1	Handling hardware	3.53	-0.06	*Rejected*
1.2	Handling software	4.35	0.76	Accepted
1.3	Handling social media and the internet	4.24	0.76	Accepted
1.4	Sharing information and data	4.12	0.76	Accepted
1.5	Solving basic digital problems	4.18	0.65	Accepted
2	***Advanced Digital Working Skills***			
2.1	Programming	3.71	0.18	*Rejected*
2.2	Digital content creation	4.35	0.76	Accepted
2.3	Dealing with laws, copyrights and licenses	4.53	0.88	Accepted
2.4	Digital safety	4.06	0.53	Accepted
3	***Fundamental Entrepreneurial Skills***			
3.1	Creativity and innovation	4.24	0.88	Accepted
3.2	Problem solving	4.41	0.76	Accepted
4	***Openness to Novelty***			
4.1	Spotting opportunities	4.24	0.76	Accepted
4.2	Sensemaking	4.18	0.76	Accepted
5	***Value Creation Skills***			
5.1	Taking initiative	4.53	0.88	Accepted

No	Skills	Mean	CVR	Result
5.2	Strategic planning	3.71	0.18	*Rejected*
5.3	Decision making	4.18	0.76	Accepted
5.4	Anticipation	4.00	0.65	Accepted
5.5	Risk taking	3.35	0.06	*Rejected*
5.6	Risk management	4.06	0.53	Accepted
5.7	Leadership	4.00	0.65	Accepted
6	***Fundamental Evidence-Based Working Skills***			
6.1	Formulating research questions	3.71	0.18	*Rejected*
6.2	Critical thinking	4.24	0.88	Accepted
7	***Information Processing Skills***			
7.1	Searching and selecting information	4.59	0.88	Accepted
7.2	Information interpretation and evaluation	4.29	0.65	Accepted
7.3	Information management	4.12	0.76	Accepted
8	***Data Fluency Skills***			
8.1	Data collection	4.06	0.65	Accepted
8.2	Data management	4.24	0.88	Accepted
8.3	Data analysis	4.12	0.65	Accepted
8.4	Data interpretation	4.06	0.53	Accepted
8.5	Data application	4.00	0.65	Accepted
8.6	Data ethics and security	4.29	0.76	Accepted
9	***Collaboration Skills***			
9.1	Negotiation	4.00	0.65	Accepted
9.2	Multidisciplinary teamwork	3.88	0.29	*Rejected*
9.3	Cultural awareness	4.00	0.65	Accepted
9.4	Networking	4.24	0.76	Accepted
10	***Adaptation Skills***			
10.1	Self-directed learning	4.53	0.76	Accepted
10.2	Experiential learning	4.35	0.88	Accepted
10.3	Training others	3.35	0.06	*Rejected*
10.4	Resilience	4.00	0.53	Accepted
11	**Communication Skills**			
11.1	Using appropriate ways to communicate	4.35	0.88	Accepted
11.2	Storytelling	3.65	0.06	*Rejected*
11.3	Netiquette	4.00	0.53	Accepted
11.4	Digital identity management	4.18	0.65	Accepted

In the information technology sector, a total of 14 experts were surveyed to evaluate 44 sub-skills categorized into 11 skill groups, with item retention determined by two criteria: a mean score of ≥ 4.0 and a CVR of ≥ 0.51. Of the 44 sub-skills, 39 were accepted, while 5 were rejected. The sub-skills that did not meet the acceptance criteria included: Strategic planning (Mean = 3.86; CVR = 0.43), Anticipation (Mean = 3.93; CVR = 0.57), Negotiation (Mean = 3.86; CVR = 0.43), Cultural awareness (Mean = 3.86; CVR = 0.43), and Storytelling (Mean = 3.64; CVR = 0.00). The accepted sub-skills were primarily concentrated in clusters such as digital literacy, entrepreneurial competencies, information processing, data fluency, and adaptive communication, reflecting a strong consensus among experts regarding the core digital capabilities required in the IT sector.

Table 4: The Results of the First Delphi round for IT sector

No	Skills	Mean	CVR	Result
1	***Fundamental Digital Working Skills***			
1.1	Handling hardware	4.36	0.57	Accepted
1.2	Handling software	4.36	0.71	Accepted
1.3	Handling social media and the internet	4.29	0.71	Accepted
1.4	Sharing information and data	4.21	0.86	Accepted
1.5	Solving basic digital problems	4.14	0.57	Accepted
2	***Advanced Digital Working Skills***			
2.1	Programming	4.07	0.57	Accepted
2.2	Digital content creation	4.36	0.71	Accepted
2.3	Dealing with laws. copyrights and licenses	4.64	0.88	Accepted
2.4	Digital safety	4.14	0.57	Accepted
3	***Fundamental Entrepreneurial Skills***			
3.1	Creativity and innovation	4.29	0.86	Accepted
3.2	Problem solving	4.36	0.71	Accepted
4	***Openness to Novelty***			
4.1	Spotting opportunities	4.29	0.71	Accepted
4.2	Sensemaking	4.29	0.86	Accepted
5	***Value Creation Skills***			
5.1	Taking initiative	4.64	0.86	Accepted
5.2	Strategic planning	3.86	0.43	*Rejected*
5.3	Decision making	4.21	0.71	Accepted
5.4	Anticipation	3.93	0.57	*Rejected*
5.5	Risk taking	4.07	0.71	Accepted
5.6	Risk management	4.14	0.57	Accepted
5.7	Leadership	4.00	0.57	Accepted
6	***Fundamental Evidence-Based Working Skills***			
6.1	Formulating research questions	4.00	0.57	Accepted
6.2	Critical thinking	4.21	0.86	Accepted
7	***Information Processing Skills***			
7.1	Searching and selecting information	4.71	0.86	Accepted
7.2	Information interpretation and evaluation	4.43	0.71	Accepted
7.3	Information management	4.14	0.71	Accepted
8	***Data Fluency Skills***			
8.1	Data collection	4.07	0.57	Accepted
8.2	Data management	4.29	0.86	Accepted

No	Skills	Mean	CVR	Result
8.3	Data analysis	4.07	0.57	Accepted
8.4	Data interpretation	4.21	0.57	Accepted
8.5	Data application	4.00	0.57	Accepted
8.6	Data ethics and security	4.29	0.71	Accepted
9	***Collaboration Skills***			
9.1	Negotiation	3.86	0.43	*Rejected*
9.2	Multidisciplinary teamwork	4.00	0.57	Accepted
9.3	Cultural awareness	3.86	0.43	*Rejected*
9.4	Networking	4.29	0.71	Accepted
10	***Adaptation Skills***			
10.1	Self-directed learning	4.50	0.71	Accepted
10.2	Experiential learning	4.29	0.86	Accepted
10.3	Training others	4.07	0.71	Accepted
10.4	Resilience	4.07	0.57	Accepted
11	**Communication Skills**			
11.1	Using appropriate ways to communicate	4.43	0.86	Accepted
11.2	Storytelling	3.64	0.00	*Rejected*
11.3	Netiquette	4.21	0.57	Accepted
11.4	Digital identity management	4.21	0.57	Accepted

In the manufacturing sector, insights were gathered from 15 domain experts to assess 44 sub-skills distributed across 11 skill groups. The inclusion of each item was contingent upon meeting two predetermined thresholds: a mean score of at least 4.0 and a CVR value equal to or exceeding 0.49. Based on these criteria, 36 sub-skills were retained, while 8 were excluded from further consideration. The excluded items were: Programming (Mean = 3.87; CVR = 0.43), Anticipation (Mean = 3.80; CVR = 0.43), Risk taking (Mean = 3.93; CVR = 0.57), Formulating research questions (Mean = 3.80; CVR = 0.43), Negotiation (Mean = 3.80; CVR = 0.43), Cultural awareness (Mean = 3.87; CVR = 0.43), Storytelling (Mean = 3.60; CVR = 0.00), and Netiquette (Mean = 3.87; CVR = 0.29). The sub-skills that met the inclusion criteria reflect a strong alignment among experts on the competencies essential for navigating digital transformation in the manufacturing context—particularly in domains related to digital operations, data fluency, entrepreneurial thinking, and adaptive capacity.

Table 5: The Results of the First Delphi round for Manufacturing sector

No	Skills	Mean	CVR	Result
1	***Fundamental Digital Working Skills***			
1.1	Handling hardware	4.33	0.57	Accepted
1.2	Handling software	4.40	0.71	Accepted
1.3	Handling social media and the internet	4.27	0.71	Accepted
1.4	Sharing information and data	4.20	0.86	Accepted
1.5	Solving basic digital problems	4.13	0.57	Accepted
2	***Advanced Digital Working Skills***			
2.1	Programming	3.87	0.43	*Rejected*
2.2	Digital content creation	4.27	0.71	Accepted
2.3	Dealing with laws. copyrights and licenses	4.53	0.88	Accepted
2.4	Digital safety	4.07	0.43	Accepted
3	***Fundamental Entrepreneurial Skills***			
3.1	Creativity and innovation	4.27	0.86	Accepted
3.2	Problem solving	4.33	0.71	Accepted
4	***Openness to Novelty***			
4.1	Spotting opportunities	4.27	0.71	Accepted
4.2	Sensemaking	4.27	0.86	Accepted
5	***Value Creation Skills***			
5.1	Taking initiative	4.60	0.86	Accepted
5.2	Strategic planning	4.00	0.57	Accepted
5.3	Decision making	4.21	0.71	Accepted
5.4	Anticipation	3.80	0.43	*Rejected*
5.5	Risk taking	3.93	0.57	*Rejected*
5.6	Risk management	4.13	0.57	Accepted
5.7	Leadership	4.00	0.57	Accepted
6	***Fundamental Evidence-Based Working Skills***			
6.1	Formulating research questions	3.80	0.43	*Rejected*
6.2	Critical thinking	4.20	0.86	Accepted
7	***Information Processing Skills***			
7.1	Searching and selecting information	4.73	0.86	Accepted
7.2	Information interpretation and evaluation	4.40	0.71	Accepted
7.3	Information management	4.13	0.71	Accepted
8	***Data Fluency Skills***			
8.1	Data collection	4.13	0.57	Accepted
8.2	Data management	4.33	0.86	Accepted
8.3	Data analysis	4.13	0.57	Accepted
8.4	Data interpretation	4.13	0.57	Accepted
8.5	Data application	4.00	0.57	Accepted
8.6	Data ethics and security	4.27	0.71	Accepted
9	***Collaboration Skills***			
9.1	Negotiation	3.80	0.43	*Rejected*
9.2	Multidisciplinary teamwork	4.00	0.57	Accepted
9.3	Cultural awareness	3.87	0.43	*Rejected*
9.4	Networking	4.27	0.71	Accepted
10	***Adaptation Skills***			
10.1	Self-directed learning	4.47	0.71	Accepted
10.2	Experiential learning	4.33	0.86	Accepted
10.3	Training others	4.13	0.71	Accepted
10.4	Resilience	4,07	0,57	Accepted

No	Skills	Mean	CVR	Result
11	**Communication Skills**			
11.1	Using appropriate ways to communicate	4.40	0.86	Accepted
11.2	Storytelling	3.60	0.00	*Rejected*
11.3	Netiquette	3.87	0.29	*Rejected*
11.4	Digital identity management	4.20	0.57	Accepted

4.2. Round 2

In the second Delphi round, expert panels were reconvened to evaluate additional sub-skills related to communication and collaboration. Specifically, 11 experts participated in the construction sector, 10 in the information technology sector, and 11 in the manufacturing sector. The criteria for item retention remained consistent across all sectors, with a mean score of ≥ 4.0. The CVR thresholds were adjusted based on panel size: ≥ 0.59 for the construction and manufacturing sectors, and ≥ 0.62 for the IT sector.

These sub-skills were initially proposed by experts in the open-ended question section of Round 1, and were subsequently included in Round 2 to verify whether there was a high level of consensus regarding their relevance.

In the construction sector, all four evaluated sub-skills met the acceptance criteria: Coordinating and arranging tasks (Mean = 4.00; CVR = 0.82), Feedback and suggestions (Mean = 4.09; CVR = 0.82), Non-verbal communication (Mean = 4.18; CVR = 0.64), and Active listening (Mean = 4.27; CVR = 0.82).

Table 6: The Results of the Second Delphi round for Construction sector

No	Skills	Mean	CVR	Result
1	Coordinating and arranging tasks	4.00	0.82	Accepted
2	Feedback and suggestions	4.09	0.82	Accepted
3	Non-verbal communication	4.18	0.64	Accepted
4	Active listening	4.27	0.82	Accepted

In the IT sector, three sub-skills were assessed and all were accepted: Coordinating and arranging tasks (Mean = 4.00; CVR = 0.82), Feedback and suggestions (Mean = 4.09; CVR = 0.82), and Active listening (Mean = 4.18; CVR = 0.64).

Table 7: The Results of the Second Delphi round for IT sector

No	Skills	Mean	CVR	Result
1	Coordinating and arranging tasks	4.00	0.82	Accepted
2	Feedback and suggestions	4.09	0.82	Accepted
3	Active listening	4.18	0.64	Accepted

Similarly, in the manufacturing sector, the same three sub-skills were evaluated and retained: Coordinating and arranging tasks (Mean = 4.10; CVR = 1.00), Feedback and suggestions (Mean = 4.20; CVR = 0.80), and Active listening (Mean = 4.50; CVR = 0.80). These results reflect continued consensus across sectors on the importance of communication-related competencies in digitally transforming work environments.

Table 8: The Results of the Second Delphi round for Manufacturing sector

No	Skills	Mean	CVR	Result
1	Coordinating and arranging tasks	4.10	1.00	Accepted
2	Feedback and suggestions	4.20	0.80	Accepted
3	Active listening	4.50	0.80	Accepted

5. Conclusions

This study aims to address two research questions: “In the context of widespread digital transformation driven by AI, what digital skills are required in the construction, manufacturing, and information technology sectors?” and “What are the similarities and differences in digital skill requirements across the construction, manufacturing, and information technology sectors?" Drawing on the results of a two-round Delphi process, the study successfully answers this question by identifying both a core set of common digital skills and unique skill sets specific to each sector. As illustrated in the Venn diagram (Fig. 1), the findings provide a comprehensive overview of the digital skill landscape, highlighting the extent of cross-sectoral overlap as well as sector-specific needs. These insights not only validate the central premise of the study but also offer practical guidance for organizational management in tailoring workforce development strategies to the digital demands of their respective sectors.

The majority of digital skills identified in this study are consistent with the DTSF proposed by Bouwmans et al. (2024). However, expert evaluations in the present research have highlighted three additional cross-sectoral digital skills not previously emphasized: Coordinating and arranging tasks, Feedback and suggestions, and Active listening. These competencies emphasize the growing importance of human-centered skills in the context of GenAI. While the advancement of AI offers substantial benefits in terms of automation and efficiency, these findings suggest that uniquely human capabilities remain critical to workplace effectiveness. The inclusion of these interpersonal and cognitive skills reinforces the view that successful digital transformation requires not only technological adaptation but also the development of human capacities that support collaboration, communication, and task management. This insight contributes to a more holistic understanding of digital skill demands in AI-augmented work environments.

The emergence of sector-specific skill clusters is largely shaped by the unique characteristics of each profession. In the construction sector, required competencies must align with cultural expectations and broader societal trends in architectural and infrastructural design. In manufacturing, workers are expected to possess capabilities that ensure production processes are integrated effectively within the firm's supply chain and distribution networks. Finally, in the IT sector, skills are primarily oriented toward programming proficiency and creativity in the application of information technologies. Consequently, each industry inevitably develops its own distinctive set of competencies tailored to its professional demands.

In terms of the Construction sector, the identification of four unique digital skills—anticipation, negotiation, cultural awareness, and non-verbal communication—comprising 8.7% of the total skill set, highlights the sector's distinct emphasis on soft skills embedded within digital competence. This finding reflects the project-based and frequently multicultural nature of construction work, where effective communication and foresight are essential for coordinating diverse teams and managing complex stakeholder relationships. Notably, the absence of any overlapping skills with the Manufacturing sector (0.0%) further reinforces the uniqueness of Construction's digital profile, potentially rooted in its reliance on localized knowledge and conventional work practices despite ongoing technological adoption. These results suggest that workforce development in the Construction industry should focus on the integration of digital tools with interpersonal capabilities, thereby addressing a critical skills gap. Enhancing such competencies may significantly improve project delivery and stakeholder engagement in an increasingly global and digitized construction environment.

In the Manufacturing sector, two distinctive digital skills—strategic planning and training others—accounting for 4.3% of the total, were identified as unique to this industry. Their presence reflects the sector's strong focus on structured processes and long-term coordination. 'Strategic planning' is essential for integrating new technologies into production systems, ensuring that digital transformation supports broader organizational goals. In addition, 'training others' highlights the need to build internal capacity by sharing knowledge across teams and roles, especially in environments where standardization and consistency are critical. These findings suggest that digital transformation in manufacturing is not only about adopting new tools but also about managing change in a way that is aligned, systematic, and people-centered. Therefore, workforce development in this sector should prioritize planning skills and peer-based training to enhance operational efficiency and adaptability in increasingly automated and data-driven environments.

Within the IT sector, three digital skills—programming, risk-taking, and formulating research questions—were identified as uniquely representative, comprising 6.5% of the sector-specific skills. These skills reflect the sector's strong emphasis on innovation, experimentation, and analytical thinking. Programming remains a core technical capability that underpins most digital solutions, while risk-taking indicates the sector's tolerance for uncertainty and its orientation toward rapid technological advancement. The inclusion of formulating research questions highlights the importance of curiosity-driven inquiry and the ability to define and explore complex problems in dynamic digital environments. In sum, these skills illustrate how the IT sector demands not only technical expertise but also a proactive, exploratory mindset. Therefore, workforce development in this sector should aim to strengthen both technical skills and flexible thinking, so that employees can adapt and contribute to innovation in rapidly changing environments.

Notably, the IT and manufacturing sectors share two distinctive digital skills: handling hardware and multidisciplinary teamwork. This overlap reflects the technical nature of both industries and the reliance on cross-functional collaboration to implement complex digital systems. In contrast, netiquette—the ability to communicate appropriately in online environments—emerges as a shared skill between IT and construction. This connection highlights the growing importance of digital communication norms in sectors where remote coordination and digital interaction are increasingly integrated into daily operations. These shared skills indicate that digital transformation leads to some overlap in skill requirements across sectors, even as each sector retains its distinct competencies.

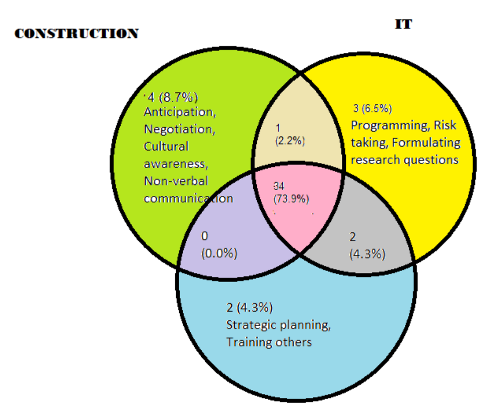

Figure 1: Summary of Digital Skills Across Sectors

As illustrated in Fig. 1, a substantial portion (73.9%) of the 34 identified skills are common across all three sectors. In addition, the heatmap (Fig.2) provides a detailed visualization of 34 digital skills commonly recognized across the Construction, IT, and Manufacturing sectors. This representation captures the relative importance of each skill, offering valuable guidance for organizations in designing more targeted training programs and recruitment strategies. In the context of increasing AI integration, searching and selecting information emerges as a critical competency. With the growing prevalence of fake information, employees must be capable of identifying accurate and relevant data—a skill consistently rated as highly important across all three sectors. However, information access alone is insufficient. The ability to take initiative is equally essential, enabling individuals to act on emerging opportunities and adapt to evolving demands.

Another key finding is the importance of dealing with laws, copyrights, and licenses, which reflects the growing need for digital legal literacy. As digital operations expand, understanding legal frameworks is vital to ensure compliance and mitigate risks. This highlights the value of incorporating legal awareness into digital skills training. Additionally, self-directed learning is identified as a foundational skill, equipping employees to continuously update their competencies in fast-changing, AI-driven environments. Its strong endorsement across sectors emphasize the importance of lifelong learning for sustained employability. Taken together, these core skills—information filtering, proactive engagement, legal understanding, and self-directed learning—have important implications for workforce development, highlighting the need for a holistic approach to preparing adaptable and future-ready employees.

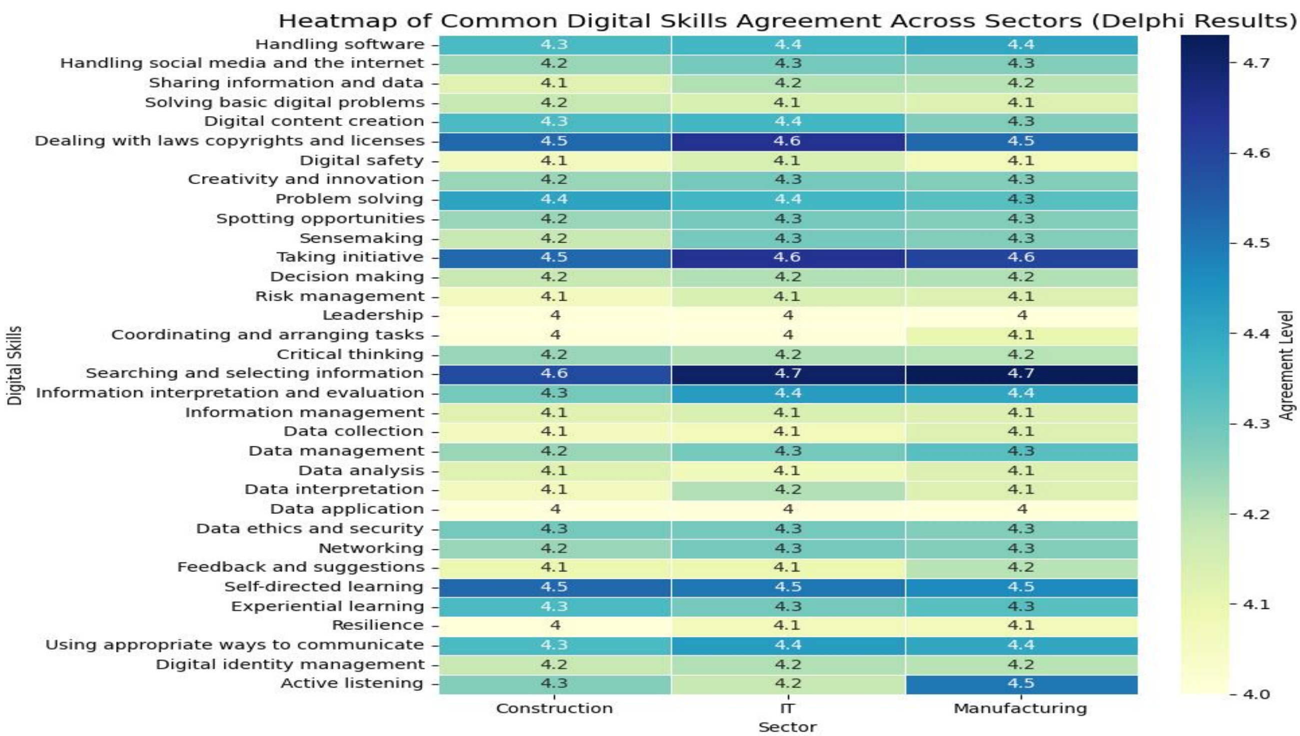

Figure 2: Heatmap of Common Digital skills across sectors

5.1. Practical Implications

This study advances organizational understanding of digital skill requirements by proposing a sector-specific framework for construction, manufacturing, and information technology. By distinguishing between shared and unique digital competencies, the findings offer strategic insights to align human capital development with AI-driven transformation. Recognizing the relative importance of each skill enables more informed decision-making in training design, workforce planning, and talent acquisition.

In the context of employee training, the study underscores the importance of aligning in-house development programs with expert-informed skill priorities. Rather than adopting a one-size-fits-all approach to training, firms should provide learning content based on the most relevant digital skills identified within their industry. Sector-specific differences—such as the emphasis on interpersonal communication in construction, strategic planning in manufacturing, or programming and inquiry-based thinking in IT—highlight the need for differentiated training strategies. Where internal resources are limited, organizations are encouraged to facilitate employee access to external training opportunities, including industry-certified courses, partnerships with educational institutions, or participation in professional learning networks. However, it is essential that these opportunities remain aligned with the digital skill priorities outlined in this framework, to ensure both efficiency and relevance in workforce development investments.

Beyond training, the study offers practical implications for recruitment and talent selection. The hierarchical structure of digital skills identified through the Delphi process can serve as a useful reference point for evaluating job applicants. By embedding these prioritized skill sets into hiring criteria, firms can better assess candidates' readiness to operate in the workplace of the AI age. This approach not only improves the accuracy of candidate-job fit but also supports the development of a workforce that is responsive to the pace and direction of digital change.

This study advances the digital skills literature by highlighting the distinctive role of AI compared with broader digitalisation. Whereas digitalisation traditionally emphasized basic competencies such as digital literacy, communication, and collaboration, the rise of AI reshapes skill requirements toward predictive analytics, algorithmic decision-making, human–machine collaboration, and adaptation skills. By differentiating AI-driven transformations from generic digitalisation effects, this research enriches theory on how technological paradigms create industry-specific competency demands. Therefore, organizations should remain attentive to the sector-specific nature of digital skills. While certain core ones—such as searching and selecting information, self-directed learning, take initiative, or dealing with laws, copyrights, and licenses—are universally important, others are uniquely aligned with the operational demands of particular industries. For example, construction requires strong anticipation and negotiation skills, while manufacturing places greater emphasis on strategic planning and training others. Recognizing these distinctions allows firms to recruit individuals whose digital skills are not only technically relevant but also contextually appropriate to the workflows, cultures, and structures within each sector.

Taken together, the findings of this study provide a solid foundation for developing more targeted and effective human resource strategies. Since construction, manufacturing, and IT collectively contribute to the broader supply chain and distribution networks of the economy, it is essential to design training programs that enable these sectors to build a workforce capable of operating across disciplinary boundaries. Beyond this shared foundation, tailored training initiatives and evidence-based recruitment practices—aligned with sector-specific digital skill frameworks—can further enhance workforce agility and strengthen long-term competitiveness in an era of AI-driven transformation. For example, predictive analytics skills enable employees to anticipate demand fluctuations, while data-driven decision-making supports dynamic route planning in last-mile logistics. Moreover, communication and coordination skills are being redefined in the AI age, as employees increasingly interact with algorithmic systems and must interpret machine-generated outputs for operational execution. By contrast, in production environments AI-related skills are more closely tied to process automation and machinery oversight, whereas in the IT sector they revolve around AI system design, maintenance, and cybersecurity.

5.2. Limitation and Future Suggestions

Similar to prior studies, the present research is subject to certain limitations. First, its focus on three engineering-oriented sectors—construction, manufacturing, and IT—may limit the generalizability of the findings. Future research could extend the comparison to include both engineering and social science sectors to offer a more balanced and comprehensive understanding of digital skills across disciplines. Second, the application of digital skills to workplace performance was not examined in this study. Subsequent studies could employ quantitative methodologies to explore the relationship between digital skills and job performance. Third, the influence of socio-contextual factors was not considered. Future studies could incorporate socio-contextual factors, such as higher education systems and general societal skill levels across different economies, to identify a universal set of digital skills applicable to diverse economic contexts. Fourth, the study relied on a panel of experts working in domestic and multinational companies in Vietnam, which may limit the generalizability of the findings to other geographical contexts. Expanding the research to include experts from multiple countries would enhance the external validity and reliability of the proposed competency framework. Fifth, although the use of the Content Validity Ratio (CVR) threshold is common practice, it may be sensitive to the composition and size of the expert panel. Therefore, broadening the panel to include more multinational experts would also serve as a means to test the robustness of the CVR measure. The last limitation of this study lies in its cross-sectional perspective. While the findings provide valuable insights into current digital skill requirements across construction, manufacturing, and IT, they do not capture how these competencies may evolve over time as AI technologies mature. In particular, distribution environments are undergoing rapid transformation, where automation and human workers are expected to collaborate in increasingly complex ways. A longitudinal design would be better suited to examine how such dynamics reshape skill demands, allowing researchers to trace the progression of digital and AI-related competencies as technologies diffuse and organizational practices adapt.

Declarations

Ethics Approval and Consent to Participate

Not applicable. This study did not involve human participants or animal subjects.

Competing Interests / Conflicts of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions

Author 1 - Thi Thanh Van NGUYEN: Conceptualization, Methodology, Investigation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization.
Corresponding Author - Thi Thanh Thuy NGUYEN: Conceptualization, Methodology, Resources, Writing – review & editing, Supervision, Project administration.
All authors have read and approved the final manuscript.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

We confirm that generative AI tools were used solely for permitted copy-editing purposes, including improving language clarity, grammar, and formatting of our own original text. No AI tools were used to generate, modify, or contribute to the intellectual content of the manuscript.

References

Benko, A., & Lányi, C. S. (2009). History of artificial intelligence. In *Encyclopedia of Information Science and Technology, Second Edition* (pp. 1759-1762). IGI global.

Bouwmans 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. https://doi.org/10.1371/journal.pone.0304127

Dondi, M., Klier, J., Panier, F. & Schubert, J. (2021). Defining the skills citizens will need in the future world of work. *McKinsey & Company* https://www.mckinsey.com/industries/public-sector/our-insights/defining-the-skills-citizens-will-need-in-the-future-world-of-work

Ekanayake, E.M.A.C., Shen, G., & Kumaraswamy, M.M. (2021). Critical capabilities of improving supply chain resilience in industrialized construction in Hong Kong. *Engineering, Construction and Architectural Management*, *28*(10), 3236-3260. https://dx.doi.org/10.1108/ECAM-05-2020-0295

Gekara, V., Snell, D., Molla, A., Karanasios, S. & Thomas, A (2019). Skilling the Australian workforce for the digital economy. *National Centre for Vocational Education Research.* https://www.ncver.edu.au/research-and-statistics/publications/all-publications/skilling-the-australian-workforce-for-the-digital-economy

Ginigaddara, B., Perera, S., Feng, Y., & Rahnamayiezekavat, P. (2019, June). Skills required for offsite construction. In *Constructing Smart Cities: Proceedings of the 22nd CIB World Building Congress*.

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, *18*(4), 1189-1220.

Kasmono, A., Purwono, R., & Herawati, N. (2025). Electronic Procurement to Improve Sustainability and Digital Transformation in Government Procurement., *23*(4), 91-102, https://doi.org/10.15722/jds.23.04.202504.91

Khan, S., Mehmood, S., & Khan, S. U. (2025). Navigating innovation in the age of AI: how generative AI and innovation influence organizational performance in the manufacturing sector. *Journal of Manufacturing Technology Management*, *36*(3), 597-620.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering, 6*(4), 239–242. https://doi.org/10.1007/s12599-014-0334-4

Lawshe, C. H. (1975). A Quantitative Approach To Content Validity. *Personnel Psychology*, *28*(4), 563–575. https://doi.org/10.1111/j.1744-6570.1975.tb01393.x

Li, G., Yuan, C., Kamarthi, S., Moghaddam, M., & Jin, X. (2021). Data science skills and domain knowledge requirements in the manufacturing industry: A gap analysis. *Journal of Manufacturing Systems*, *60*, 692-706. https://doi.org/10.1016/j.jmsy.2021.07.007

Liu, A., & Wang, S. (2024). Generative artificial intelligence (GenAI) and entrepreneurial performance: implications for entrepreneurs. *The Journal of Technology Transfer*, *49*(6), 2389-2412.

Majeed, M. T., & Sharif, F. (2024). The role of digitalization in driving green growth: A global panel data perspective. *Pakistan Journal of Commerce and Social Sciences, 18*(2), 435-467.

McKinsey & Company. (2023). The economic potential of generative AI: The next productivity frontier. *McKinsey & Company.* https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier

Nguyen, T. A. Van, Tucek, D., & Pham, N. T. (2023). Indicators for TQM 4.0 model: Delphi Method and Analytic Hierarchy Process (AHP) analysis. *Total Quality Management & Business Excellence, 34*(1–2), 220–234. https://doi.org/10.1080/14783363.2022.2039062

OECD. (2016). *Getting Skills Right: Assessing and Anticipating Changing Skill Needs*. OECD Publishing. https://www.oecd.org/publications/getting-skills-right-assessing-and-anticipating-changing-skill-needs-9789264252073-en.htm

OECD. (2021). The OECD Framework for digital talent and skills in the public sector. *OECD Working Papers on Public Governance,* 45 https://dx.doi.org/10.1787/4e7c3f58-en

Oran, İ. B., Yilmaz, S., Ertürk, M., & Gün, H. (2023). Technology, Artificial Intelligence, and Robotics in Future Wars. *Journal of Organizational Behavior Research, 8*(1), 244-258. https://doi.org/10.51847/pr1EaWSiNa

Palanimally, Y. R., Tazilah, M. D. A. K., Mohamad, Z. Z., Ramasamy, M., Ramdan, M. R., Syariff, M. F. D. R., & Alwi, N. H. (2024). Distribution of skill and encouraging motivation to enhance resilience: Evidence from accounting personnel during COVID-19 crisis. *Journal of Distribution Science, 22*(2), 41–50. https://doi.org/10.15722/jds.22.02.202402.41

Şahin, O., & Karayel, D. (2024). Generative Artificial Intelligence (GenAI) in Business and Industry: A Systematic Review on the Threshold of Transformation. *Journal of Smart Systems Research*, *5*(2), 156-175.

Siddiqui, F. H., Thaheem, M. J., & Abdekhodaee, A. (2023). A Review of the Digital Skills Needed in the Construction Industry: Towards a Taxonomy of Skills. *Buildings*, *13*(11), 2711. https://doi.org/10.3390/buildings13112711

Sousa, M. J., & Rocha, Á. (2019). Digital learning: Developing skills for digital transformation of organizations. *Future Generation Computer Systems*, *91*, 327-334.

Succar, B. (2009). Building information modelling framework: A research and delivery foundation for industry stakeholders. *Automation in Construction*, *18*(3), 357–375. https://doi.org/10.1016/j.autcon.2008.10.003

Ramirez, J., Herrera, H., Redondo, O., & Sulbaran, S. (2024). Implementation of Artificial Intelligence Systems for Agri-food Supply Chains: A Bibliometric Approach. *The Journal of Distribution Science, 22*(6), 83-93, https://doi.org/10.15722/jds.22.06.202406.83

United Nations Industrial Development Organization. (2023). *International yearbook of industrial statistics 2023* (29th ed.). UNIDO. https://stat.unido.org/publications/international-yearbook-industrial-statistics-2023

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

Vuorikari, R., Punie, Y., Carretero, S., & Van den Brande, G. (2016). DigComp 2.0: The Digital Competence Framework for Citizens. Update Phase 1: The Conceptual Reference Model. *Publications Office of the European Union.* https://doi.org/10.2791/11517

Vuorikari, R., Punie, Y., Carretero, S., & Van den Brande, G. (2022). DigComp 2.2: The Digital Competence Framework for Citizens. *Publications Office of the European Union*. https://doi.org/10.2760/115376

Wassan, A. N., & Kalwar, M. A. (2025). The Role of Logistics 4.0 and Industry 4.0 in Promoting Sustainable Operations and Performance. *Jordan Journal of Mechanical and Industrial Engineering, 19*(1), 105–128. https://doi.org/10.59038/jjmie/190108

Wartman, S. A., & Combs, C. D. (2018). Medical education must move from the information age to the age of artificial intelligence. *Academic Medicine*, *93*(8), 1107-1109.

World Economic Forum. (2025). *The future of jobs report 2025.* World Economic Forum. https://www.weforum.org/publications/the-future-of-jobs-report-2025/

World Economic Forum. (2025). The Future of Jobs Report 2025: Drivers of labour-market transformation. *World Economic forum* https://www.weforum.org/publications/the-future-of-jobs-report-2025/in-full/1-drivers-of-labour-market-transformation

World Economic Forum. (2025). The Future of Jobs Report 2025: Skills Outlook. *World Economic forum.* https://www.weforum.org/publications/the-future-of-jobs-report-2025/in-full/3-skills-outlook/

Wu, T., He, S., Liu, J., Sun, S., Liu, K., Han, Q. L., & Tang, Y. (2023). A brief overview of ChatGPT: The history, status quo and potential future development. *IEEE/CAA Journal of Automatica Sinica*, *10*(5), 1122-1136. http://dx.doi.org/10.1109/JAS.2023.123618

Yue, Y., Ng, S. I., & Norazlyn, K.B. (2024). Consumption values, attitudes and continuance intention to adopt ChatGPT-driven e-commerce AI chatbot (LazzieChat). *Pakistan Journal of Commerce and Social Sciences, 18*(2), 249-284.