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AI-Driven Digitalization and Construction Productivity: A Socio-Technical Systematic Literature Review

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ABSTRACT

Purpose: This study aims to analyze the role of digitalization and artificial intelligence (AI) in improving productivity in industrial and construction sectors, identify the supporting and inhibiting factors influencing their implementation, and formulate research gaps and novelty opportunities from previous literature. **Methods:** This study employed a Systematic Literature Review using the PRISMA 2020 framework. The literature search was primarily conducted through Scopus using keyword clusters related to AI-driven automation, skills mismatch, and vocational workforce, complemented by additional relevant scholarly sources. From 272 initial records, the selection and eligibility process resulted in 66 reports, which were analyzed through narrative and thematic synthesis. **Findings:** The findings indicate that digitalization and AI contribute to productivity through process automation, information integration, work accuracy, quality control, resource optimization, and data-driven decision-making. However, their effectiveness depends on human resource readiness, digital literacy, interoperability, system security, data governance, standardization, and organizational support. **Research Implications:** The study implies that productivity improvement through digitalization and AI should not be approached solely as technological adoption. Industrial and construction organizations need to strengthen workforce competencies, data quality, governance mechanisms, system integration, and organizational readiness to ensure that digital transformation produces sustainable productivity outcomes. **Originality:** This study offers an integrative socio-technical perspective that connects AI-driven automation, skills mismatch, vocational workforce readiness, governance, and multidimensional productivity. Its originality lies in positioning productivity as the result of interaction among technology, people, processes, data, and organizations, rather than as a direct consequence of digital technology adoption.

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INTRODUCTION

Digitalization and Artificial Intelligence (AI) have become strategic drivers of productivity improvement in the industrial and construction sectors, particularly because they address persistent inefficiencies, fragmented information flows, and the increasing need for data-driven decision-making. In construction, AI-driven digital twins enable real-time monitoring and predictive maintenance, thereby improving coordination and quality control across the project lifecycle (Najafzadeh & Yeganeh, 2025). Similarly, digital technologies have been associated with productivity improvement through better safety management, collaboration, and waste reduction, although their relationship with productivity remains complex and non-linear (Zulu et al., 2023). AI applications also contribute to facility management, design optimization, planning, and risk identification, which support more proactive project control and improved operational outcomes (Egwim et al., 2023; Zabala-Vargas et al., 2023). Therefore, digitalization and AI should be understood not merely as technological tools, but as mechanisms that reshape how productivity is planned, monitored, and achieved in industrial and construction environments.

In line with this development, productivity in the industrial and construction sectors can no longer be defined only through output volume or cost reduction. It has evolved into a multidimensional construct involving technology, human resources, data, work processes, and organizational governance. This perspective is consistent with the emergence of Industry 5.0, which emphasizes human-centered, resilient, and sustainable value creation rather than efficiency alone (Pollack et al., 2026). In construction, the productivity gap is often intensified by fragmented value streams, inconsistent performance indicators, and weak integration between operational, tactical, strategic, and normative levels of management (Bühler et al., 2025). Standardized processes, real-time data monitoring, and hierarchical productivity frameworks are therefore required to produce more measurable and context-sensitive productivity improvements (Annunen & Haapasalo, 2023; Bühler et al., 2025; Günter & Gopp, 2022).

Within this broader understanding of productivity, AI-driven automation, Building Information Modeling (BIM), the Internet of Things (IoT), digital twins, robotics, cloud systems, and predictive analytics provide important technological foundations for improving construction performance. These technologies support real-time monitoring, predictive maintenance, dynamic scheduling, and automated data capture, which are closely related to work accuracy, quality control, and resource optimization (Kookalani et al., 2026; Najafzadeh & Yeganeh, 2025). The integration of digital twins with BIM and IoT, for instance, strengthens decision-making throughout the project lifecycle by connecting design information, field conditions, and operational data (Kookalani et al., 2026). Intelligent construction models have also demonstrated the potential to increase operational efficiency through automation and real-time information processing (Zhou, 2025). However, high implementation costs and data interoperability problems remain important barriers to the full realization of these technological benefits (Alnajjar et al., 2025; Kookalani et al., 2026).
Nevertheless, the productivity benefits of digitalization and AI cannot be assumed to occur automatically after technology adoption. Their effectiveness depends on the quality of data, interoperability between systems, cybersecurity, explainability, user acceptance, and the extent to which digital tools are embedded into existing work processes. In construction, these issues become more critical because projects involve multiple actors, temporary organizational arrangements, fragmented responsibilities, and heterogeneous data sources. Previous studies have shown that digitalization may improve coordination and reduce errors, but the translation of these improvements into measurable productivity outcomes is often ambiguous and context-dependent (Zulu et al., 2023). Barriers such as data fragmentation, limited interoperability, weak integration with existing workflows, and reluctance to adopt new technologies continue to restrict digital transformation in construction businesses (Akhavan et al., 2025; Avogaro et al., 2025; Ehtsham et al., 2025).

Beyond technological readiness, the human dimension is equally decisive in determining whether digitalization and AI can generate productive outcomes. Skills mismatch, limited digital literacy, insufficient training, and uneven vocational workforce readiness may weaken the impact of advanced technologies in industrial and construction settings. The adoption of digital manufacturing technologies is often constrained by workers' concerns about ease of use, job relevance, and the need for upskilling, particularly among workers with lower levels of formal education (Oostveen et al., 2025). In construction, the identification of essential digital skills has become increasingly important for supporting the transition toward Industry 4.0 and digitally enabled project delivery (Siddiqui et al., 2023). Human-centered change management, organizational competency, and continuous training are therefore necessary to ensure that technologies such as BIM, AI, robotics, and digital twins are not only adopted but also effectively integrated into everyday work practices (Bidhendi et al., 2026; Rikala et al., 2024; Soltani et al., 2023).
Despite the growing literature on digitalization, AI, automation, workforce competence, and productivity, these topics are often examined separately rather than synthesized within a coherent socio-technical framework. Previous research has shown that AI, robotics, and BIM are transforming construction practices, yet the skills required for workers to adapt to these transformations remain dispersed across different bodies of literature (Souza & Debs, 2023). Moreover, the relationship between digitalization and productivity is not linear, which explains why many firms remain cautious in adopting new technologies despite their potential benefits (Zulu et al., 2023). Studies on automation and digitalization in steel construction also show technological progress, but they do not always consolidate these developments into an integrated productivity framework (Šokić et al., 2025). Similarly, research on AI-supported human-robot collaboration highlights the need to better understand how technological capabilities, human roles, and project constraints interact in construction settings (Peng et al., 2025). Therefore, a more integrated approach is needed to explain how digitalization, AI, workforce readiness, and governance jointly influence productivity outcomes (Ershadi & Lijauco, 2026).

This study responds to that gap by systematically connecting AI-driven automation, skills mismatch, vocational workforce readiness, governance, and multidimensional productivity outcomes. Unlike prior studies that focus mainly on specific technologies, isolated productivity indicators, or general digital transformation trends, this study positions productivity as the result of interaction between technological advancement and labor market readiness. In the broader industrial context, AI and automation reshape workforce requirements by increasing the demand for digital, analytical, and technical competencies (Gangoda et al., 2023). Although AI adoption has been associated with significant productivity potential, its uneven impact on workers, especially low-skilled groups, raises concerns about job displacement, inequality, and access to reskilling opportunities (Gao & Feng, 2023; Okur & Özdemir, 2025; Tyson & Zysman, 2022). Consequently, a governance framework is required to ensure that digital transformation improves productivity while also supporting workforce adaptation and equitable skills development (Ekuma, 2024; Okur & Özdemir, 2025).

Accordingly, this study aims to conduct a Systematic Literature Review on the role of digitalization and AI in improving productivity in the industrial and construction sectors. Specifically, the study seeks to analyze how digitalization and AI contribute to productivity, identify the supporting and inhibiting factors that shape their implementation, and formulate research gaps and novelty opportunities based on previous literature. This focus is important because current studies still show several unresolved issues, including ambiguous links between digitalization and productivity gains, limited quantitative evidence, fragmented discussions of AI and workforce readiness, and insufficient integration of technological, human, data, and governance dimensions (Avogaro et al., 2025; Ehtsham et al., 2025; Zulu et al., 2023). By synthesizing these dimensions, this study seeks to provide a more comprehensive explanation of how productivity can be enhanced through responsible and human-centered digital transformation.

The main contribution of this study lies in the development of an integrative framework that explains productivity as a multifaceted outcome of the interplay among technology, people, processes, data, and organizations. This framework strengthens both theoretical understanding and practical application by emphasizing that successful digital transformation depends not only on technological capability, but also on human readiness, organizational alignment, and data governance. Previous studies have highlighted the importance of human factors and organizational readiness in construction digitalization (Bidhendi et al., 2026), the complementary role of technology, data, and human capital in value creation (Gillani et al., 2024), and the need to align AI and data analytics with organizational dynamics and ethical considerations (Bondarenko & Mylyanyk, 2025). Building on these insights, this study offers a socio-technical perspective for understanding digital productivity in industrial and construction contexts, thereby providing a foundation for more adaptive, measurable, and sustainable digital transformation strategies (Abiodun et al., 2023).

METHOD

Research Design

This study employed a Systematic Literature Review (SLR) design guided by the PRISMA 2020 reporting framework. The SLR approach was selected because the study aimed to identify, screen, evaluate, and synthesize previous literature on the role of digitalization and Artificial Intelligence (AI) in improving industrial and construction productivity. The review also focused on supporting factors, inhibiting factors, implementation challenges, skills mismatch, vocational workforce readiness, research gaps, and potential novelty opportunities in the intersection of AI-driven automation, digital transformation, and productivity. The unit of analysis in this study was scholarly literature relevant to AI-driven automation, skills mismatch, vocational workforce development, digitalization, and productivity in industrial and construction contexts. This review positioned digitalization and AI not merely as technical instruments, but as socio-technical systems involving technology, human resources, work processes, data integration, governance structures, and organizational readiness.

Database Selection and Search Strategy

Scopus was used as the primary database because it provides broad interdisciplinary coverage of peer-reviewed publications in engineering, construction management, industrial productivity, computer science, vocational education, and technology management. The use of Scopus also enabled the identification of journal quartile information, publication metadata, and subject-area relevance, which were useful for the initial filtering process. However, journal quartile was not treated as the sole indicator of article quality. Instead, it was used only as an initial source-filtering criterion before a more substantive quality appraisal was conducted. The search strategy was developed using three main keyword clusters: AI-driven automation, skills mismatch, and vocational workforce. These keyword clusters were selected because they represented the main conceptual focus of the study, namely the relationship between technological transformation, workforce readiness, and productivity. To reduce the possibility of database bias, the Scopus search was complemented with additional sources derived from a previously compiled research reference collection. These additional sources were not included automatically, but were reassessed based on relevance, full-text availability, scholarly credibility, and contribution to the research focus.

Table 1. Search Strategy and Source Identification

Component	Description
Primary database	Scopus
Main keyword clusters	"AI-driven automation", "skills mismatch", "vocational workforce"
Supporting thematic scope	Artificial Intelligence, digitalization, industrial productivity, construction productivity, workforce readiness, digital literacy, and governance
Publication year range	2022–2026
Initial journal tier filter	Scopus-indexed Q1 and Q2 journals
Additional source type	Previously compiled scholarly references relevant to AI, digitalization, vocational workforce, and productivity
Purpose of additional sources	To complement Scopus results and reduce the exclusion of relevant studies not captured by the main keyword search

Eligibility Criteria

The eligibility criteria were designed to ensure that the reviewed literature was relevant, credible, and suitable for synthesis. The initial Scopus corpus was limited to publications from 2022 to 2026, articles published in Q1 and Q2 journals, and records that contained abstracts. These initial criteria were applied to ensure that the main database corpus reflected recent, reputable, and sufficiently traceable publications. In addition to the initial bibliographic criteria, all retrieved reports were assessed based on substantive eligibility. Articles were included when they discussed at least one major aspect of AI-driven automation, digitalization, skills mismatch, vocational workforce readiness, or productivity in industrial and construction contexts. Articles were excluded when they were outside the publication year range, did not contain an abstract, were not accessible in full text, were not relevant to the research focus, or did not provide sufficient methodological or conceptual clarity for synthesis.

Table 2. Inclusion and Exclusion Criteria

Criterion	Inclusion Criteria	Exclusion Criteria
Publication period	Studies published between 2022 and 2026	Studies published outside the specified period
Source type	Peer-reviewed journal articles and relevant scholarly reports	Popular articles, opinion pieces, and non-scholarly documents
Database status	Scopus-indexed publications for the primary corpus	Publications not meeting the initial Scopus filtering requirements for the primary corpus
Journal quality filter	Q1 and Q2 journals for Scopus-based records	Scopus records outside Q1 and Q2 journals
Abstract availability	Records with abstracts available for screening	Records without abstracts
Full-text availability	Reports available in full text	Reports that could not be retrieved in full text after the retrieval process
Topical relevance	Studies related to AI, digitalization, automation, skills mismatch, vocational workforce, and productivity	Studies unrelated to the research focus
Methodological clarity	Studies with sufficient methodological or conceptual information	Studies with insufficient information for extraction and synthesis

Study Selection Process

The article selection process followed the PRISMA 2020 flow. The initial identification through the Scopus database produced 272 records. No duplicate records were found at this stage. Before screening, 153 records were removed because they were outside the publication year range of 2022–2026. A further 31 records were excluded because they did not meet the Q1 and Q2 journal tier criteria, and two records were removed because they did not contain abstracts. After the initial filtering process, 86 records were retained for screening. No records were excluded during the initial title and abstract screening stage because all remaining records were considered potentially relevant to the research focus. The 86 reports were then sought for full-text retrieval. However, 64 reports could not be obtained in full text. In this study, a report was categorized as not retrieved when the full text could not be accessed through the available journal platform, open-access search, institutional access, repository tracing, or academic search channels. These unretrieved reports were documented as access limitations and were not included in the synthesis because their contents could not be assessed comprehensively.

A total of 22 Scopus-based reports were successfully retrieved and assessed for eligibility. In addition, 44 reports from other scholarly sources were identified from the previously compiled research reference collection. To maintain the systematic nature of the review, these additional reports were assessed using the same substantive eligibility criteria applied to the Scopus-based reports, particularly in terms of topical relevance, full-text availability, scholarly credibility, and contribution to the research questions. After eligibility assessment, the final corpus consisted of 66 reports, comprising 22 reports from Scopus and 44 reports from additional scholarly sources.

Table 3. PRISMA 2020 Study Selection Summary

Selection Stage	Number of Records/ Reports	Description
Records identified from Scopus	272	Initial records obtained through keyword search
Duplicate records removed	0	No duplicate records were identified
Records removed due to publication year limit	153	Records outside the 2022–2026 range
Records removed due to journal tier criteria	31	Records not meeting Q1/Q2 criteria
Records removed due to absence of abstract	2	Records without abstracts
Records screened	86	Records entering screening stage
Records excluded during screening	0	No records excluded at this stage
Reports sought for full-text retrieval	86	Reports searched for full-text access
Reports not retrieved	64	Full text could not be obtained
Scopus reports assessed for eligibility	22	Full-text Scopus reports assessed
Additional reports assessed for eligibility	44	Reports from other scholarly sources assessed
Final reports included in synthesis	66	Total corpus analyzed in the study

Quality Appraisal

To address the limitation of using journal quartiles as the only quality criterion, this study applied an additional quality appraisal process after the eligibility stage. Journal quartile information was used only as an initial indicator of source reputation for Scopus-indexed articles, whereas the quality of the included studies was assessed through an adapted appraisal framework informed by CASP and AMSTAR principles. This appraisal was used to evaluate the clarity, credibility, and analytical usefulness of each report before synthesis. The quality appraisal focused on five domains: clarity of research aims, appropriateness of methodology, transparency of data collection or literature search, credibility of findings, and relevance to the present review. Each report was examined to determine whether it provided sufficient information to support narrative and thematic synthesis. Studies with weak methodological transparency were not used as primary evidence for strong claims, although they could be used cautiously when they provided relevant conceptual support.

Table 4. Quality Appraisal Framework

Appraisal Domain	Assessment Focus
Clarity of aim	Whether the study clearly stated its purpose, problem, or research focus
Methodological appropriateness	Whether the method was suitable for the study objective
Transparency of data collection or search process	Whether the study explained its data source, sampling, literature search, or evidence base
Credibility of findings	Whether the findings were supported by data, analysis, or sufficient argumentation
Relevance to the review focus	Whether the study contributed to understanding AI, digitalization, workforce readiness, skills mismatch, or productivity

Data Extraction

Data extraction was conducted using a structured extraction sheet. The extraction sheet was designed to ensure consistency across all included reports and to capture both bibliographic and analytical information. The extracted information included article identity, author name, year of publication, research location, research objectives, theoretical foundation, research method, main findings, research limitations, and relevance to digitalization, AI, and industrial or construction productivity. In addition to general bibliographic information, the extraction process also focused on the relationship between technology, human resources, governance, and productivity. This was necessary because the review aimed to synthesize AI and digitalization as socio-technical phenomena. Therefore, the extraction sheet included analytical categories related to technological roles, supporting factors, inhibiting factors, workforce readiness, digital literacy, data integration, digital governance, productivity indicators, research gaps, and novelty opportunities.

Table 5. Data Extraction Framework

Extracted Information	Description
Article identity	Title, author, year, source, and publication information
Research context	Country, sector, industry, or construction-related context
Research objective	Main purpose or research question of the study
Theoretical basis	Theory, model, or conceptual framework used in the article
Methodology	Research design, data source, sample, and analytical approach
Main findings	Key results related to AI, digitalization, workforce, and productivity
Limitations	Methodological, contextual, or conceptual limitations reported by the article
Relevance to review	Contribution to understanding AI-driven automation, skills mismatch, vocational workforce, and productivity
Thematic code	Classification into technology, human resources, governance, productivity, barriers, enablers, or novelty opportunities

Data Analysis and Synthesis

The data were analyzed using narrative and thematic synthesis. Narrative synthesis was used to explain the development of research findings across the reviewed literature, while thematic synthesis was used to classify findings into recurring conceptual categories. The synthesis process began with reading and coding each included report, followed by grouping similar findings into broader analytical themes. The themes were then compared across studies to identify convergences, differences, implementation challenges, and research gaps. The thematic analysis focused on the role of technology, supporting factors, inhibiting factors, human resource readiness, data integration, digital governance, productivity outcomes, and novelty opportunities. Productivity was not treated only as an economic output, but as the result of interactions among technology, people, data, work processes, and organizational systems. This analytical position allowed the review to examine how AI and digitalization influence productivity through technical, human, and institutional mechanisms.

Table 6. Thematic Coding Framework

Key Variable	Sub-Variables	Analytical Focus
Digitalization	BIM, IoT, digital twin, cloud systems, dashboard	Coordination, information quality, error reduction, and process integration
Artificial Intelligence	Automation, machine learning, AI vision, predictive systems	Accuracy improvement, reduction of manual burden, and decision acceleration
Human Resources	Digital literacy, competence, training, agency	Workforce readiness and effective use of technology
Governance	SOP, interoperability, security, standardization	Consistency, accountability, and responsible technology implementation
Productivity	Time, cost, quality, accuracy, energy efficiency, materials, decision-making	Output of interaction among technology, people, data, and organizations

Bibliometric and Visual Analysis Support

To support the thematic synthesis, bibliometric visualizations were used to map the conceptual relationships among keywords and research themes. Network analysis was used to identify clusters of related concepts, trend analysis was used to observe the temporal development of research themes, and density analysis was used to identify dominant and emerging areas in the literature. These visual analyses were used as complementary tools to support interpretation, not as replacements for critical reading and thematic synthesis. The bibliometric mapping helped identify the concentration of studies around artificial intelligence, automation, vocational education, digitalization, and productivity. It also helped reveal how research on AI-driven automation is connected to workforce competence, skills mismatch, governance, and industrial transformation. The results of this mapping were then integrated into the narrative synthesis to strengthen the identification of research gaps and novelty opportunities.

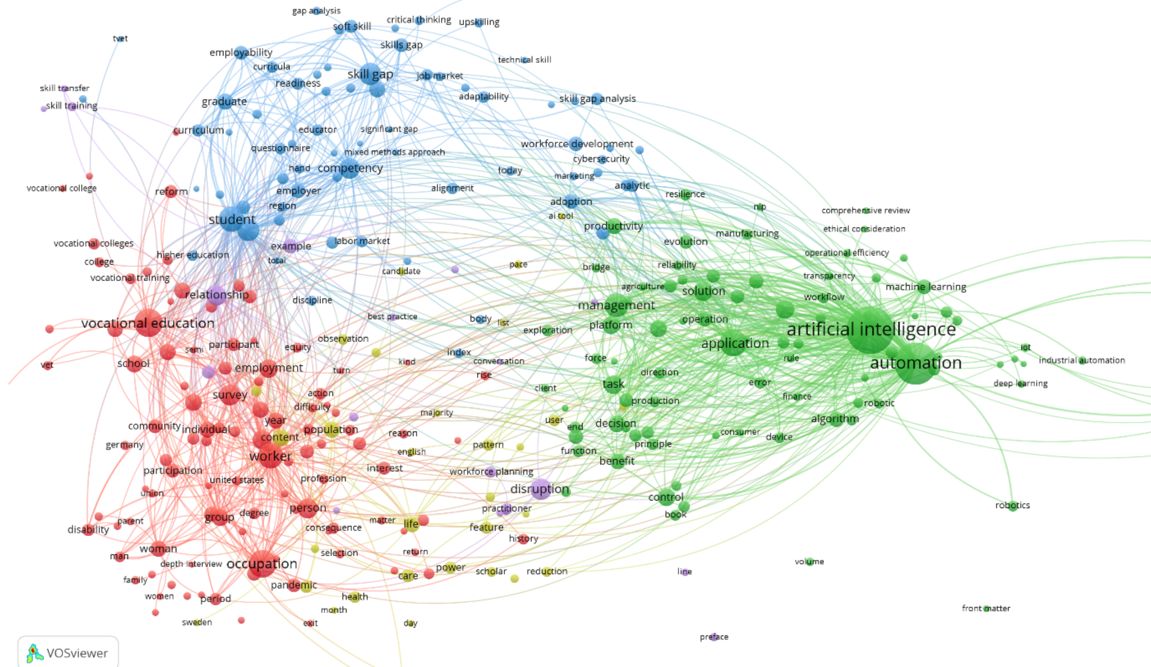

Figure 1. Network Analysis

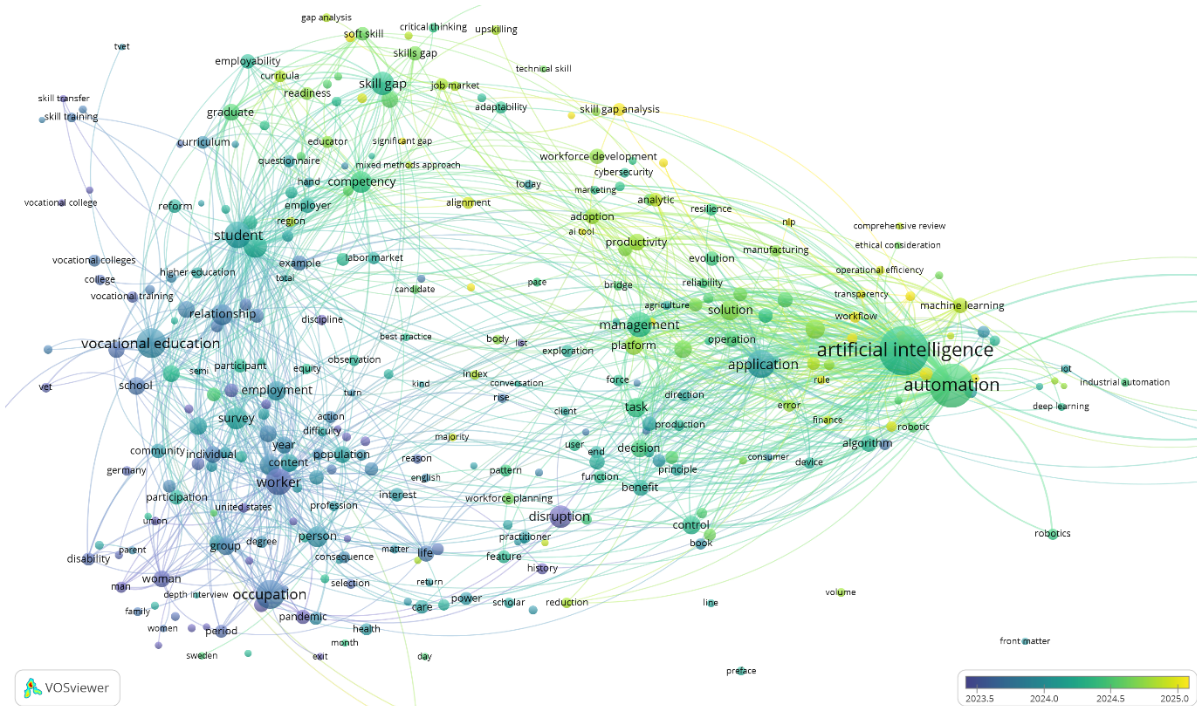

Figure 2. Trend Analysis

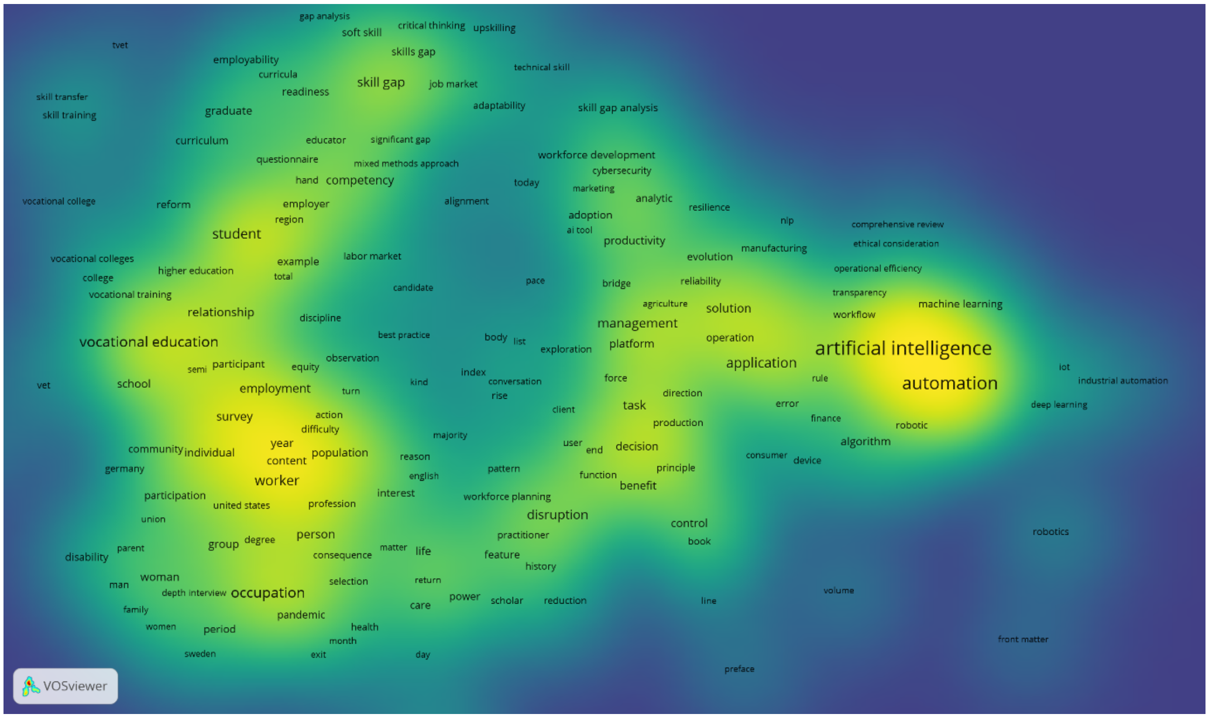

Figure 3. Density Analysis

Methodological Rigor and Replicability

Several procedures were applied to improve the rigor and replicability of the review. First, the search process was documented through the PRISMA 2020 flow so that the number of identified, screened, retrieved, and included reports could be traced transparently. Second, the basis for database selection, keyword use, publication year limitation, journal tier filtering, and additional source inclusion was explicitly explained. Third, full-text non-retrieval was reported as an access limitation to avoid inflating the evidence base with reports that could not be assessed. Fourth, the additional 44 sources were subjected to substantive eligibility and quality appraisal to maintain consistency with the Scopus-based reports. Finally, data extraction and synthesis were conducted using predefined analytical categories to ensure that the review remained systematic, transparent, and aligned with the research objectives.

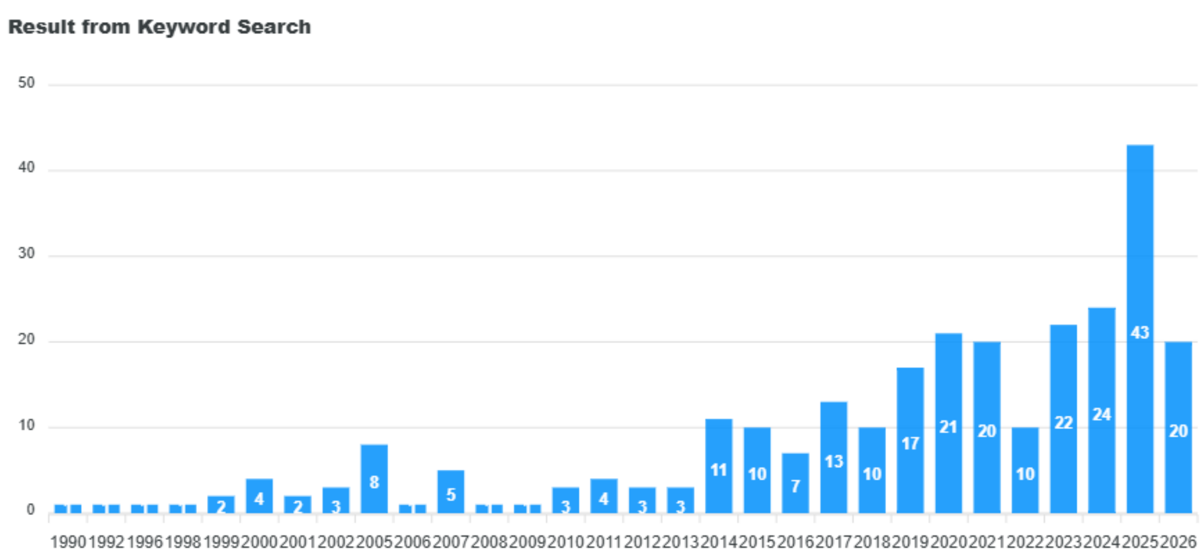

Figure 4. Publication Diagram

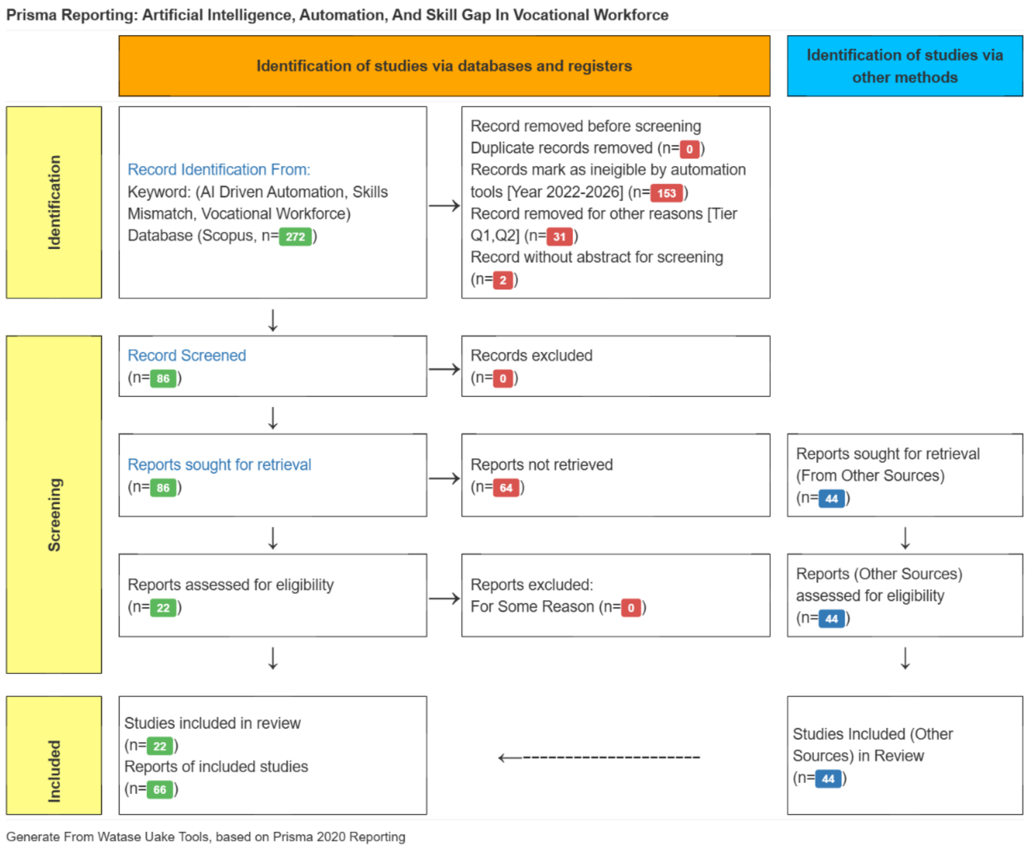

Figure 5. Prisma Reporting

RESULTS

Study Corpus and Publication Pattern

The final corpus of this review consisted of 66 reports, including 22 reports retrieved from the Scopus database and 44 reports from additional scholarly sources that met the eligibility and relevance criteria. These reports were synthesized to answer three research questions concerning the role of digitalization and Artificial Intelligence in industrial and construction productivity, the supporting and inhibiting factors affecting implementation, and the research gaps and novelty opportunities identified in the literature.

The broader keyword-based publication mapping showed that academic attention to digitalization, AI-driven automation, skills mismatch, vocational workforce, industry, and construction productivity has increased gradually over time. Publications were relatively limited in the early period, then began to increase more visibly after 2014. The largest concentration of publications appeared during 2019–2026, with the highest number recorded in 2025. This pattern indicates that the relationship between digital technologies, automation, workforce readiness, and productivity has become an increasingly prominent research focus in recent literature.

The network, trend, and density analyses showed that the reviewed literature was concentrated around several recurring themes, including artificial intelligence, automation, digitalization, BIM, IoT, digital twins, robotics, blockchain, business intelligence, vocational workforce, skills mismatch, digital literacy, and productivity. These clusters suggest that productivity research in industrial and construction contexts has increasingly moved from a purely technical discussion toward a broader concern with data systems, human resources, governance, and organizational transformation.

The Role of Digitalization and Artificial Intelligence in Productivity

The first research question examined how previous literature explains the role of digitalization and Artificial Intelligence in improving industrial and construction productivity. The synthesis shows that digitalization and AI contribute to productivity through several recurring mechanisms, namely process automation, improvement of work accuracy, quality control, decision-making acceleration, resource optimization, and coordination enhancement. These findings were not treated as pooled statistical effects because the reviewed studies used different designs, indicators, contexts, and measurement approaches. Therefore, the results are presented as thematic patterns rather than meta-analytic estimates.

Digitalization was mainly associated with the strengthening of information flow, coordination, monitoring, and project control. Technologies such as BIM, IoT, digital twins, cloud systems, dashboards, and project information platforms were frequently reported as tools that help organizations reduce fragmented communication, improve data availability, and support more structured decision-making. In the construction context, digitalization was also linked to collaboration, quality improvement, error reduction, and project management effectiveness.

Artificial Intelligence was more frequently associated with automation, prediction, inspection, and decision support. AI-based technologies such as machine learning, computer vision, AI vision, predictive systems, and design automation were reported to reduce manual workload, improve accuracy, accelerate operational processes, and support quality control. In industrial and construction settings, AI was also linked to predictive maintenance, resource allocation, energy management, workflow optimization, and adaptive decision-making.

Human-AI collaboration emerged as an important pattern in the reviewed literature. Several studies emphasized that AI becomes more productive when combined with human validation, particularly in complex, high-risk, or judgment-sensitive tasks. Human-in-the-loop mechanisms were identified as a way to combine the speed and consistency of AI systems with human contextual understanding, ethical judgment, and practical experience.

Supporting and Inhibiting Factors in the Implementation of Digitalization and AI

The second research question focused on the factors that support or inhibit the implementation of digitalization and AI in improving productivity. The results show that the most frequently identified supporting factors were data quality, digital infrastructure, interoperability, human resource readiness, digital literacy, training, organizational support, governance, standardization, system security, and human-in-the-loop validation. These factors appeared repeatedly across the reviewed literature as conditions that allow digital technologies and AI systems to produce more reliable productivity outcomes.

Data quality was one of the most central supporting factors. AI and digital systems depend on accurate, complete, integrated, and accessible data to support automation, prediction, monitoring, and decision-making. Digital infrastructure also appeared as a key enabler because technologies such as IoT, blockchain, digital twins, cloud-to-edge computing, dashboards, sensors, databases, and real-time data systems provide the technical foundation for productive digital transformation.

Human resource readiness was another recurring factor. Digital literacy, technical competence, training, technology acceptance, and vocational workforce readiness influenced whether workers and managers were able to use, interpret, and integrate digital technologies into work practices. The reviewed literature shows that technology adoption alone is insufficient when users do not have the capacity to operate digital systems, validate AI outputs, and translate data into productive decisions.

The synthesis also identified several inhibiting factors. The most frequent barriers were interoperability problems, inconsistent data quality, skills mismatch, resistance to change, organizational fragmentation, limited infrastructure, data security risks, limited explainability, and non-uniform productivity measurement. In construction, these barriers are intensified by project-based work, multiple actors, fragmented responsibilities, and heterogeneous productivity indicators.

Table 7. Thematic Results Organized by Research Questions

Research Question	Main Result Category	Thematic Finding	Productivity-Related Outcome
RQ1: How do digitalization and AI improve industrial and construction productivity?	Digitalization systems	BIM, IoT, digital twins, cloud systems, dashboards, and project data platforms strengthen coordination, information flow, and monitoring.	Improved coordination, better information quality, reduced errors, and stronger project control.
RQ1	AI-driven automation and inspection	Machine learning, computer vision, predictive systems, embedded automation, and AI vision support automation, inspection, and quality control.	Reduced manual workload, improved accuracy, faster inspection, and more stable quality control.

Research Question	Main Result Category	Thematic Finding	Productivity-Related Outcome
RQ1	AI-based decision support	Predictive analytics, closed-loop workflows, digital simulation, and decision support systems assist planning, design, maintenance, and operational decisions.	Faster decisions, resource optimization, reduced downtime, and improved operational efficiency.
RQ2: What factors support or inhibit implementation?	Supporting factors	Data quality, interoperability, digital infrastructure, digital literacy, training, governance, system security, and organizational support enable more effective implementation.	Technology produces stronger productivity outcomes when supported by people, data, and governance readiness.
RQ2	Inhibiting factors	Skills mismatch, resistance to change, fragmented systems, weak infrastructure, low data quality, limited explainability, and security risks constrain implementation.	Productivity gains may weaken when technology is not integrated into work processes and organizational systems.
RQ3: What gaps and novelty opportunities can be identified?	Research gap	Existing studies often discuss AI, digitalization, competence, governance, and productivity separately.	There is limited synthesis connecting technology, workforce readiness, governance, and productivity in one framework.
RQ3	Novelty opportunity	An integrative socio-technical framework is needed to explain productivity as the interaction among technology, people, processes, data, and organizations.	Future research can develop multidimensional productivity models for industrial and construction digital transformation.

Research Gaps and Novelty Opportunities

The third research question examined the research gaps, implementation challenges, and novelty opportunities found in the literature. The synthesis shows that the main research gap lies in the fragmented treatment of digitalization, Artificial Intelligence, workforce competence, data governance, and productivity. Some studies focus on digital construction and project coordination, while others examine AI from technical perspectives such as automation, computer vision, robotics, design automation, deep learning, or decision support systems. Another group of studies focuses on human readiness through digital literacy, vocational training, skills mismatch, labor agency, and technology acceptance.

The reviewed literature also shows that governance-related issues are often discussed separately from technology and workforce readiness. Topics such as data security, interoperability, standard operating procedures, structured databases, blockchain, IoT, digital twins, audit trails, explainability, and accountability are frequently presented as technical or managerial concerns, but they are not always integrated into productivity frameworks. This separation limits the ability of existing literature to explain why similar technologies may produce different productivity outcomes across organizations, projects, and sectors.

The novelty opportunity identified in this review is the development of an integrative framework that connects AI-driven automation, digitalization, skills mismatch, vocational workforce readiness, data quality, interoperability, governance, and multidimensional productivity. Such a framework would allow productivity to be understood not only through time and cost efficiency, but also through quality, safety, accuracy, energy efficiency, material use, reduction of rework, coordination, and decision quality.

Summary of Results

Overall, the results show that digitalization and Artificial Intelligence contribute to industrial and construction productivity through automation, coordination, prediction, quality control, decision support, resource optimization, and workflow integration. However, these contributions depend on several enabling conditions, including data quality, digital infrastructure, interoperability, human resource readiness, digital literacy, training, governance, security, and organizational support.

The results also show that the main barriers to implementation are skills mismatch, resistance to change, fragmented systems, limited infrastructure, low data quality, weak explainability, security risks, and non-uniform productivity measurement. These findings confirm that digitalization and AI should be reported as socio-technical productivity enablers rather than as isolated technological tools. The most important result of this review is the need for an integrated framework that explains productivity as the outcome of interaction among technology, people, work processes, data systems, and organizational governance.

DISCUSSION

The findings of this review indicate that digitalization and Artificial Intelligence (AI) should not be understood merely as technological instruments, but as socio-technical mechanisms that influence productivity through the interaction of technology, human resources, data, work processes, and governance structures. This perspective is important because the value of AI does not arise solely from automation capability, but from its alignment with organizational routines, human competence, institutional standards, and accountable governance. A socio-technical lens therefore provides a stronger basis for explaining why similar technologies may produce different productivity outcomes across industrial and construction contexts (Sartori & Theodorou, 2022; Steinmueller, 2025; Watson et al., 2025).

Within this socio-technical perspective, digitalization and AI contribute to productivity by automating work processes, improving information flow, strengthening quality control, and optimizing resource management. In construction, hierarchical productivity frameworks emphasize the need for standardized processes and real-time monitoring to support data-driven decision-making and measurable productivity indicators such as First-Time Quality and the Overall Productivity Index (Bühler et al., 2025). AI-driven digital twins also enable dynamic scheduling, predictive maintenance, and real-time quality control, particularly in industrialized and offsite construction environments where data fragmentation remains a major challenge (Najafzadeh & Yeganeh, 2025). These findings are consistent with studies showing that AI applications in facility management, design optimization, planning, and risk identification can improve project execution across the construction lifecycle (Adejola & Nwobodo-Anyadiegwu, 2025; Egwim et al., 2023; Zabala-Vargas et al., 2023).

However, the contribution of AI and digital systems to operational efficiency must be interpreted carefully because productivity gains are stronger when technological functions are embedded within coordinated work systems. Previous studies show that AI adoption can increase total factor productivity and improve value creation through technological upgrading and better data utilization (Gao & Feng, 2023; Wang & Li, 2025). Nevertheless, superior organizational performance is more likely to emerge from the synergistic combination of AI applications across business functions rather than from isolated technological adoption (Cao et al., 2025). This implies that digital productivity depends not only on the5. This implies that digital productivity depends presence of advanced tools, but also on the ability of organizations to integrate these tools into coherent operational, managerial, and strategic frameworks (Angelopoulos et al., 2023; Zhai & Liu, 2023).

The reviewed literature also shows that the technical success of AI in specific construction tasks does not automatically lead to immediate cost savings or direct productivity improvement. Although AI has considerable potential in risk management, design optimization, predictive maintenance, and cost control, its implementation is often constrained by limited adaptability, fragmented data systems, interoperability problems by limited adaptability, fragmented, and socio-organizational resistance (Avogaro et al., 2025; Tian et al., 2025). Similar challenges appear in studies on AI, BIM, and Life Cycle Costing integration, where the anticipated benefits of AI remain difficult to realize because the digital ecosystem is not yet fully mature (Regona et al., 2024; Zhang & Jiang, 2026). This indicates that construction productivity cannot be inferred only from the technical performance of AI systems, as project-based environments involve complex coordination, heterogeneous actors, project-based environments involve complex coordination and highly contextual work conditions.

This complexity reinforces the need to interpret AI implementation through a socio-technical framework rather than a purely techno-economic perspective. A techno-economic view tends to treat technological innovation as an external driver of productivity, whereas a socio-technical approach explains productivity as the outcome of interactions among human capability, data reliability, workflow integration, institutional standards, and governance mechanisms (Steinmueller, 2025). In construction, this explanation is particularly relevant because digital tools must operate within temporary project organizations, multi-actor collaboration, changing site conditions, and safety-sensitive decision environments. Therefore, the productivity value of AI depends on whether organizations can translate technical capability into reliable, whether organizations can translate technical capability into reliable, explainable, and accountable work practices.

In relation to human roles, this review suggests that augmented intelligence is a more relevant productivity model than full automation. AI can accelerate analysis, automate repetitive processes, and improve operational accuracy, but human actors remain essential for validation, contextual judgment, and critical decision-making. Studies on task complementarity show that augmentation is particularly valuable when human and AI capabilities need to be combined, while full automation is more suitable for simpler and more repetitive tasks (Fügener et al., 2026). This distinction is crucial in construction because many project decisions involve safety, cost, design changes, quality control, and field uncertainty. Thus, AI should be positioned as a system that enhances human performance rather than as a substitute for professional expertise (Altrock et al., 2025; Jain et al., 2021; Mazurova & Standaert, 2024).

The productivity value of AI is also strongly influenced by data governance and organizational readiness. Abundant digital data will not become governance and organizational readiness. Ab productive knowledge unless organizations have clear data standards, interoperability mechanisms, accountability structures, and quality assurance procedures. Effective AI governance requires the management of data, machine learning models, and AI systems through defined roles and responsibilities to ensure data quality, security, and reliability (Schneider et al., 2023). Organizations also need to assess data readiness because poor data quality can weaken the accuracy and usefulness of AI models (Hiniduma et al., 2025). In this regard, organizational capabilities such as data management, project planning, explainability, and workflow integration are essential for converting digital information into actionable productivity gains (Armanios & Tucci, 2025; Dai & Swaminathan, 2025; Weber et al., 2023).

The scientific contribution of this study lies in its integrative analytical framework, which connects AI-driven automation, digitalization, skills mismatch, vocational workforce readiness, governance, and multidimensional productivity. This framework responds to the persistent productivity gap in construction by showing that productivity should not be measured only through cost and time efficiency, but also through quality, accuracy, safety, coordination, efficiency, but also through quality, accuracy rework reduction, resource utilization, and decision quality. The framework also highlights the importance of education, reskilling, and workforce adaptation, especially because the rapid adoption of AI and automation may produce new skills mismatches and employment transitions (Lee et al., 2024; Okur & Özdemir, 2025). Practically, these findings imply that construction firms need to balance investment in digital technologies with workforce development, data governance, and organizational reform to achieve sustainable productivity improvement (Alnaser & Elmousalami, 2025; Ershadi & Lijauco, 2026).

Finally, this review indicates that future research should empirically validate the proposed framework using objective productivity indicators in specific industrial and construction projects. Existing performance measurement approaches in construction are often insufficient because they rely heavily on financial indicators and do not fully capture stakeholder performance, safety, environmental impacts, process reliability, and decision quality (Ibrahim et al., 2024). The development of hierarchical productivity models and real-time monitoring systems offers a promising direction for improving measurement accuracy and managerial responsiveness (Bühler et al., 2025). Future studies should also examine how Lean Construction, BIM, AI, digital twins, and integrated project delivery methods interact in improving construction productivity, as empirical evidence on these combined approaches remains limited (Alnajjar et al., 2025; Rebai et al., 2025; Taghaddos et al., 2024). Thus, further empirical work is needed to move the discussion from conceptual integration toward measurable productivity transformation in real project environments.

CONCLUSION

This study concludes that digitalization and Artificial Intelligence play an important role in improving industrial and construction productivity through automation, information integration, quality control, predictive analysis, resource optimization, and data-driven decision-making. However, the review also shows that productivity gains do not emerge automatically from the adoption of digital technologies. Their effectiveness depends on the readiness of human resources, data quality, interoperability, organizational support, governance mechanisms, system security, and the ability of users to understand and validate AI-based outputs. Therefore, digitalization and AI should be understood as socio-technical enablers of productivity rather than as standalone technological solutions.

The main contribution of this study lies in its integrative framework, which connects AI-driven automation, digitalization, skills mismatch, vocational workforce readiness, data governance, and multidimensional productivity within a single analytical perspective. This framework emphasizes that productivity in industrial and construction contexts should not be measured only through time and cost efficiency, but also through quality, accuracy, safety, rework reduction, energy efficiency, coordination, and decision quality. Future research is recommended to empirically test this framework in specific industrial and construction projects using objective productivity indicators and by examining the mediating or moderating roles of digital literacy, organizational readiness, data quality, and technology governance.

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AUTHOR CONTRIBUTION STATEMENT

KS, in the capacity of principal author and student, assumes responsibility for the conceptualization, research design, data collection, data analysis, and the preparation of the manuscript. AH, serving as an advisor, offers guidance on the research framework, conducts a critical evaluation of the methodology, and maintains overall oversight of the research process. NY, acting as co-promoter, has made significant contributions to the formulation of the theoretical background, the interpretation of results, and the critical revision of the manuscript with respect to its intellectual content. CA lends expertise in the domains of vocational education and the integration of artificial intelligence, providing counsel on the discussion, implications for policy, and validation of the findings. All authors engaged in a thorough review and granted their approval for the final version of the manuscript.

AI DISCLOSURE STATEMENT

The author engaged the services of ChatGPT (OpenAI) in composing this manuscript for linguistic enhancement and to elucidate intricate concepts. Subsequent to the utilization of this tool, the author conducted a comprehensive review and made requisite revisions to the content, thereby assuming complete accountability for the integrity of the publication. The authors assert that this research was conceived, investigated, articulated, and refined independently of artificial intelligence (AI) methodologies concerning the fundamental intellectual efforts, data analysis, and interpretative processes.

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