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Artificial Intelligence and Building Information Modelling for Sustainable Construction Project Management and Digitalization in Construction

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Abstract

The rapid development of digital technologies presents both a challenge and an opportunity for strengthening sustainability in construction project management. Within the broader digitalization agenda, Building Information Modelling (BIM) and Artificial Intelligence (AI) have emerged as key tools for improving environmental and economic performance through resource optimization. While traditional methods for optimizing resources, costs, and time remain relevant, the integration of BIM and AI introduces innovative capabilities that support decision-making, process automation, and data-driven sustainability strategies. The aim of this research is to analyze the extent to which BIM and AI are used for sustainable resource optimization in construction and to quantify their potential impact on the optimization of costs, resources, and time in the sector. A cross-sectional survey was conducted among construction companies operating in three European markets, Slovakia, Slovenia, and Croatia. The collected data were analyzed using descriptive statistics, correlation and regression analysis, and statistical hypothesis testing to assess the significance of relationships between technology adoption and sustainability outcomes. The results confirm that BIM adoption is positively correlated with improved sustainability management and optimization practices, with usage levels varying by company size and project scale. In contrast, AI adoption remains at a low level, indicating untapped potential for broader application. These findings contribute to understanding the role of digital tools in driving sustainable transformation in the construction sector and highlight areas for further research and practical deployment. BIM demonstrates particularly strong correlations with cost planning (r = 0.983), resource planning (r = 0.964), and schedule planning (r = 0.867), while AI shows robust associations with cost planning (r = 0.925), schedule planning (r = 0.865), and resource planning (r = 0.809). The findings indicate that maximum effectiveness is achieved when BIM and AI are deployed in a complementary manner under skilled human oversight.

Keywords: Artificial Intelligence; BIM; sustainability; optimization in construction; construction project management; digital transformation

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1. Introduction

The construction industry stands as one of the most resource-intensive sectors globally, consuming approximately 40% of total energy and generating nearly one-third of greenhouse gas emissions worldwide [1,2]. As urbanization accelerates and infrastructure demands increase, the imperative for sustainable construction practices has never been more urgent [3]. The European Green Deal and related policy frameworks have established ambitious targets for decarbonization and resource efficiency, placing the construction sector at the center of sustainability transformation efforts [4,5]. Despite its economic significance, the construction industry remains one of the least digitized sectors [6,7]. This technological lag contributes to persistent inefficiencies, cost overruns, schedule delays, and suboptimal resource utilization that characterize many construction projects [8,9]. The Industry 4.0 paradigm, characterized by cyber-physical systems, the Internet of Things, cloud computing, and artificial intelligence, offers a comprehensive framework for addressing these challenges through digital transformation [10,11]. Within this context, Building Information Modelling (BIM) and Artificial Intelligence (AI) have emerged as particularly promising technologies for revolutionizing construction processes and enhancing sustainability outcomes [12,13].

BIM represents a fundamental shift from traditional two-dimensional design approaches to integrated, information-rich digital representations of building assets across their entire lifecycle [14,15]. By facilitating co-ordination among project stakeholders and enabling simulation of building performance, BIM provides a foundation for improved decision-making in design, construction, and facility management [16,17]. The technology has demonstrated significant potential for reducing material waste, optimizing energy performance, and enhancing overall project efficiency [18,19].

Artificial Intelligence complements BIM capabilities by enabling advanced data analytics, pattern recognition, and predictive modeling [20,21]. Machine learning algorithms can process vast quantities of project data to forecast costs, identify risks, optimize schedules, and support complex decision-making processes that would be impractical through traditional methods [22,23]. The integration of AI with BIM creates opportunities for automated design optimization, real-time performance monitoring, and intelligent resource allocation [24,25].

While the theoretical advantages of these technologies are well-documented, empirical evidence regarding their practical implementation and measurable impacts on sustainability outcomes remains fragmented [26,27]. Previous research has predominantly focused on case studies from highly developed economies or has examined technologies in isolation rather than investigating their combined effects [28,29]. Furthermore, there is a notable scarcity of quantitative studies examining digital technology adoption in Central and Southeastern European construction markets, where specific economic, regulatory, and structural conditions shape the pace and nature of technological transformation [30,31]. This research addresses these gaps by providing systematic empirical evidence on the implementation of BIM and AI technologies in the construction sectors of Slovakia, Slovenia, and Croatia, and by quantifying their contribution to resource optimization and sustainability planning. The study responds to calls for rigorous quantitative investigations that can inform evidence-based policy development and industry practice [32,33].

The specific contributions of this research are as follows:

- Quantitative assessment of BIM and AI adoption levels across three Central European construction markets, providing baseline data for regional digital maturity evaluation.
- Empirical validation of statistically significant relationships between digital technology implementation and key sustainability indicators including resource planning, cost optimization, and schedule management.

- Comparative analysis of BIM versus AI effectiveness, revealing that BIM demonstrates stronger correlations with sustainability outcomes while AI provides complementary value in dynamic forecasting and operational decision-making.
- Identification of cross-country variations in technology utilization patterns that reflect different market conditions, regulatory frameworks, and organizational capacities.
- Evidence-based recommendations for policymakers and industry practitioners seeking to accelerate digital transformation in alignment with European Green Deal objectives.

The remainder of this paper is organized as follows: Section 2 presents a comprehensive review of the state of the art in BIM, AI, and sustainable construction, establishing the theoretical foundation and identifying research gaps. Section 3 describes the research methodology, including the survey instrument, sampling strategy, and analytical procedures. Section 4 presents and discusses the empirical results. Section 5 concludes with a summary of key findings, practical implications, and directions for future research.

In this study, BIM and AI are conceptualized not merely as standalone digital tools but as socio-technical systems whose performance and sustainability impact depend on their embedding in organizational routines, data infrastructures, and institutional environments. In practice, value creation from BIM–AI adoption requires the alignment of technological components (software, data models, interoperability, automation) with social and organizational elements (skills, roles, collaboration practices, governance, and decision rights). This perspective is consistent with technology adoption frameworks that (1) emphasize multi-level determinants, such as the Technology–Organization–Environment (TOE) lens, where adoption and outcomes are shaped by (technological readiness and data quality, (2) organizational capabilities (e.g., BIM execution planning, AI readiness, change management, and absorptive capacity), and (3) external pressures and enablers (e.g., standards, procurement requirements, regulation, and supply-chain interoperability). Consequently, the sustainability benefits attributed to BIM and AI, particularly for cost, schedule, and resource planning, should be interpreted as outcomes of a broader socio-technical configuration rather than as direct effects of software availability alone. This framing also explains why certain sustainability dimensions (e.g., materials/circularity) may lag: they often require deeper supply-chain integration, traceability, and governance structures beyond project-level digitalization.

2. Literature Review

2.1. Industry 4.0 and the Digital Transformation of Construction

The Fourth Industrial Revolution, commonly referred to as Industry 4.0, represents a paradigm shift characterized by the convergence of digital, physical, and biological systems [10,34]. Originating in manufacturing contexts, Industry 4.0 principles are increasingly being adapted for the construction sector under the concept of Construction 4.0 [35,36]. This transformation encompasses the integration of cyber-physical systems, the Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence into construction processes [37,38]. The construction industry has historically lagged behind other sectors in technological adoption, exhibiting productivity growth rates significantly below manufacturing and services [6,39]. Factors contributing to this techno-logical inertia include project-based organizational structures, fragmented supply chains, workforce skill gaps, and the unique characteristics of construction products [40,41]. However, mounting pressures related to sustainability, cost efficiency, and quality have intensified interest in digital transformation strategies [42,43]. Digital twins represent an emerging paradigm within Construction 4.0 that extends BIM capabilities through real-time data integration and bidirectional information flow between physical assets and their digital representations [44,45]. By enabling continuous performance monitoring and predictive maintenance,

digital twins offer substantial potential for optimizing building operations and extending asset lifecycles [46,47]. Research indicates that digital twin implementation can reduce operational costs by 10–30% while significantly enhancing sustainability performance [48]. The European construction industry faces imperatives for digital transformation given ambitious policy targets for decarbonization and circular economy transition [49,50]. Studies examining digital maturity across European markets reveal substantial variation, with Nordic countries and the United Kingdom generally demonstrating higher adoption rates than Central and Eastern European nations [51,52]. This digital divide has implications for competitiveness, sustainability outcomes, and the ability to participate in increasingly digitized supply chains [53].

2.2. Building Information Modelling: Foundations and Evolution

Building Information Modelling has evolved from a design visualization tool to a comprehensive framework for managing building information across the entire asset lifecycle [14,54]. The seminal BIM Handbook by Eastman and colleagues established foundational concepts and demonstrated BIM's potential for improving coordination, reducing errors, and enhancing project delivery [55]. Subsequent research has expanded understanding of BIM implementation challenges, success factors, and organizational impacts [56,57]. BIM adoption has progressed through distinct maturity levels, from basic 3D modeling (Level 1) through integrated project delivery (Level 2) to fully integrated lifecycle management (Level 3) [58,59]. While many organizations have achieved Level 2 capability, particularly in response to government mandates in countries such as the United Kingdom and Scandinavian nations, progression to Level 3 remains limited [60,61]. International standards including ISO 19650 have provided frameworks for in-formation management using BIM, facilitating interoperability and establishing common protocols [62,63]. Research on BIM implementation barriers has identified factors including high initial investment costs, lack of skilled personnel, resistance to change, interoperability challenges, and unclear return on investment [64,65]. Small and medium-sized enterprises face challenges due to limited resources and technical capacity [66]. Studies from Central and Eastern European contexts indicate that while awareness of BIM benefits is growing, practical implementation remains constrained by market conditions and regulatory frameworks that have not kept pace with technological developments [67,68]. The integration of BIM with lean construction principles has demonstrated synergies for waste reduction and process optimization [69]. Sacks and colleagues developed a theoretical framework explaining interactions between BIM functionalities and lean principles, showing how both approaches reinforce each other in pursuit of improved project outcomes [70]. This integration is particularly relevant for sustainability, as lean-BIM approaches can significantly reduce material waste and improve resource efficiency [71].

2.3. Building Information Modelling for Sustainable Construction Project Management

Artificial The application of BIM for sustainability purposes, often termed Green BIM, has emerged as a significant research domain [18,72]. BIM provides a platform for integrating environmental performance data, enabling lifecycle assessments, and supporting design optimization for reduced energy consumption and carbon emissions [73,74]. Wong and Zhou's comprehensive review established that Green BIM enhances environmental sustainability throughout building lifecycles by facilitating performance simulation, material selection, and compliance verification [75]. BIM-based energy analysis enables designers to evaluate building performance early in the design process when the potential for optimization is greatest [76,77]. Studies demonstrate that integrating energy simulation tools with BIM can reduce building energy consumption by 15–30% compared to

conventional design approaches [78]. Furthermore, BIM facilitates compliance with green building certification systems such as LEED, BREEAM, and DGNB by automating documentation and enabling performance verification [79,80]. Material efficiency represents another dimension of BIM's sustainability contribution. Accurate quantity take-offs and clash detection reduce material waste during construction, while lifecycle information management supports material reuse and recycling at end-of-life [81,82]. Research indicates that BIM implementation can reduce construction waste by 4–15% depending on project type and implementation maturity [83]. The integration of BIM with circular economy principles offers further potential for closing material loops and reducing resource depletion [84,85]. Despite demonstrated benefits, the adoption of BIM for sustainability purposes remains inconsistent [86]. Chong and colleagues' mixed review identified that while BIM is increasingly mandated for public projects in developed economies, sustainability applications often remain underutilized [87]. Barriers include limited integration between BIM platforms and sustainability assessment tools, insufficient environmental data in BIM libraries, and the need for specialized expertise [88,89].

2.4. Artificial Intelligence in Construction

Artificial Intelligence encompasses a range of computational techniques that enable systems to perform tasks typically requiring human intelligence, including learning, reasoning, and problem-solving [20,90]. In construction contexts, AI applications span project planning and scheduling, cost estimation, risk management, quality control, safety monitoring, and resource optimization [21,91]. Machine learning, deep learning, and natural language processing represent the primary AI techniques applied in construction research and practice [92,93]. Cost estimation represents one of the most extensively researched AI applications in construction. Traditional estimation methods based on historical data and expert judgment are time-consuming and prone to inaccuracies [94]. Machine learning models, including neural networks, support vector machines, and ensemble methods, have demonstrated improved accuracy in cost prediction while reducing estimation time [95,96]. Hashemi and colleagues' systematic review concluded that AI-based cost estimation can improve accuracy by 15–25% compared to conventional methods [97]. Schedule optimization through AI techniques enables more effective project planning and resource allocation. Genetic algorithms, ant colony optimization, and reinforcement learning have been applied to solve complex scheduling problems with multiple objectives and constraints [98,99]. These approaches can simultaneously optimize time, cost, and resource utilization while accounting for uncertainties and dynamic project conditions [100]. Recent research has explored deep learning approaches for schedule prediction and delay forecasting with promising results [101]. AI applications for construction safety have grown substantially, particularly computer vision systems for automated hazard detection and worker monitoring [102,103]. These systems can identify unsafe conditions and behaviors in real-time, enabling proactive intervention before incidents occur. Studies indicate that AI-based safety monitoring can reduce accident rates by 20–40% when combined with appropriate management responses [104]. Despite significant research activity, AI adoption in construction practice remains limited compared to other industries [105,106]. Barriers include data availability and quality challenges, lack of standardized datasets for model training, concerns about algorithm transparency, and workforce skill gaps [107,108]. Small and medium-sized enterprises face challenges in accessing AI technologies and developing necessary capabilities [109].

2.5. Integration of BIM and Artificial Intelligence

The integration of BIM and AI represents an emerging research frontier with substantial potential for construction transformation [24,110]. BIM provides structured geometric and semantic data that can serve as input for AI algorithms, while AI capabilities can enhance BIM functionality through automated analysis, optimization, and decision support [111,112]. This synergy addresses limitations of each technology when applied in isolation. Generative design represents one prominent integration domain where AI algorithms explore design alternatives within BIM environments to optimize specified objectives [113,114]. By evaluating thousands of design options against performance criteria including structural efficiency, energy consumption, and cost, generative design can identify solutions that would not emerge from conventional design processes [115]. Research demonstrates that AI-optimized designs can improve building performance by 10–20% across multiple sustainability metrics [116]. Automated code compliance checking combines BIM's semantic information with AI's reasoning capabilities to verify regulatory compliance [117,118]. Natural language processing extracts requirements from building codes, while rule-based or machine learning systems check BIM models against these requirements. This automation reduces checking time and improves consistency while freeing human reviewers for higher-value tasks [119]. Predictive maintenance applications integrate BIM's building data with AI analytics to forecast equipment failures and optimize maintenance schedules [120,121]. By combining historical maintenance records, sensor data, and building system information, these approaches can reduce maintenance costs by 10–25% while extending equipment lifecycles [122]. The integration with digital twin concepts enables real-time performance monitoring and adaptive maintenance planning [123]. Pan and Zhang's comprehensive review of BIM-AI integration identified significant growth in research activity, particularly since 2018 [24]. However, practical implementation remains limited, with most applications confined to research prototypes rather than industry deployment. Challenges include interoperability between platforms, computational requirements, and the need for specialized expertise spanning both domains [124,125].

2.6. Resource Optimization and Construction Project Sustainability

Resource optimization in construction encompasses the efficient allocation and utilization of materials, labor, equipment, time, and financial resources to achieve project objectives [126,127]. Traditional optimization approaches relied on linear programming, critical path methods, and expert judgment, which often proved inadequate for the complexity of modern construction projects [128]. Advanced optimization techniques including evolutionary algorithms, simulation-based methods, and AI approaches offer improved capability for multi-objective resource optimization [129,130]. Cost optimization extends beyond minimizing expenditures to encompass value engineering, lifecycle cost analysis, and investment in technologies that generate long-term returns [131,132]. Research indicates that projects incorporating systematic cost optimization achieve savings of 5–15% compared to conventional approaches [133]. Integration of cost optimization with sustainability considerations enables identification of solutions that deliver both economic and environmental benefits [134]. Time optimization through improved scheduling directly impacts resource consumption and project sustainability [135,136]. Schedule compression techniques can reduce project durations but may increase resource intensity if not carefully managed. Conversely, schedule optimization considering resource leveling can reduce peak demands and improve efficiency [137]. AI-based schedule optimization demonstrates promise for balancing time, cost, and resource objectives [138]. Material optimization addresses both quantity and quality dimensions of resource consumption [139,140]. Accurate material quantification through BIM reduces over-ordering and associated waste, while

material selection considering lifecycle impacts supports sustainability objectives [141]. Emerging research explores optimization of material logistics including delivery scheduling, storage, and on-site handling to minimize waste and improve efficiency [142]. The integration of sustainability principles with resource optimization represents a key challenge for contemporary construction management [143,144]. Multi-criteria decision-making frameworks that balance economic, environmental, and social objectives are increasingly applied to support sustainable resource allocation [145]. These approaches recognize that optimal solutions must consider multiple stakeholder perspectives and long-term impacts rather than focusing solely on short-term cost minimization [146].

2.7. Digital Technology Adoption in Central and Southeastern Europe

Central and Southeastern European construction markets present distinct characteristics that influence digital technology adoption patterns [147,148]. These countries have experienced rapid economic development since accession to the European Union, but construction sectors often retain traditional practices and organizational structures [149]. Small and medium-sized enterprises dominate these markets, facing resource constraints that limit technology investment capacity [150,151]. Studies examining digital maturity in Central European construction indicate lower adoption rates compared to Western European counterparts [52,152]. Factors contributing to this gap include limited government mandates for BIM adoption, workforce skill shortages, and lower levels of industry collaboration [153]. However, recent years have witnessed growing recognition of digitalization imperatives, with emerging initiatives to promote technology adoption and develop necessary competencies [154]. Slovakia, Slovenia, and Croatia represent relevant cases for examining digital technology adoption in this regional context. All three countries are European Union member states with developed construction sectors, yet they exhibit different characteristics in terms of market size, economic conditions, and regulatory frameworks [155,156]. Comparative analysis across these markets can reveal how contextual factors shape technology implementation patterns and outcomes. Previous research in these specific markets remains limited, particularly regarding quantitative assessment of technology impacts on sustainability outcomes. Studies have examined BIM awareness and adoption intentions, but empirical evidence regarding actual implementation and measurable benefits is scarce [157,158]. This gap motivates the present investigation, which seeks to provide rigorous quantitative evidence on BIM and AI contribution to resource optimization and sustainability in these Central European contexts.

2.8. Research Gap and Study Contribution

The literature review reveals several gaps that the present research addresses. First, while extensive research has examined BIM and AI capabilities in isolation, empirical studies that quantify their combined contribution to sustainability outcomes remain limited [159]. In particular, the interaction effects between these technologies, including possible complementarities (for example, AI-driven prediction and optimization built on BIM-based information structures), and their relative effectiveness for different optimization objectives (time, cost, carbon, and resource tradeoffs) require further investigation.

Second, empirical research on digital technology adoption and its impacts has largely focused on developed economies with mature construction markets and supportive regulatory frameworks [160]. Evidence from Central and Southeastern European contexts, where institutional and market conditions shape technology adoption in different ways, remains scarce. In Croatia, findings indicate that BIM adoption is still at an early stage, with uneven uptake across stakeholder groups and limited diffusion beyond design-oriented actors, while national policy and standardization initiatives are still evolving [161–164]. Quanti-

tative studies also report generally low BIM usage rates and point to the need for clearer national implementation pathways and more transparent pilot project feedback to accelerate learning across the market [162,163]. At the same time, research focused on higher education suggests that targeted curriculum improvements can significantly increase BIM awareness, making education an important lever for strengthening implementation capacity in Croatia and comparable regional settings [165]. In Slovakia, recent empirical evidence similarly shows that BIM adoption is progressing, but is often constrained by organizational readiness, process maturity, and uneven implementation capabilities. More advanced BIM-enabled automation use cases, such as hazard detection workflows, illustrate both the potential of digitalization and the practical limitations that persist [166,167]. Understanding how BIM and AI perform under these varied conditions is essential for designing implementation strategies and policy recommendations that fit the regional context.

Third, much of the existing research relies on case studies or qualitative assessments. While these approaches are valuable for explaining implementation processes, they provide a limited basis for statistical inference regarding technology impacts [161]. More rigorous quantitative studies using appropriate analytical methods are needed to strengthen the evidence base for both policy and practice, especially when comparing countries with different adoption baselines and institutional settings.

The present study responds to these gaps by providing systematic quantitative evidence on BIM and AI implementation in the Slovak, Slovenian, and Croatian construction sectors, and by assessing their measurable contributions to resource optimization and sustainability planning. The findings contribute both to the theoretical understanding of how digital technologies influence sustainability outcomes and to practical knowledge for stakeholders aiming to support construction sustainability through technological innovation, including circular economy-oriented project management supported by BIM-centric information structures [168,169].

To consolidate the novelty of this study, Table 1 summarizes key literature relevant to BIM, AI, and their integration for sustainability and resource optimization in construction. The key prior studies and their research focus, methods, main findings, and identified gaps are synthesized in Table 1.

Table 1. Summary of key literature on BIM, AI, and sustainability/resource optimization in construction.

Ref.	Research Focus	Design/Method	Key Results	Limitations/Gaps
[69]	Lean–BIM synergies	Conceptual/industry view	Identifies opportunities for integrating lean principles with BIM for process improvement.	Limited empirical quantification; context-specific.
[70]	Lean + BIM interaction	Conceptual framework	Explains how BIM supports lean workflows and collaboration.	Lacks cross-country evidence on sustainability/resource outcomes.
[71]	BIM maturity & lean interactions	Survey/assessment approach	Links BIM capability maturity to lean implementation benefits.	Needs broader validation and linkage to AI + sustainability metrics.
[83]	BIM for waste/resource efficiency	Empirical/case-oriented	Shows BIM can reduce waste via better coordination and planning.	Often project-specific; limited generalizability/quant metrics.
[87]	BIM for sustainability	Review/outlook	Summarizes sustainability-related BIM benefits across lifecycle.	Gaps in standardized KPIs and quantitative impact assessment.

Table 1. *Cont.*

Ref.	Research Focus	Design/Method	Key Results	Limitations/Gaps
[94]	AI for cost prediction	Machine-learning model	Demonstrates ML can improve construction cost estimation accuracy.	Data availability/transferability issues; interpretability.
[97]	AI in cost estimation	Review	Maps AI/ML techniques for cost prediction and drivers.	Need benchmarking and integration with BIM data structures.
[100]	AI optimization of time–cost–quality	Optimization/AI	Optimizes multi-objective project performance.	Often assumes ideal data; limited real-world BIM–AI pipelines.
[101]	AI-based scheduling optimization	Optimization/ML	Improves scheduling efficiency via optimized algorithms.	Requires high-quality data; limited adoption barriers analysis.
[104]	AI for safety/risk identification	Computer vision/ML	Detects hazards/unsafe behaviors to improve site safety.	Generalization across sites; integration into BIM workflows.
[109]	AI applications in construction	Review	Synthesizes AI use-cases (planning, safety, maintenance).	Need maturity/adoption evidence and sustainability linkage.
[115]	Performance-driven design optimization	Computational optimization	Uses AI/optimization to enhance design performance.	Limited integration with practical BIM-based project delivery.
[142]	BIM-enabled lifecycle information mgmt.	Framework	Proposes BIM-based lifecycle info management for decision support.	Implementation challenges; limited empirical validation.
[160]	Benefits of BIM–AI integration	Survey/prioritization study	Identifies and prioritizes benefits of integrating BIM with emerging digital tech/AI.	Context-dependent; limited evidence in C/SE Europe markets.
[161]	Barriers to BIM adoption	Survey/review	Highlights organizational, technical, and policy barriers.	Need region-specific analysis and link to BIM–AI uptake.
[149]	EU support for construction digitalization	Policy report	Sets policy drivers and support actions for sector digitalization.	Does not quantify project-level sustainability/resource impacts.
[153]	BIM implementation analysis (SK context)	Empirical analysis	Discusses BIM implementation status and challenges in Slovakia.	Needs extension toward AI integration and sustainability outcomes.

As shown in Table 1, prior work often examines BIM or AI in isolation and provides limited quantitative evidence on their combined contribution to sustainability-oriented resource optimization in Central and Southeastern European contexts, which motivates the present study.

The reviewed literature demonstrates that BIM and AI are increasingly discussed as enablers of performance improvement in construction, yet empirical evidence remains fragmented. First, many studies examine BIM and AI in isolation, while quantitative work assessing their joint relevance for sustainability-oriented resource optimization is still limited. Second, reported digital benefits tend to be stronger in planning and control domains (e.g., cost estimation, scheduling, and forecasting) than in materials-related sus-

tainability, which often requires supply-chain traceability and life-cycle integration. Third, adoption and impact depend on socio-technical conditions, data governance, organizational readiness, and external standards, yet these are not consistently operationalized in quantitative assessments. Addressing these gaps, this study provides comparative evidence from three national contexts and tests explicit hypotheses linking BIM/AI utilization to sustainability-oriented planning outcomes.

Hypotheses are followed:

H1. *AI utilization is positively associated with sustainability-oriented cost planning outcomes.*

H2. *AI utilization is positively associated with sustainability-oriented schedule planning outcomes.*

H3. *AI utilization is positively associated with sustainability-oriented resource planning outcomes.*

H4. *BIM utilization is positively associated with sustainability-oriented cost planning outcomes.*

H5. *BIM utilization is positively associated with sustainability-oriented schedule planning outcomes.*

H6. *BIM utilization is positively associated with sustainability-oriented resource planning outcomes.*

H7. *The association between BIM utilization and sustainability-oriented planning outcomes is stronger than (or at least not weaker than) the corresponding association for AI utilization.*

3. Methodology

3.1. Research Problem, Questions and Goal

Despite its significant impact on economic growth and the environment, the construction industry remains one of the least digitized sectors globally. This technological lag contributes to persistent inefficiencies, high resource consumption, and limited integration of sustainability principles within construction processes. While the Industry 4.0 paradigm offers a comprehensive framework for digital transformation, its practical implementation in the construction domain, particularly through technologies such as Building Information Modelling (BIM) and Artificial Intelligence (AI), has yet to reach its full potential.

Although the adoption of BIM has expanded in recent years, its application remains largely confined to the design and planning phases. Artificial Intelligence, despite its high potential for processing complex data and enabling predictive analytics, continues to be significantly underutilized, especially among small and medium-sized enterprises and within emerging market contexts.

Previous research has frequently focused on the theoretical advantages of these technologies or has presented case studies from highly developed economies. However, there is a notable lack of empirical evidence on how the implementation of BIM and AI concretely contributes to improving sustainability and optimizing resources under real-world conditions in Central and Southeastern Europe, particularly in countries such as Slovakia, Slovenia, and Croatia. These nations face specific economic, structural, and regulatory challenges that shape the pace and form of digitalization in the construction sector.

Accordingly, there is a pressing need for a systematic and comparative investigation that would quantify the contribution of these technologies to the efficient planning of sustainability and the optimization of cost, time, and resource management.

This study aims to address the identified research gap by providing quantitative evidence on the contribution of digital technologies to sustainability in the construction sector. In doing so, it seeks to support the development of more effective policies, innovation strategies, and the promotion of digital transformation within the construction industry

under the specific conditions of Central European countries. The core research questions formulated for this study are as follows:

- To what extent does the integration of Building Information Modelling (BIM) and Artificial Intelligence (AI) contribute to resource optimization and the enhancement of sustainability in construction projects?
- How widespread is the use of BIM and AI technologies among construction companies of different sizes and across different countries (Slovakia, Slovenia, and Croatia)?

The objective of this research is to analyze the extent of implementation of Building Information Modelling (BIM) and Artificial Intelligence (AI) tools in the construction sector within Slovakia, Slovenia, and Croatia, and to quantify their impact on resource optimization and project sustainability in accordance with the principles of Industry 4.0.

3.2. Data Collection and Processing

Guided by this socio-technical framing, the survey instrument includes items that capture not only perceived technology usefulness but also organizational and capability-related conditions (e.g., awareness, experience, perceived feasibility, and readiness indicators). This enables interpretation of the quantitative results as reflecting the broader organizational embedding of BIM and AI, rather than treating the technologies as generic tools independent of context.

Data were collected through an online questionnaire survey. Although the survey was conducted anonymously, several participating companies voluntarily provided their company names but requested that their responses be presented confidentially. A wide range of construction stakeholders was invited to participate, including contractors, architects, developers, investors, and small subcontracting firms. The sample was stratified to reflect the proportional representation of companies by country and size, as documented in Eurostat's official statistics of construction-sector entities. Respondents were selected at random from a contact database while maintaining proportional representation across key attributes. Participants were drawn from an internal contact database of construction-sector stakeholders (contractors, designers, developers/investors, and subcontractors). Invitations were distributed to achieve proportional representation by country and company size based on official sector statistics; within each stratum, contacts were approached randomly where available. As with most voluntary online surveys, some degree of self-selection cannot be excluded (e.g., respondents with higher interest in digital technologies may be more likely to participate). Therefore, results are interpreted as stakeholder perceptions and the paper does not claim precise population-level adoption rates.

A total of 199 responses were received, which represents a satisfactory response rate given the sample size and indicates solid engagement across different segments of the market. The survey was conducted online, anonymously, and participation was voluntary. Informed consent was obtained at the beginning of the questionnaire; no sensitive personal data were collected.

The primary focus of the survey was the use of BIM technologies and Artificial Intelligence in construction, with an emphasis on gathering data on their impact on resource optimization—particularly in relation to cost, materials, and time management. The first section of the questionnaire included an introduction to the research, an explanation of the key terms and objectives, context, and verification of the respondent's qualification to provide information on behalf of their organization. To ensure data validity, IP tracking was used to prevent multiple entries from the same individual.

The structure and content of the questionnaire were carefully tailored to the nature of the data sought. The first section captured baseline characteristics of the sample, including the country of operation, company or project size, and other demographic variables.

The second section addressed the extent to which BIM and AI technologies were applied across specific construction activities. The third section focused on assessing the impact of these technologies on resource optimization—specifically costs, material efficiency, and time savings.

The questionnaire was developed based on the structured literature review with the aim of translating the most frequently discussed BIM–AI application domains and performance-relevant outcomes into measurable survey dimensions. The literature consistently highlights AI-enabled decision support and automation across the project lifecycle, particularly in planning-related tasks (cost, time, and resource planning), documentation and design support, on-site monitoring (quality and safety), facility management, and emerging areas such as advanced materials, prefabrication, and autonomous machinery. These recurring themes were therefore operationalized into a set of dimensions capturing:

- respondents' awareness and prior experience with AI tools;
- perceived usefulness of AI across key project phases;
- perceived productivity potential of AI across core construction functions;
- organizational readiness, acceptance, and perceived feasibility of implementation.

To ensure transparency and reproducibility, the questionnaire is described below in a desensitized form (i.e., without any identifying information). Items were primarily measured using 5-point Likert-type scales, complemented by binary/ordinal items, percentage estimates, and open-ended prompts.

First, the awareness and experience block included items asking whether respondents are familiar with commonly available AI tools and whether they have used such tools personally and/or professionally (Yes/No/Partly), and whether they perceive AI as applicable in the construction sector (Yes/No/Not sure). Second, perceived usefulness across project phases was assessed by asking respondents to rate the usefulness of AI in the preparatory/planning phase, the construction phase, and the operation/facility-use phase using a 5-point scale (1 = not at all; 5 = very much). Third, perceived productivity potential across construction functions was captured through Likert-scale ratings (1 = very low; 5 = very high) for key functional areas identified in the literature, including: generative/conceptual design, 3D design and 2D documentation, facility management, on-site quality and safety monitoring, new materials design/optimization, cost estimation and optimization, schedule planning/optimization, prefabrication/off-site manufacturing, and autonomous construction machinery.

Finally, to complement the quantitative items with contextual insight, the instrument included open-ended questions focused on expected on-site applications of AI and its potential contribution to environmental impact reduction and worker safety. In addition, respondents provided percentage estimates regarding expected productivity change, the share of projects suitable for AI implementation, and the share of tasks potentially automatable, and rated organizational preparedness using Likert-scale items reflecting company awareness, confidence in successful implementation, and employee knowledge regarding AI. Together, these measures reflect literature-derived dimensions and enable consistent quantitative analysis while retaining qualitative nuance relevant to implementation conditions.

Data analysis involved both descriptive and inferential statistical methods. Descriptive statistics included frequency distributions, means, and standard deviations. For hypothesis testing, Pearson's correlation, ANOVA, *t*-tests, and regression analysis were employed. Statistical significance was evaluated at a threshold of $p < 0.05$. Data analysis was conducted using SPSS IBM SPSS Statistics, Version 30.0.0.0 (172) (IBM Corp., Armonk, NY, USA) and Microsoft Excel.

Because the study relies on self-reported questionnaire data, we implemented both procedural and statistical steps to mitigate and assess potential method-related biases.

Procedurally, participation was anonymous, responses were reported only in aggregate form, question blocks were separated by topic, and multiple response formats were used (Likert-type scales, binary/ordinal items, percentage estimates, and open-ended prompts). Statistically, we assessed common method bias using Harman's single-factor test (unrotated exploratory factor analysis). For multivariate models, multicollinearity was examined using variance inflation factors (VIF) and tolerance diagnostics. Regarding measurement validity, several key outcomes (e.g., sustainability of cost/schedule/resource planning) were captured as single-item indicators grounded in the literature, and therefore CFA is not applicable to these variables. In contrast, the organizational readiness block (Items 17–19) was treated as a multi-item scale and evaluated using internal consistency metrics (Cronbach's alpha).

In addition, a sensitivity (robustness) analysis was performed by stratifying respondents according to type of construction activity (respondent role). Because subgroup comparisons involve Likert-type measures and highly unequal group sizes, two-sided Mann–Whitney U tests (exact) were used for group comparisons; results were additionally checked against Welch's *t*-test and led to consistent conclusions.

The survey captures self-reported perceptions of BIM/AI utilization and sustainability-oriented planning outcomes. Therefore, all statistical relationships reported in this study should be interpreted as associations between perceived constructs rather than as evidence of objectively measured performance changes.

3.3. Research Sample

The research sample reflects multiple perspectives and respondent distribution across various attributes. The first analytical perspective concerns the distribution of respondents by country (Figure 1).

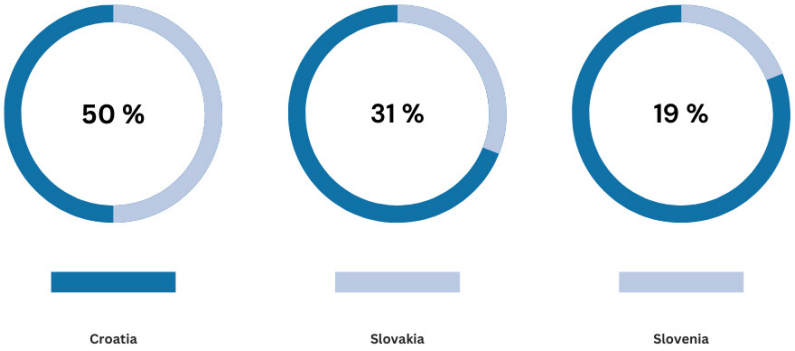

Figure 1. Distribution of respondents by country.

Almost 50% of respondents come from Croatia. The second-highest representation is from Slovakia, while the smallest proportion comes from Slovenia. This distribution reflects not only the population ratio but, more importantly, the relative presence of construction companies within the market. Another analytical perspective of the research sample is based on construction activity according to the NACE classification (Figure 2).

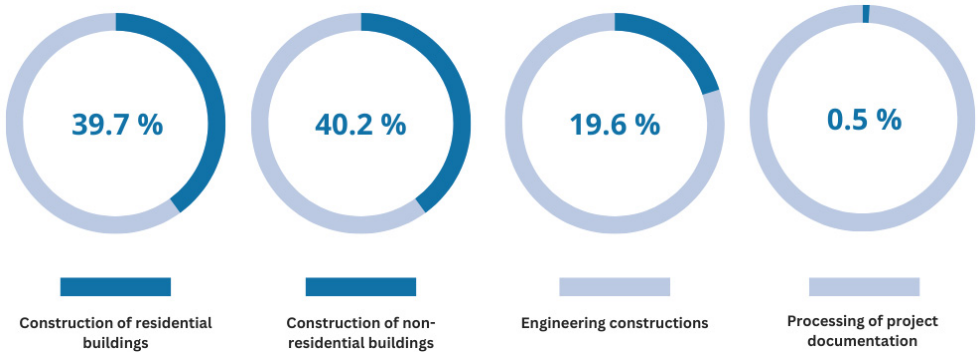

Figure 2. Distribution of respondents by type of construction Activity (NACE Classification).

Most respondents are engaged in activities related to the construction of residential and non-residential buildings. Engineering construction accounts for nearly 20% of the sample, while the lowest representation is in the processing of project documentation. In the context of digital technology adoption, it is also essential to consider the age and experience of respondents, as illustrated in Figure 3.

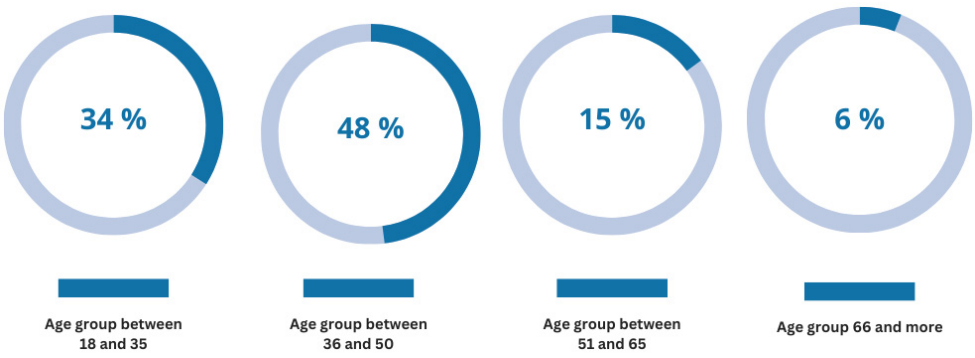

Figure 3. Distribution of respondents by age and experiences.

The largest proportion of respondents falls within the 36–50 age group, representing experienced professionals who are still likely to maintain a strong affinity for digital technologies. This is followed by younger respondents, whose relationship with technology is generally positive, despite their relatively limited experience in the construction industry. Conversely, respondents aged over 51 represent a group with significant industry experience, but potentially a lower inclination toward the adoption of information technologies.

3.4. Research Limitations

Despite the valuable findings and statistically significant results obtained, the study is subject to several limitations that must be acknowledged when interpreting its conclusions.

The geographic scope of the research sample may be viewed as a constraint in the context of deriving broader, globally applicable insights. The countries involved rep-resent only a portion of the overall EU population. However, given that Slovakia, Slovenia, and Croatia are respected EU member states, the localized findings provide meaningful insights that reflect regional realities and can inform locally applicable strategies within this part of Europe. This, in turn, opens avenues for future research expansion.

The empirical investigation was conducted exclusively within these three countries. While they represent a relevant region in Central and Southeastern Europe, the results may not be fully generalizable to countries with different construction markets, levels of digital maturity, regulatory environments, or economic conditions.

Data were collected via a structured questionnaire targeting professionals within construction firms (e.g., project managers, BIM coordinators, technical directors). Although every effort was made to ensure clarity of terminology and that responses came from qualified personnel, there remains a possibility that subjective perceptions influenced the objectivity of the responses—particularly regarding the level of technology implementation and its impact on sustainability. Nevertheless, mitigation measures were implemented, including the inclusion of clearly defined concepts, contextual explanations, and targeted distribution to competent respondents, thereby enhancing the reliability and validity of the data.

Moreover, the study relied solely on quantitative methods, focusing on correlation and regression analyses. While key sustainability indicators such as resource planning, cost, and scheduling optimization were examined, the study did not explore additional dimensions of sustainability such as carbon footprint, social impact, employee satisfaction, the use of renewable energy sources, or the implementation of digital twins.

This study relies on self-reported Likert-scale data and therefore reflects stakeholders' perceptions rather than objectively measured performance. While perceptions are important predictors of adoption and managerial decision-making, future research should triangulate these findings with project-level KPIs (e.g., cost variance, schedule variance, material waste rates, or life-cycle indicators) and longitudinal designs to establish causal links between BIM/AI adoption and realized sustainability outcomes.

This study is based on three Central and Eastern European countries and therefore reflects contexts with specific levels of digital maturity, regulatory settings, and market structures. Accordingly, the findings should be interpreted as context-specific evidence and are primarily transferable at the level of directional relationships (i.e., perceived associations between BIM/AI utilization and sustainability-oriented planning), while the magnitude and adoption dynamics may differ in more digitally mature or differently regulated regions. Future research should validate these relationships using broader multi-region samples and/or objective adoption and performance indicators.

4. Results

The utilization of digital technologies in addressing resource optimization and enhancing sustainability within the construction industry has become a central theme in professional and academic discourse, particularly in alignment with the objectives of the European Green Deal. The findings of this research further confirm this relevance. The construction sector remains one of the key industries in which long-standing efforts toward sustainability and resource efficiency continue to be emphasized, an observation reaffirmed by the participants in this study.

Many respondents highlighted the importance of integrating sustainability principles through rational resource management and optimization practices. Based on the collected data and its subsequent analysis, several trends emerged that illustrate current practices and the perceived significance of sustainability-oriented resource optimization within selected construction markets. Notably, cost optimization was not merely associated with financial savings but was also linked to appropriate cost structuring and strategic investments in green solutions, initiatives expected to yield benefits and resource efficiencies over the longer term. A similar pattern was observed in the domain of other resources, including human capital.

While traditional optimization methods remain valid, innovations and digital technologies are increasingly seen as enablers of more effective and dynamic optimization processes. BIM is perceived as a comprehensive tool that facilitates the management of both graphical and non-graphical data, substantially enhancing the quality and availability

of information across the construction lifecycle. AI tools, on the other hand, significantly increase the speed and scale of data processing. As several respondents noted, the effectiveness of these technologies depends largely on the quality and relevance of the outputs they generate.

Although the application of AI and BIM technologies is viewed as having substantial potential to improve operational efficiency, these tools are not yet capable of functioning autonomously. In the context of achieving higher levels of sustainability, these technologies can serve as powerful instruments—but only when coordinated and supervised by qualified human actors. This finding points to the continued importance of human involvement and suggests a reconceptualization of optimization efforts in which traditional methods coexist with digitally supported strategies.

The research demonstrates that resource optimization outcomes are significantly better when BIM and AI tools are precisely aligned with human decision-making processes, clearly defined goals, and specific deliverables. The human factor remains essential and irreplaceable in this framework. This underscores the growing need for skilled human resources whose roles and competencies are evolving. In fact, despite increasing automation, there is a paradoxical rise in demand for highly qualified professionals. Human involvement must be sophisticated, particularly in setting goals, defining tasks, and evaluating optimization outcomes facilitated by BIM and AI systems.

The study's analysis of resource use and data processing highlights the current state of BIM adoption in the investigated construction markets, especially with respect to its application for resource optimization and sustainability impact. While the general use of BIM and AI remains relatively limited in the observed countries, there is considerable room for more intensive application, particularly in resource optimization and the advancement of sustainability goals within the construction sector.

Among the key indicators of economic sustainability, cost optimization achieved the highest reported levels of BIM and AI use, in contrast to material resource optimization, which recorded the lowest. The following visual (Figure 4) illustrates the extent to which BIM and AI tools are employed to optimize cost, time, human resources, and overall project delivery. The size of each segment reflects the intensity of tool utilization.

As shown in Figure 4, the perceived contribution of BIM and AI to sustainability-related outcomes differs across the three countries and across assessed areas. Slovenia reports the highest average scores for both cost sustainability (3.52) and schedule planning sustainability (3.51), while the score for materials sustainability is lower (2.49). In Slovakia, respondents rate BIM and AI similarly for schedule planning (3.03) and cost (3.02), whereas the perceived contribution to materials sustainability is substantially lower (1.34). In Croatia, the responses are more balanced across areas, with cost sustainability (2.99) and schedule planning sustainability (2.80) rated higher than materials sustainability (2.21). Overall, these quantitative results indicate that BIM–AI adoption is most strongly associated with cost and schedule-related sustainability perceptions, while materials-related sustainability benefits are consistently evaluated lower, particularly in Slovakia.

As illustrated in the diagram, the highest level of BIM and AI utilization is focused on cost optimization, particularly in Slovenia. Conversely, the lowest reported use of these technologies for optimization purposes is observed in Slovakia, an outcome that is somewhat unexpected but can be attributed to several influencing factors.

On one hand, the pressure to reduce costs inherently involves efforts toward material optimization. However, these material-related decisions are often not supported by BIM or AI tools. Instead, cost reduction tends to be pursued through aggressive pricing strategies rather than through reductions in material volume or efficient material planning enabled by digital technologies.

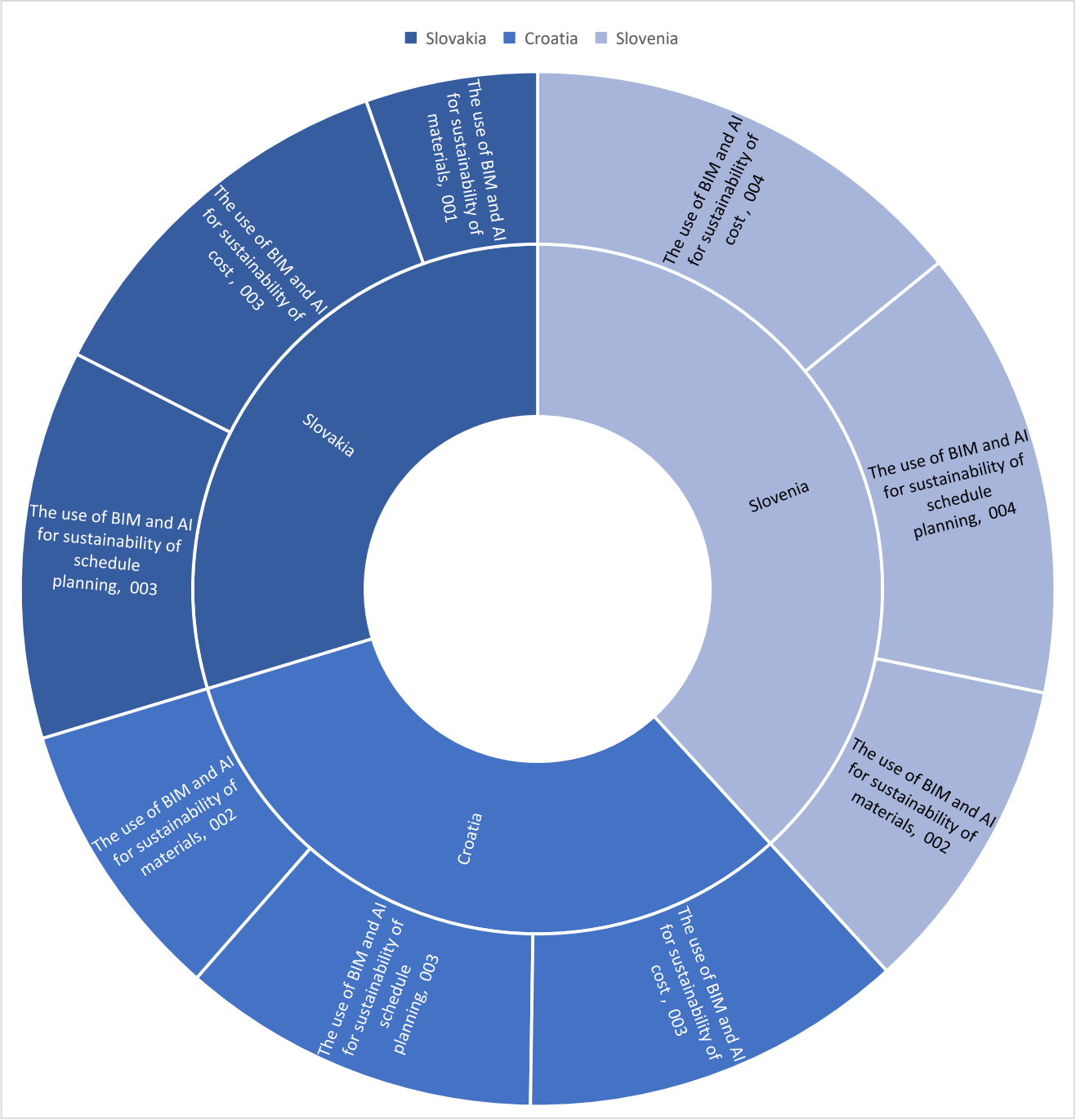

Figure 4. Diagram of BIM and AI utilization in resource optimization for sustainable construction.

As a result, material savings are not necessarily achieved through optimized resource consumption, but rather through procurement of lower-cost materials—often at the expense of quality. This approach may not directly affect time scheduling optimization. Interestingly, the study revealed relatively higher levels of BIM and AI use for scheduling purposes, suggesting that while cost and material decisions may not be digitally optimized, time management processes are more commonly supported by such tools.

Figure 5 summarizes the Pearson correlation coefficients between BIM/AI utilization and sustainability-oriented planning outcomes (cost, schedule, and resource planning)

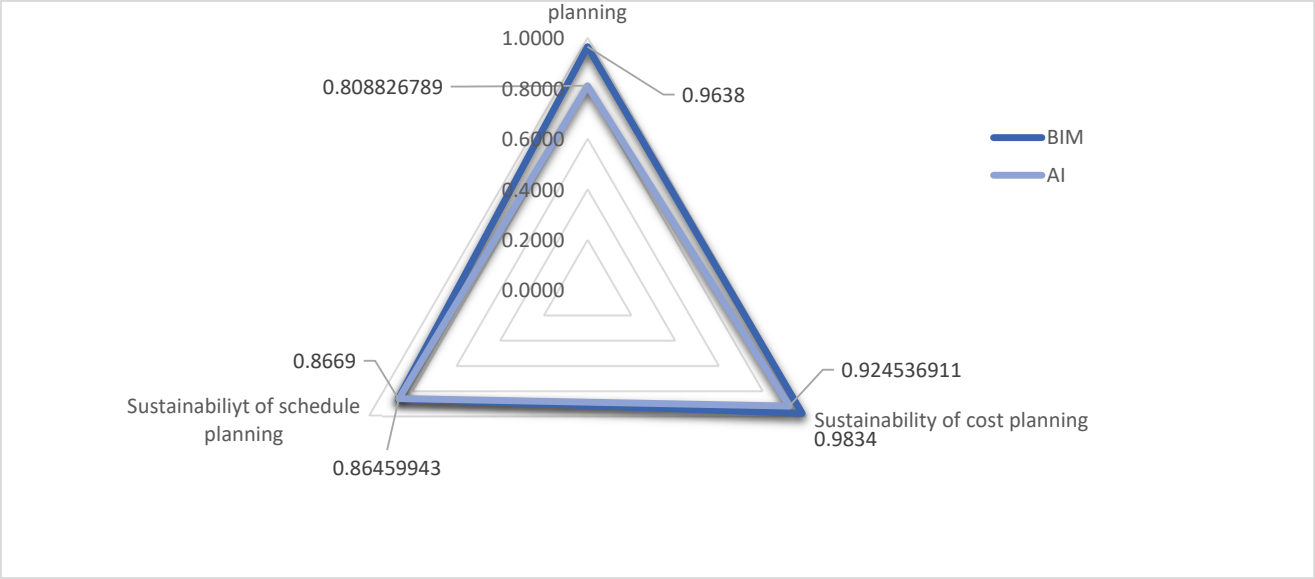

Figure 5. Diagram of BIM and AI utilization and correlation in optimization.

The results from the statistical evaluation reveal several robust and statistically significant relationships between the use of digital technologies (AI and BIM) and key indicators of sustainable construction planning. The following insights emerge from the correlation coefficients and the associated significance values (RA—regression analysis/*p*-values).

Based on the correlation analysis (N = 49), the relationships between digital-technology utilization and sustainability-related planning outcomes are strong and statistically significant ($p < 0.00001$). Specifically, AI utilization is strongly associated with cost planning (r = 0.9245; $p < 0.00001$), schedule planning (r = 0.8646; $p < 0.00001$), and resource planning (r = 0.8088; $p < 0.00001$). In practical terms, these coefficients indicate substantial explanatory strength ($r^2 \approx 0.855$ for cost, 0.748 for schedule, and 0.654 for resource planning).

Even stronger relationships are observed for BIM utilization, particularly for cost planning (r = 0.9834; $p < 0.00001$) and resource planning (r = 0.9638; $p < 0.00001$), followed by schedule planning (r = 0.8669; $p < 0.00001$) ($r^2 \approx 0.967$, 0.929, and 0.752, respectively). Overall, while both technologies demonstrate robust positive associations with sustainability planning outcomes, BIM shows consistently higher coefficients, suggesting a stronger linkage to cost- and resource-related sustainability planning, whereas AI complements these effects, particularly in cost and schedule-oriented decision support.

As shown in Figure 5, AI utilization is positively associated with sustainability-oriented resource planning (r = 0.8088), cost planning (r = 0.9245), and schedule planning (r = 0.8646) (all $p < 0.00001$), supporting H1–H3. BIM utilization shows similarly strong positive associations with resource planning (r = 0.9638), cost planning (r = 0.9834), and schedule planning (r = 0.8669) (all $p < 0.00001$), supporting H4–H6. BIM correlations are higher than AI for cost and resource planning and comparable for schedule planning, providing partial support for H7.

The reported correlations reflect self-reported (perceived) constructs. Very high coefficients (e.g., above 0.95) may indicate conceptual overlap between closely related survey items and/or common method variance; therefore, these associations are interpreted cautiously and complemented with diagnostic checks reported below. Correlation results indicate association and do not establish causality (Table 2).

Table 2. Correlation analysis of AI utilization.

	Use of AI	Resource Planning	Cost Planning	Schedule Planning
Use of AI	1			
Sustainability of resource planning	0.808826789	1		
Sustainability of cost planning	0.924536911	0.620994387	1	
Sustainability of schedule planning	0.86459943	0.47772585	0.776160412	1

Artificial Intelligence and Sustainability Indicators

The use of AI is strongly correlated with the sustainability of:

- Cost planning (r = 0.9245; $p < 0.00001$)
- Schedule planning (r = 0.8646; $p < 0.00001$)
- Resource planning (r = 0.8088; $p < 0.00001$)

These findings suggest that AI is particularly effective when applied to the economic and time-related dimensions of project sustainability. The highest coefficient is observed in cost planning, indicating that AI tools are likely being leveraged for predictive budgeting, financial forecasting, and optimization of cost structures (Table 3).

Table 3. Correlation analysis of AI and BIM utilization.

	BIM	AI
Sustainability of resource planning	0.9638	0.808826789
Sustainability of cost planning	0.9834	0.924536911
Sustainability of schedule planning	0.8669	0.86459943

Building Information Modelling (BIM) and Sustainability Indicators

The use of BIM exhibits even stronger correlation coefficients than AI, particularly in:

- Cost planning (r = 0.9834)
- Resource planning (r = 0.9638)
- Schedule planning (r = 0.8669)

These results reflect BIM's ability to serve as a comprehensive integrative platform that facilitates both data visualization and optimization of project components across the full lifecycle. The extremely high correlation with cost planning confirms the strategic value of BIM in cost estimation, control, and investment planning, while its near-perfect relationship with resource planning highlights BIM's utility in material quantification and logistics.

To explore whether these relationships differ by national context, we additionally examined the correlations separately for Slovakia, Croatia, and Slovenia. The direction of associations remained positive across all three subsamples; however, the country-level sample sizes are smaller, and these country-specific correlations are therefore reported as exploratory and interpreted with caution.

To evaluate whether the key findings are sensitive to the composition of respondents by construction activity, we conducted a robustness check by stratifying the sample into a dominant Design/Engineering group (project/design roles) versus other stakeholder roles ($n = 3$). We compared the main quantitative indicators used in the Results (mean perceived usefulness of AI across project phases and AI potential for cost, schedule, and materials optimization). Overall, the central tendencies were comparable between the two strata, and the differences were not statistically significant (Table 4). This suggests that the main patterns reported in the Results are not driven by respondent role; however, due to the small size of the non-design subgroup, subgroup-level inference should be interpreted cautiously.

Table 4. Sensitivity analysis by respondent role (type of construction activity).

Indicator	Design/Engineering Mean ± SD	Other Roles (n = 3) Mean ± SD	Median (IQR) Design/Engineering	Median (IQR) Other Roles	p-Value
Use of AI (mean across phases)	3.39 ± 1.08	3.33 ± 0.58	3.50 (2.75–3.92)	3.00 (3.00–3.50)	0.930
AI potential: Cost optimization	3.63 ± 1.30	4.00 ± 1.00	4.00 (2.25–5.00)	4.00 (3.50–4.50)	0.745
AI potential: Schedule optimization	3.53 ± 1.22	4.33 ± 0.58	3.00 (3.00–5.00)	4.00 (4.00–4.50)	0.317
AI potential: Materials optimization	3.20 ± 1.24	4.00 ± 1.00	3.00 (2.00–4.00)	4.00 (3.50–4.50)	0.317

Comparative View: BIM vs. AI

While both BIM and AI positively contribute to sustainability outcomes, BIM demonstrates slightly higher correlation coefficients across all three planning dimensions.

This suggests that BIM remains the dominant digital technology in current construction practices for achieving sustainability, particularly in early-phase planning, quantity take-offs, and resource alignment.

AI, on the other hand, appears to complement BIM by enhancing data processing, automation, and decision-support in more dynamic or operational contexts—especially in real-time cost tracking and scheduling.

All relationships presented show extremely low p-values (RA), confirming that the observed correlations are highly statistically significant ($p < 0.00001$). This validates the reliability of the data and reinforces the empirical contribution of the study to understanding the role of digital tools in advancing sustainable construction practices.

The data confirm that both BIM and AI technologies are positively and significantly associated with enhanced sustainability in construction planning. While BIM demonstrates broader and stronger effects—particularly in resource and cost planning—AI proves especially valuable in dynamic forecasting and schedule management.

The results emphasize that maximum effectiveness is achieved when AI and BIM are deployed in a complementary and coordinated manner, guided by clearly defined human oversight, as noted earlier. The findings serve as a compelling argument for policymakers, industry leaders, and technology developers to further integrate and scale digital solutions in construction as a means of delivering on the sustainability goals of the European Green Deal.

5. Discussion

5.1. Interpreting the Key Findings in a Quantitative Context

This study provides quantitative evidence on how construction stakeholders perceive the contribution of BIM and AI to sustainability-oriented resource optimization. Across the three examined markets, the perceived contribution is strongest for cost- and schedule-related sustainability planning, while materials-related sustainability is consistently rated lower. In addition, the correlation analysis indicates robust positive relationships between technology utilization (BIM and AI) and sustainability-oriented planning outcomes, with BIM generally exhibiting higher coefficients than AI. Together, these results suggest that, in practice, digital adoption is currently most strongly linked to managerial and planning domains where data availability, standardization, and performance tracking are more mature (e.g., cost and time), whereas materials-related sustainability benefits may require deeper integration of supply-chain data, material traceability, and circularity-oriented processes.

5.2. Geographical Boundary: From Three Countries to EU and Global Relevance

Although the empirical sample is limited to Slovakia, Croatia, and Slovenia, the main mechanisms identified in this study are not unique to these markets: BIM and AI function as enabling technologies for data-driven planning, coordination, and optimization, and these functions are broadly relevant across construction contexts. The findings are therefore transferable at the level of directional insights—namely, that digital tools are perceived to deliver clearer sustainability benefits in cost and schedule management than in materials-related optimization, and that higher utilization is associated with stronger sustainability planning outcomes.

At the same time, the magnitude and speed of adoption are likely shaped by context-specific factors, including regulatory maturity, procurement practices, digital skills, and the diffusion of BIM standards and data governance across supply chains. Central and Southeastern European markets typically exhibit heterogeneous digital maturity and a larger share of small and medium-sized firms, which may constrain the availability of structured datasets and limit advanced AI deployment. From an EU perspective, this implies that policy instruments (e.g., public procurement requirements, harmonized BIM mandates, training and capacity building, and interoperability standards) can accelerate diffusion and strengthen comparability across Member States. From a global perspective, the study highlights a common challenge for emerging and mid-maturity markets: without standardized data structures and interoperable information flows, materials- and circularity-focused outcomes may lag cost and schedule benefits even when digital tools are adopted.

5.3. Managerial and Implementation Implications

The results offer several practical implications for construction management and sustainability-oriented decision-making:

Prioritize quick-win integration in planning functions. Since cost and schedule domains show the strongest perceived benefits and the strongest quantitative associations with technology utilization, organizations can achieve early sustainability gains by focusing BIM–AI integration on estimating, budgeting, schedule optimization, and risk forecasting. This supports performance-oriented management by improving predictability, reducing rework, and lowering resource waste associated with delays and cost overruns.

Strengthen data governance and interoperability as managerial enablers. The observed differences between planning-related and materials-related sustainability perceptions suggest that organizations should treat data governance (data ownership, quality assurance, common data environments, and interoperability) as a strategic management capability. This aligns BIM execution planning and AI readiness with consistent data pipelines, enabling reliable analytics and decision support.

Embed sustainability KPIs into BIM–AI workflows. To translate digital adoption into sustainability outcomes, firms should explicitly connect BIM objects and project controls to sustainability metrics (e.g., embodied carbon proxies, material waste rates, procurement and delivery efficiency, and safety indicators). This allows sustainability to be operationalized as measurable performance rather than a generic aspiration.

Operational readiness and capability building. The study suggests that benefits are linked not only to tool availability but also to organizational readiness and user competence. Training, change management, and role adaptation (e.g., moving toward supervision/validation roles for AI-generated outputs) are therefore critical to sustaining value creation.

5.4. Beyond Cost, Time, and Materials: Broader Sustainability Implications

This study operationalized sustainability-oriented resource optimization through three dimensions: cost, time/schedule, and materials. The findings nonetheless have implications for broader sustainability dimensions:

- Environmental sustainability (planet). Improved cost and schedule performance can indirectly reduce environmental impacts through less rework, fewer delays, and reduced fuel and energy consumption on site. However, direct environmental performance (e.g., embodied carbon, life-cycle impacts, waste streams) requires additional data layers such as LCA databases, digital material passports, and traceable procurement information.
- Social sustainability and safety (people). AI-enabled monitoring and predictive analytics can support worker safety management (e.g., hazard detection, proactive safety planning), which contributes to social sustainability outcomes. Digital workflows also affect job design and skills requirements, underlining the importance of upskilling and fair transition practices.
- In practical terms, improved planning reliability can translate into fewer unplanned deliveries, reduced idle time of machinery, and less rework, which are typical sources of avoidable fuel/energy use and emissions on site. On the social side, respondents' emphasis on AI use for monitoring and prediction aligns with reducing exposure to hazardous situations and supporting proactive safety planning; however, these outcomes require clear governance to avoid over-reliance and to ensure fair role transitions.
- Governance and transparency (governance). BIM–AI integration supports governance by enabling auditability of decisions, clearer documentation, and improved compliance tracking. This is particularly relevant for public procurement, ESG reporting, and accountability in sustainability claims.
- Circularity and life-cycle performance. The consistently lower material-related sustainability perceptions indicate that circular economy benefits are not yet fully realized in practice. Achieving circular outcomes requires integration across the asset life cycle, including design for disassembly, materials traceability, reuse pathways, and facility management data continuity.

Overall, the results indicate that BIM and AI can contribute to sustainability-oriented construction management in a measurable way, but the depth of sustainability outcomes depends on the maturity of data ecosystems and the alignment of digital tools with lifecycle and circularity objectives.

While the study provides quantitative evidence on perceived associations, it was not designed to estimate a full mediating causal model. Nevertheless, the findings can be interpreted through a simple socio-technical mechanism: BIM/AI utilization may enable

- process standardization and data integration, which supports,
- process innovation and learning (e.g., faster feedback, fewer errors), ultimately improving,
- sustainability-oriented planning performance (cost/schedule/resource outcomes).

Testing such mediation pathways requires longitudinal or multi-source data and is proposed as a focused direction for future research.

6. Conclusions

This study has explored the extent to which digital technologies—specifically Building Information Modelling (BIM) and Artificial Intelligence (AI)—contribute to the optimization of resources and the advancement of sustainability in the construction industry, with empirical data drawn from Slovakia, Slovenia, and Croatia. The findings confirm that both BIM and AI exhibit statistically significant and positive relationships with key sustainability dimensions, namely resource planning, cost optimization, and schedule management.

Among these, BIM demonstrates the highest correlation across all three planning areas, underscoring its role as a foundational digital tool in sustainable construction. AI, while slightly trailing in magnitude, also presents strong correlations, particularly in cost and time optimization, which affirms its potential to support dynamic decision-making, real-time forecasting, and advanced analytics. Notably, the study highlights that the most effective outcomes are achieved when these technologies are not used in isolation but are strategically integrated and guided by well-defined human oversight.

However, the study also reveals disparities in the level of digital adoption across countries and across planning dimensions. For example, Slovenia reports the highest level of technology use in cost optimization, whereas Slovakia shows relatively lower usage of BIM and AI, particularly for material and resource-related optimization. This suggests that while cost considerations often drive digital adoption, they may not always lead to deeper material efficiency or sustainability unless supported by comprehensive digital planning frameworks.

Looking ahead, future research should aim to expand the research sample to include a broader and more diverse set of countries and construction markets. While this study provides valuable insights into the Central and Southeastern European context, the inclusion of additional EU member states as well as non-European economies would enhance the generalizability of findings. Such an expansion would enable the identification of global patterns in digital technology adoption and provide a more nuanced understanding of how regional differences shape the digital transformation of the construction industry.

Moreover, there is a need for comparative studies that examine differences in digital tool utilization across various markets, project types, and organizational structures. These analyses could, for instance, compare public vs. private sector projects, large vs. small enterprises, or different procurement models. Understanding how institutional, economic, and regulatory factors influence digital adoption can help stakeholders design more effective and context-sensitive strategies.

Another promising direction involves the disaggregation of BIM and AI usage according to specific construction activities and purposes. While this study focused on resource, cost, and schedule optimization, future research should explore how digital technologies are applied in diverse functions such as energy modelling, safety planning, construction logistics, waste reduction, or post-construction asset management. Such granularity would help determine which tools are most effective for which tasks and support the development of best-practice frameworks tailored to different project phases.

Finally, future investigations should also broaden the scope of sustainability indicators considered. Beyond cost, material, and time dimensions, it is essential to evaluate the influence of digitalization on carbon footprint reduction, the integration of renewable energy, circular economy practices, workforce wellbeing, and social value creation. A multidimensional approach would provide a more holistic view of how digital tools support not only efficiency but also long-term resilience and responsibility in construction.

In conclusion, the present study reaffirms that BIM and AI are not merely supplementary technologies but are essential enablers of sustainable construction. As the industry faces growing pressure to reduce its environmental impact while increasing efficiency and resilience, the strategic deployment of these tools, guided by skilled human expertise, will be critical. The challenge moving forward lies not in whether to adopt digital technologies, but in how to embed them meaningfully across all stages of the construction process and throughout global markets.

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supervision, P.M.; project administration, T.M. All authors have read and agreed to the published version of the manuscript.

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Informed Consent Statement: Informed consent was obtained from all participants at the start of the online questionnaire.

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy and confidentiality restrictions.

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References

1. Ding, G.K.C. Life cycle assessment (LCA) of sustainable building materials: An overview. In *Eco-Efficient Construction and Building Materials*; Pacheco-Torgal, F., Cabeza, L.F., Labrincha, J., de Magalhães, A., Eds.; Woodhead Publishing: Cambridge, UK, 2014; pp. 38–62. [CrossRef]
2. Zuo, J.; Pullen, S.; Rameezdeen, R.; Bennetts, H.; Wang, Y.; Mao, G.; Zhou, Z.; Du, H.; Duan, H. Green building evaluation from a life-cycle perspective in Australia: A critical review. *Renew. Sustain. Energy Rev.* **2017**, *70*, 358–368. [CrossRef]
3. Sartori, T.; Drogemuller, R.; Omrani, S.; Lamari, F. A schematic framework for life cycle assessment (LCA) and green building rating system (GBRS). *J. Build. Eng.* **2021**, *38*, 102180. [CrossRef]
4. Bruce-Hyrkäs, T.; Pasanen, P.; Castro, R. Overview of whole building life-cycle assessment for green building certification and ecodesign through industry surveys and interviews. *Procedia CIRP* **2018**, *69*, 178–183. [CrossRef]
5. Lee, N.; Tae, S.; Gong, Y.; Roh, S. Integrated building life-cycle assessment model to support South Korea's green building certification system (G-SEED). *Renew. Sustain. Energy Rev.* **2017**, *76*, 43–50. [CrossRef]
6. Chen, X.; Chang-Richards, A.Y.; Pelosi, A.; Jia, Y.; Shen, X.; Siddiqui, M.K.; Yang, N. Implementation of technologies in the construction industry: A systematic review. *Eng. Constr. Archit. Manag.* **2022**, *29*, 3181–3209. [CrossRef]
7. Begić, H.; Galić, M. A systematic review of Construction 4.0 in the context of the BIM 4.0 premise. *Buildings* **2021**, *11*, 337. [CrossRef]
8. Flyvbjerg, B. What you should know about megaprojects and why: An overview. *Proj. Manag. J.* **2014**, *45*, 6–19. [CrossRef]
9. Love, P.E.D.; Edwards, D.J.; Irani, Z. Moving beyond optimism bias and strategic misrepresentation: An explanation for social infrastructure project cost overruns. *IEEE Trans. Eng. Manag.* **2012**, *59*, 560–571. [CrossRef]
10. Schwab, K. *The Fourth Industrial Revolution*; Crown Business: New York, NY, USA, 2017.
11. Kagermann, H.; Wahlster, W.; Helbig, J. *Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0*; Acatech: Munich, Germany, 2013.
12. Oesterreich, T.D.; Teuteberg, F. Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Comput. Ind.* **2016**, *83*, 121–139. [CrossRef]
13. Dallasega, P.; Rauch, E.; Linder, C. Industry 4.0 as an enabler of proximity for construction supply chains: A systematic literature review. *Comput. Ind.* **2018**, *99*, 205–225. [CrossRef]

14. Eastman, C.; Teicholz, P.; Sacks, R.; Liston, K. *BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors*, 2nd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2011.
15. Sacks, R.; Eastman, C.; Lee, G.; Teicholz, P. *BIM Handbook: A Guide to Building Information Modeling for Owners, Designers, Engineers, Contractors, and Facility Managers*, 3rd ed.; John Wiley & Sons: Hoboken, NJ, USA, 2018.
16. Azhar, S. Building information modeling (BIM): Trends, benefits, risks, and challenges for the AEC industry. *Leadersh. Manag. Eng.* **2011**, *11*, 241–252. [CrossRef]
17. Ghaffarianhoseini, A.; Tookey, J.; Ghaffarianhoseini, A.; Naismith, N.; Azhar, S.; Efimova, O.; Raahemifar, K. Building Information Modelling (BIM) uptake: Clear benefits, understanding its implementation, risks and challenges. *Renew. Sustain. Energy Rev.* **2017**, *75*, 1046–1053. [CrossRef]
18. Wong, J.K.W.; Zhou, J. Enhancing environmental sustainability over building life cycles through green BIM: A review. *Autom. Constr.* **2015**, *57*, 156–165. [CrossRef]
19. Lu, Y.; Wu, Z.; Chang, R.; Li, Y. Building Information Modeling (BIM) for green buildings: A critical review and future directions. *Autom. Constr.* **2017**, *83*, 134–148. [CrossRef]
20. Russell, S.J.; Norvig, P. *Artificial Intelligence: A Modern Approach*, 4th ed.; Pearson: London, UK, 2020.
21. Baduge, S.K.; Thilakarathna, S.; Perera, J.S.; Arashpour, M.; Sharafi, P.; Teodosio, B.; Shringi, A.; Mendis, P. Artificial intelligence and smart vision for building and construction 4.0: Machine and deep learning methods and applications. *Autom. Constr.* **2022**, *141*, 104440. [CrossRef]
22. Datta, S.D.; Islam, M.; Sobuz, M.H.R.; Ahmed, S.; Kar, M. Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review. *Heliyon* **2024**, *10*, e26888. [CrossRef] [PubMed]
23. Waqar, A.; Othman, I.; Almujibah, H.; Khan, M.B.; Alotaibi, S.; Elhassan, A.A.M. Factors influencing residential building envelope energy efficiency through building information modelling (BIM). *Ain Shams Eng. J.* **2024**, *15*, 102340. [CrossRef]
24. Pan, Y.; Zhang, L. Integrating BIM and AI for smart construction management: Current status and future directions. *Arch. Comput. Methods Eng.* **2023**, *30*, 1081–1110. [CrossRef]
25. Rahimian, F.P.; Seyedzadeh, S.; Oliver, S.; Rodriguez, S.; Dawood, N. On-demand monitoring of construction projects through a game-like hybrid application of BIM and machine learning. *Autom. Constr.* **2020**, *110*, 103012. [CrossRef]
26. Chong, H.Y.; Lee, C.Y.; Wang, X. A mixed review of the adoption of Building Information Modelling (BIM) for sustainability. *J. Clean. Prod.* **2017**, *142*, 4114–4126. [CrossRef]
27. Datta, S.D.; Tayeh, B.A.; Hakeem, I.Y.; Abu Aisheh, Y.I. Benefits and barriers of implementing building information modeling techniques for sustainable practices in the construction industry—A comprehensive review. *Sustainability* **2023**, *15*, 12466. [CrossRef]
28. Miettinen, R.; Paavola, S. Beyond the BIM utopia: Approaches to the development and implementation of building information modeling. *Autom. Constr.* **2014**, *43*, 84–91. [CrossRef]
29. Ullah, K.; Lill, I.; Witt, E. An overview of BIM adoption in the construction industry: Benefits and barriers. In *10th Nordic Conference on Construction Economics and Organization*; Lill, I., Witt, E., Eds.; Emerald Publishing Limited: Bingley, UK, 2019; pp. 297–303. [CrossRef]
30. Stojanovska-Georgievska, L.; Sandeva, I.; Krleski, A.; Spasevska, H.; Ginovska, M.; Panchevski, I.; Ivanov, R.; Perez Arnal, I.; Cerovsek, T.; Funtik, T. BIM in the center of digital transformation of the construction sector—The status of BIM adoption in North Macedonia. *Buildings* **2022**, *12*, 218. [CrossRef]
31. Brodny, J.; Tutak, M. The level of digitization of small, medium and large enterprises in the central and eastern European countries and its relationship with economic parameters. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 113. [CrossRef]
32. Liu, Z.; Lu, Y.; Peh, L.C. A review and scientometric analysis of global building information modeling (BIM) research in the architecture, engineering and construction (AEC) industry. *Buildings* **2019**, *9*, 210. [CrossRef]
33. Opoku, D.G.J.; Perera, S.; Osei-Kyei, R.; Rashidi, M. Barriers to the adoption of digital twin in the construction industry: A literature review. *Informatics* **2023**, *10*, 14. [CrossRef]
34. Lasi, H.; Fettke, P.; Kemper, H.G.; Feld, T.; Hoffmann, M. Industry 4.0. *Bus. Inf. Syst. Eng.* **2014**, *6*, 239–242. [CrossRef]
35. Craveiro, F.; Duarte, J.P.; Bartolo, H.; Bartolo, P.J. Additive manufacturing as an enabling technology for digital construction: A perspective on Construction 4.0. *Autom. Constr.* **2019**, *103*, 251–267. [CrossRef]
36. Sawhney, A.; Riley, M.; Irizarry, J. (Eds.) *Construction 4.0: An Innovation Platform for the Built Environment*; Routledge: London, UK, 2020.
37. Deng, M.; Menassa, C.C.; Kamat, V.R. From BIM to digital twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry. *J. Inf. Technol. Constr.* **2021**, *26*, 58–83. [CrossRef]
38. Ozturk, G.B. Digital twin research in the AECO-FM industry. *J. Build. Eng.* **2021**, *40*, 102730. [CrossRef]
39. McKinsey Global Institute. *Reinventing Construction: A Route to Higher Productivity*; McKinsey & Company: Chicago, IL, USA, 2017.
40. Agarwal, R.; Chandrasekaran, S.; Sridhar, M. Imagining construction's digital future. *McKinsey Q.* **2016**, *24*, 1–15.
41. Barbosa, F.; Woetzel, J.; Mischke, J.; Ribeirinho, M.J.; Sridhar, M.; Parsons, M.; Bertram, N.; Brown, S. *Reinventing Construction through a Productivity Revolution*; McKinsey Global Institute: New York, NY, USA, 2017.

42. Wang, M.; Wang, C.C.; Sepasgozar, S.; Zlatanova, S. A systematic review of digital technology adoption in off-site construction: Current status and future direction towards industry 4.0. *Buildings* **2020**, *10*, 204. [CrossRef]
43. Kor, M.; Yitmen, I.; Alizadehsalehi, S. An investigation for integration of deep learning and digital twins towards Construction 4.0. *Smart Sustain. Built Environ.* **2023**, *12*, 461–487. [CrossRef]
44. Rafsanjani, H.N.; Nabizadeh, A.H. Towards digital architecture, engineering, and construction (AEC) industry through virtual design and construction (VDC) and digital twin. *Energy Built Environ.* **2023**, *4*, 169–178. [CrossRef]
45. Hu, W.; Lim, K.Y.H.; Cai, Y. Digital twin and industry 4.0 enablers in building and construction: A survey. *Buildings* **2022**, *12*, 2004. [CrossRef]
46. Hosamo, H.H.; Imran, A.; Cardenas-Cartagena, J.; Svennevig, P.R.; Svidt, K.; Nielsen, H.K. A review of the digital twin technology in the AEC-FM industry. *Adv. Civ. Eng.* **2022**, *2022*, 2185170. [CrossRef]
47. Sepasgozar, S.M.E.; Khan, A.A.; Smith, K.; Romero, J.G.; Shen, X.; Shirowzhan, S.; Li, H.; Tahmasebinia, F. BIM and digital twin for developing convergence technologies as future of digital construction. *Buildings* **2023**, *13*, 441. [CrossRef]
48. Boje, C.; Guerriero, A.; Kubicki, S.; Rezgui, Y. Towards a semantic Construction Digital Twin: Directions for future research. *Autom. Constr.* **2020**, *114*, 103179. [CrossRef]
49. European Commission. *The European Green Deal; COM(2019) 640 Final*; European Commission: Brussels, Belgium, 2019.
50. European Commission. *A Renovation Wave for Europe—Greening Our Buildings, Creating Jobs, Improving Lives*; COM(2020) 662 Final; European Commission: Brussels, Belgium, 2020.
51. Turk, Ž. Structured analysis of ICT adoption in the European construction industry. *Int. J. Constr. Manag.* **2023**, *23*, 1151–1163. [CrossRef]
52. Aleksandrova, E.; Vinogradova, V.; Tokunova, G. Integration of digital technologies in the field of construction in the Russian Federation. *Eng. Manag. Prod. Serv.* **2019**, *11*, 38–47. [CrossRef]
53. Hossain, M.A.; Nadeem, A. Towards digitizing the construction industry: State of the art of construction 4.0. In Proceedings of the 10th International Structural Engineering and Construction Conference (ISEC-10), Chicago, IL, USA, 20–25 May 2019.
54. Succar, B. Building information modelling framework: A research and delivery foundation for industry stakeholders. *Autom. Constr.* **2009**, *18*, 357–375. [CrossRef]
55. Eastman, C.; Teicholz, P.; Sacks, R.; Liston, K. *BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors*, 1st ed.; John Wiley & Sons: Hoboken, NJ, USA, 2008.
56. Sun, C.; Jiang, S.; Skibniewski, M.J.; Man, Q.; Shen, L. A literature review of the factors limiting the application of BIM in the construction industry. *Technol. Econ. Dev. Econ.* **2017**, *23*, 764–779. [CrossRef]
57. Hosseini, M.R.; Maghrebi, M.; Akbarnezhad, A.; Martek, I.; Arashpour, M. Analysis of citation networks in building information modeling research. *J. Constr. Eng. Manag.* **2018**, *144*, 04018064. [CrossRef]
58. Succar, B.; Kassem, M. Macro-BIM adoption: Conceptual structures. *Autom. Constr.* **2015**, *57*, 64–79. [CrossRef]
59. Bew, M.; Richards, M. Bew-Richards BIM Maturity Model. In *BuildingSMART Construct IT Autumn Members Meeting*; BuildingSMART: Brighton, UK, 2008.
60. Eadie, R.; Browne, M.; Odeyinka, H.; McKeown, C.; McNiff, S. BIM implementation throughout the UK construction project lifecycle: An analysis. *Autom. Constr.* **2013**, *36*, 145–151. [CrossRef]
61. Smith, P. BIM implementation—Global strategies. *Procedia Eng.* **2014**, *85*, 482–492. [CrossRef]
62. *ISO 19650-1:2018*; Organization and Digitization of Information about Buildings and Civil Engineering Works, Including Building Information Modelling (BIM)—Information Management Using Building Information Modelling—Part 1: Concepts and Principles. ISO: Geneva, Switzerland, 2018.
63. *ISO 19650-2:2018*; Organization and Digitization of Information about Buildings and Civil Engineering Works, Including Building Information Modelling (BIM)—Information Management Using Building Information Modelling—Part 2: Delivery Phase of the Assets. ISO: Geneva, Switzerland, 2018.
64. Bouška, R. Evaluation of maturity of BIM tools across different software platforms. *Procedia Eng.* **2016**, *164*, 481–486. [CrossRef]
65. Ahmed, A.L.; Kassem, M. A unified BIM adoption taxonomy: Conceptual development, empirical validation and application. *Autom. Constr.* **2018**, *96*, 103–127. [CrossRef]
66. Georgiadou, M.C. An overview of benefits and challenges of building information modelling (BIM) adoption in UK residential projects. *Constr. Innov.* **2019**, *19*, 298–320. [CrossRef]
67. Merschbrock, C.; Munkvold, B.E. Effective digital collaboration in the construction industry—A case study of BIM deployment in a hospital construction project. *Comput. Ind.* **2015**, *73*, 1–7. [CrossRef]
68. Winfield, M. Construction 4.0 and ISO 19650: A panacea for the digital revolution? *Proc. Inst. Civ. Eng. Manag. Procure. Law* **2020**, *173*, 175–181. [CrossRef]
69. Dave, B.; Kuber, S.; Koskela, L.; Kagioglou, M. Opportunities for enhanced lean construction management using Internet of Things standards. *Autom. Constr.* **2016**, *61*, 86–97. [CrossRef]

70. Sacks, R.; Koskela, L.; Dave, B.A.; Owen, R. Interaction of lean and building information modeling in construction. *J. Constr. Eng. Manag.* **2010**, *136*, 968–980. [CrossRef]
71. Hamdi, O.; Leite, F. BIM and lean interactions from the BIM capability maturity model perspective: A case study. In Proceedings of the 22nd Annual Conference of the International Group for Lean Construction (IGLC 22), Oslo, Norway, 25–27 June 2014; pp. 299–310.
72. Azhar, S.; Brown, J. BIM for sustainability analyses. *Int. J. Constr. Educ. Res.* **2009**, *5*, 276–292. [CrossRef]
73. Zhuang, D.; Zhang, X.; Lu, Y.; Wang, C.; Jin, X.; Zhou, X.; Shi, X. A performance data integrated BIM framework for building life-cycle energy efficiency and environmental optimization design. *Autom. Constr.* **2021**, *127*, 103712. [CrossRef]
74. Jalaei, F.; Jrade, A. Integrating building information modeling (BIM) and LEED system at the conceptual design stage of sustainable buildings. *Sustain. Cities Soc.* **2015**, *18*, 95–107. [CrossRef]
75. Wong, J.K.W.; Kuan, K.L. Implementing 'BEAM Plus' for BIM-based sustainability analysis. *Autom. Constr.* **2014**, *44*, 163–175. [CrossRef]
76. Kamel, E.; Memari, A.M. Review of BIM's application in energy simulation: Tools, issues, and solutions. *Autom. Constr.* **2019**, *97*, 164–180. [CrossRef]
77. Gao, H.; Koch, C.; Wu, Y. Building information modelling based building energy modelling: A review. *Appl. Energy* **2019**, *238*, 320–343. [CrossRef]
78. Pezeshki, Z.; Soleimani, A.; Darabi, A. Application of BEM and using BIM database for BEM: A review. *J. Build. Eng.* **2019**, *23*, 1–17. [CrossRef]
79. Ilhan, B.; Yaman, H. Green building assessment tool (GBAT) for integrated BIM-based design decisions. *Autom. Constr.* **2016**, *70*, 26–37. [CrossRef]
80. Wu, W.; Issa, R.R.A. BIM execution planning in green building projects: LEED as a use case. *J. Manag. Eng.* **2015**, *31*, A4014007. [CrossRef]
81. Liu, Z.; Osmani, M.; Demian, P.; Baldwin, A. A BIM-aided construction waste minimisation framework. *Autom. Constr.* **2015**, *59*, 1–23. [CrossRef]
82. Won, J.; Cheng, J.C.P. Identifying potential opportunities of building information modeling for construction and demolition waste management and minimization. *Autom. Constr.* **2017**, *79*, 3–18. [CrossRef]
83. Akinade, O.O.; Oyedele, L.O.; Ajayi, S.O.; Bilal, M.; Alaka, H.A.; Owolabi, H.A.; Bello, S.A.; Jaiyeoba, B.E.; Kadiri, K.O. Design for Deconstruction (DfD): Critical success factors for diverting end-of-life waste from landfills. *Waste Manag.* **2017**, *60*, 3–13. [CrossRef] [PubMed]
84. Honic, M.; Kovacic, I.; Rechberger, H. Improving the recycling potential of buildings through Material Passports (MP): An Austrian case study. *J. Clean. Prod.* **2019**, *217*, 787–797. [CrossRef]
85. Munaro, M.R.; Tavares, S.F.; Bragança, L. Towards circular and more sustainable buildings: A systematic literature review on the circular economy in the built environment. *J. Clean. Prod.* **2020**, *260*, 121134. [CrossRef]
86. Ajayi, S.O.; Oyedele, L.O.; Ceranic, B.; Gallanagh, M.; Kadiri, K.O. Life cycle environmental performance of material specification: A BIM-enhanced comparative assessment. *Int. J. Sustain. Build. Technol. Urban Dev.* **2015**, *6*, 14–24. [CrossRef]
87. Chong, H.Y.; Wang, X. The outlook of building information modeling for sustainable development. *Clean Technol. Environ. Policy* **2016**, *18*, 1877–1887. [CrossRef]
88. Jrade, A.; Jalaei, F. Integrating building information modelling with sustainability to design building projects at the conceptual stage. *Build. Simul.* **2013**, *6*, 429–444. [CrossRef]
89. Ayman, R.; Alwan, Z.; McIntyre, L. BIM for sustainable project delivery: Review paper and future development areas. *Archit. Sci. Rev.* **2020**, *63*, 15–33. [CrossRef]
90. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef] [PubMed]
91. Darko, A.; Chan, A.P.C.; Adabre, M.A.; Edwards, D.J.; Hosseini, M.R.; Ameyaw, E.E. Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Autom. Constr.* **2020**, *112*, 103081. [CrossRef]
92. Salehi, H.; Burgueño, R. Emerging artificial intelligence methods in structural engineering. *Eng. Struct.* **2018**, *171*, 170–189. [CrossRef]
93. Abioye, S.O.; Oyedele, L.O.; Akanbi, L.; Ajayi, A.; Delgado, J.M.D.; Bilal, M.; Akinade, O.O.; Ahmed, A. Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *J. Build. Eng.* **2021**, *44*, 103299. [CrossRef]
94. Rafiei, M.H.; Adeli, H. Novel machine-learning model for estimating construction costs considering economic variables and indexes. *J. Constr. Eng. Manag.* **2018**, *144*, 04018106. [CrossRef]
95. Kim, G.H.; An, S.H.; Kang, K.I. Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning. *Build. Environ.* **2004**, *39*, 1235–1242. [CrossRef]
96. Wang, R.; Asghari, V.; Cheung, C.M.; Hsu, S.C.; Lee, C. Assessing effects of economic factors on construction cost estimation using deep neural networks. *Autom. Constr.* **2022**, *134*, 104080. [CrossRef]

97. Hashemi, S.T.; Ebadati, O.M.; Kaur, H. Cost estimation and prediction in construction projects: A systematic review on machine learning techniques. *SN Appl. Sci.* **2020**, *2*, 1703. [CrossRef]
98. Ghoddousi, P.; Eshtehardian, E.; Jooybanpour, S.; Javanmardi, A. Multi-mode resource-constrained discrete time–cost-resource optimization in project scheduling using non-dominated sorting genetic algorithm. *Autom. Constr.* **2013**, *30*, 216–227. [CrossRef]
99. Rogalska, M.; Bożejko, W.; Hejducki, Z. Time/cost optimization using hybrid evolutionary algorithm in construction project scheduling. *Autom. Constr.* **2008**, *18*, 24–31. [CrossRef]
100. Kannimuthu, M.; Raphael, B.; Palaneeswaran, E.; Kuppuswamy, A. Optimizing time, cost and quality in multi-mode resource-constrained project scheduling. *Built Environ. Proj. Asset Manag.* **2019**, *9*, 44–63. [CrossRef]
101. Lin, J.C.W.; Lv, Q.; Yu, D.; Srivastava, G.; Chen, C.H. Optimized scheduling of resource-constraints in projects for smart construction. *Inf. Process. Manag.* **2022**, *59*, 103005. [CrossRef]
102. Fang, W.; Ding, L.; Zhong, B.; Love, P.E.D.; Luo, H. Automated detection of workers and heavy equipment on construction sites: A convolutional neural network approach. *Adv. Eng. Inform.* **2018**, *37*, 139–149. [CrossRef]
103. Guo, H.; Yu, Y.; Skitmore, M. Visualization technology-based construction safety management: A review. *Autom. Constr.* **2017**, *73*, 135–144. [CrossRef]
104. Li, J.; Li, H.; Umer, W.; Wang, H.; Xing, X.; Zhao, S.; Hou, J. Identification and classification of construction equipment operators' mental fatigue using wearable eye-tracking technology. *Autom. Constr.* **2020**, *109*, 103000. [CrossRef]
105. Regona, M.; Yigitcanlar, T.; Xia, B.; Li, R.Y.M. Artificial intelligence technologies and the construction industry: Current status and future trends. *Buildings* **2022**, *12*, 1989. [CrossRef]
106. Rane, N. Integrating building information modelling (BIM) and artificial intelligence (AI) for smart construction schedule, cost, quality, and safety management: Challenges and opportunities. *SSRN Electron. J.* **2023**, 4616055. [CrossRef]
107. Blanco, J.L.; Fuchs, S.; Parsons, M.; Ribeirinho, M.J. Artificial intelligence: Construction technology's next frontier. *Build. Econ* **2018**, 7–13. Available online: https://www.mckinsey.com/capabilities/operations/our-insights/artificial-intelligence-construction-technologys-next-frontier (accessed on 10 January 2025).
108. Heidari, A.; Peyvastehgar, Y.; Rashidian, S.; Nasrollahi, N.; Bahram, P. A systematic review of the BIM in construction: From smart building management to interoperability of BIM & AI. *Archit. Sci. Rev.* **2024**, *67*, 129–149. [CrossRef]
109. Bassir, D.; Lodge, H.; Chang, H.; Majak, J.; Chen, W. Application of artificial intelligence and machine learning for BIM. *Int. J. Simul. Multidiscip. Des. Optim.* **2023**, *14*, 5. [CrossRef]
110. Zhao, X.; Yeoh, J.K.W.; Tan, S.T. Artificial intelligence in the construction industry: A review of present status, opportunities, and challenges. *J. Build. Eng.* **2023**, *76*, 107363. [CrossRef]
111. Bilal, M.; Oyedele, L.O.; Qadir, J.; Munir, K.; Ajayi, S.O.; Akinade, O.O.; Owolabi, H.A.; Alaka, H.A.; Pasha, M. Big Data in the construction industry: A review of present status, opportunities, and future trends. *Adv. Eng. Inform.* **2016**, *30*, 500–521. [CrossRef]
112. Ma, Z.; Liu, S. A review of 3D reconstruction techniques in civil engineering and their applications. *Adv. Eng. Inform.* **2018**, *37*, 163–174. [CrossRef]
113. Caetano, I.; Santos, L.; Leitão, A. Computational design in architecture: Defining parametric, generative, and algorithmic design. *Front. Archit. Res.* **2020**, *9*, 287–300. [CrossRef]
114. Nagy, D.; Lau, D.; Locke, J.; Stoddart, J.; Villaggi, L.; Wang, R.; Zhao, D.; Benjamin, D. Project Discover: An application of generative design for architectural space planning. In Proceedings of the Symposium on Simulation for Architecture and Urban Design, Toronto, ON, Canada, 22–24 May 2017; pp. 1–8.
115. Shi, X.; Yang, W. Performance-driven architectural design and optimization technique from a perspective of architects. *Autom. Constr.* **2013**, *32*, 125–135. [CrossRef]
116. Touloupaki, E.; Theodosiou, T. Performance simulation integrated in parametric 3D modeling as a method for early stage design optimization—A review. *Energies* **2017**, *10*, 637. [CrossRef]
117. Zhang, J.; El-Gohary, N.M. Automated information transformation for automated regulatory compliance checking in construction. *J. Comput. Civ. Eng.* **2015**, *29*, B4015001. [CrossRef]
118. Dimyadi, J.; Pauwels, P.; Amor, R. Modelling and accessing regulatory knowledge for computer-assisted compliance audit. *J. Inf. Technol. Constr.* **2016**, *21*, 317–336.
119. Nawari, N.O. A generalized adaptive framework (GAF) for automating code compliance checking. *Buildings* **2019**, *9*, 86. [CrossRef]
120. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital twin: Enabling technologies, challenges and open research. *IEEE Access* **2020**, *8*, 108952–108971. [CrossRef]
121. Xie, X.; Lu, Q.; Parlikad, A.K.; Schooling, J.M. Digital twin enabled asset anomaly detection for building facility management. *IFAC-PapersOnLine* **2020**, *53*, 380–385. [CrossRef]
122. Matarneh, S.T.; Danso-Amoako, M.; Al-Bizri, S.; Gaterell, M.; Matarneh, R. Building information modeling for facilities management: A literature review and future research directions. *J. Build. Eng.* **2019**, *24*, 100755. [CrossRef]

123. Lu, Q.; Xie, X.; Heaton, J.; Parlikad, A.K.; Schooling, J. From BIM towards digital twin: Strategy and future development for smart asset management. In *Service Oriented, Holonic and Multi-Agent Manufacturing Systems for Industry of the Future*; Springer: Cham, Switzerland, 2020; pp. 392–404.
124. Bortolini, R.; Formoso, C.T.; Viana, D.D. Site logistics planning and control for engineer-to-order prefabricated building systems using BIM 4D modeling. *Autom. Constr.* **2019**, *98*, 248–264. [CrossRef]
125. Abanda, F.H.; Balu, B.; Adukpo, S.E.; Akintola, A. Decoding ISO 19650 through process modelling for information management and stakeholder communication in BIM. *Buildings* **2025**, *15*, 431. [CrossRef]
126. Adeli, H.; Karim, A. Scheduling/cost optimization and neural dynamics model for construction. *J. Constr. Eng. Manag.* **1997**, *123*, 450–458. [CrossRef]
127. Koulinas, G.K.; Anagnostopoulos, K.P. A new tabu search-based hyper-heuristic algorithm for solving construction leveling problems with limited resource availabilities. *Autom. Constr.* **2013**, *31*, 169–175. [CrossRef]
128. Haghani, A.; Chen, M.C. Optimizing gate assignments at airport terminals. *Transp. Res. Part A Policy Pract.* **1998**, *32*, 437–454. [CrossRef]
129. Cajzek, R.; Klanšek, U. Cost optimization of project schedules under constrained resources and alternative production processes by mixed-integer nonlinear programming. *Eng. Constr. Archit. Manag.* **2019**, *26*, 2474–2508. [CrossRef]
130. Zou, X.; Zhang, L.; Zhang, Q. Time-cost optimization in repetitive project scheduling with limited resources. *Eng. Constr. Archit. Manag.* **2022**, *29*, 669–695. [CrossRef]
131. Elbeltagi, E.; Hegazy, T.; Grierson, D. Comparison among five evolutionary-based optimization algorithms. *Adv. Eng. Inform.* **2005**, *19*, 43–53. [CrossRef]
132. Zhang, L.; Zou, X.; Qi, J. A trade-off between time and cost in scheduling repetitive construction projects. *J. Ind. Manag. Optim.* **2015**, *11*, 1423–1434. [CrossRef]
133. Marzouk, M.; Abubakr, A. Decision support for tower crane selection with building information models and genetic algorithms. *Autom. Constr.* **2016**, *61*, 1–15. [CrossRef]
134. Marzouk, M.; Azab, S. Environmental and economic impact assessment of construction and demolition waste disposal using system dynamics. *Resour. Conserv. Recycl.* **2014**, *82*, 41–49. [CrossRef]
135. Liu, S.S.; Wang, C.J. Optimizing project selection and scheduling problems with time-dependent resource constraints. *Autom. Constr.* **2011**, *20*, 1110–1119. [CrossRef]
136. Sonmez, R.; Bettemir, Ö.H. A hybrid genetic algorithm for the discrete time–cost trade-off problem. *Expert Syst. Appl.* **2012**, *39*, 11428–11434. [CrossRef]
137. Hegazy, T. Optimization of resource allocation and leveling using genetic algorithms. *J. Constr. Eng. Manag.* **1999**, *125*, 167–175. [CrossRef]
138. El-Rayes, K.; Kandil, A. Time-cost-quality trade-off analysis for highway construction. *J. Constr. Eng. Manag.* **2005**, *131*, 477–486. [CrossRef]
139. Zhong, B.; Wu, H.; Li, H.; Sepasgozar, S.; Luo, H.; He, L. A scientometric analysis and critical review of construction related ontology research. *Autom. Constr.* **2019**, *101*, 17–31. [CrossRef]
140. Han, K.K.; Golparvar-Fard, M. Potential of big visual data and building information modeling for construction performance analytics: An exploratory study. *Autom. Constr.* **2017**, *73*, 184–198. [CrossRef]
141. Deng, Y.; Cheng, J.C.P.; Anumba, C. Mapping between BIM and 3D GIS in different levels of detail using schema mediation and instance comparison. *Autom. Constr.* **2016**, *67*, 1–21. [CrossRef]
142. Xu, X.; Ma, L.; Ding, L. A framework for BIM-enabled life-cycle information management of construction project. *Int. J. Adv. Robot. Syst.* **2014**, *11*, 126. [CrossRef]
143. Akadiri, P.O.; Chinyio, E.A.; Olomolaiye, P.O. Design of a sustainable building: A conceptual framework for implementing sustainability in the building sector. *Buildings* **2012**, *2*, 126–152. [CrossRef]
144. Hwang, B.G.; Tan, J.S. Green building project management: Obstacles and solutions for sustainable development. *Sustain. Dev.* **2012**, *20*, 335–349. [CrossRef]
145. Hossain, M.U.; Ng, S.T. Critical consideration of buildings' environmental impact assessment towards adoption of circular economy: An analytical review. *J. Clean. Prod.* **2018**, *205*, 763–780. [CrossRef]
146. Ahmad, T.; Thaheem, M.J. Developing a residential building-related social sustainability assessment framework and its implications for BIM. *Sustain. Cities Soc.* **2017**, *28*, 1–15. [CrossRef]
147. Eurostat. Construction Statistics—NACE Rev. 2. Eurostat Statistics Explained. 2023. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php/Construction_statistics_-_NACE_Rev._2 (accessed on 10 January 2025).
148. European Construction Industry Federation. *Construction 2050—Building Tomorrow's Europe Today*; FIEC: Brussels, Belgium, 2019.
149. European Commission. *Supporting Digitalisation of the Construction Sector and SMEs*; European Commission: Brussels, Belgium, 2021.
150. Bašková, R.; Struková, Z.; Tažiková, A. Adoption of digital technologies in the learning process to support the platform Construction 4.0. In Proceedings of the ICERI2020 Conference, Seville, Spain, 9–10 November 2020; pp. 2988–2995.

151. Mandičák, T.; Mesároš, P.; Kozlovská, M. Information and communication technologies for sustainable construction in investment projects. In Proceedings of the International Multidisciplinary Scientific GeoConference SGEM, Sofia, Bulgaria, 28 June–7 July 2019; pp. 481–488. [CrossRef]
152. Mesároš, P.; Mandičák, T. Impact of digitalization on safety at work in the construction industry. *Civ. Eng. Archit.* **2022**, *10*, 2889–2899. [CrossRef]
153. Smetanková, J.; Mandičák, T.; Spišáková, M. Analysis of the implementation of BIM in the Slovak construction industry. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1203*, 022022. [CrossRef]
154. Mésaroš, P.; Mandičák, T. Exploitation and benefits of BIM in construction project management in Slovakia. *IOP Conf. Ser. Mater. Sci. Eng.* **2017**, *245*, 062056. [CrossRef]
155. Marović, I.; Perić, M.; Hanak, T. A multi-criteria decision support concept for selecting the optimal contractor. *Appl. Sci.* **2021**, *11*, 1660. [CrossRef]
156. Marović, I.; Car-Pušić, D.; Hrvatin, Z. Establishing a model to evaluate public administration projects. *E-Gose Stud. Proj.* **2014**, *12*, 56–66. [CrossRef]
157. Vukomanović, M.; Radujković, M.; Nahod, M.M. EFQM excellence model as the TQM model of the construction industry of southeastern Europe. *J. Civ. Eng. Manag.* **2014**, *20*, 70–81. [CrossRef]
158. Cerić, A. The role of communication and information management in project success. *Proc. Inst. Civ. Eng. Manag. Procure. Law* **2016**, *169*, 167–171. [CrossRef]
159. Olanrewaju, O.I.; Kineber, A.F.; Chileshe, N.; Edwards, D.J. Modelling the relationship between BIM adoption and construction sustainability: Towards sustainability transformation in organizations. *Buildings* **2021**, *11*, 413. [CrossRef]
160. Olawumi, T.O.; Chan, D.W.M. Identifying and prioritizing the benefits of integrating BIM and sustainability practices in construction projects: A Delphi survey of international experts. *Sustain. Cities Soc.* **2018**, *40*, 16–27. [CrossRef]
161. Tan, T.; Chen, K.; Xue, F.; Lu, W. Barriers to Building Information Modeling (BIM) implementation in China's prefabricated construction: An interpretive structural modeling (ISM) approach. *J. Clean. Prod.* **2019**, *219*, 949–959. [CrossRef]
162. Galić, M.; Venkrbec, V.; Chmelik, F.; Feine, I.; Pučko, Z.; Klanšek, U. Survey of accomplishments in BIM implementation in Croatia, the Czech Republic, Germany, and Slovenia. *Adv. Civ. Archit. Eng.* **2017**, *15*, 23–35. [CrossRef]
163. Kolarić, S.; Vukomanović, M.; Bogdan, A. Analysis of the use of BIM in Croatian construction industry. *Građevinar* **2020**, *72*, 205–214. [CrossRef]
164. Cerić, A.; Završki, I.; Vukomanović, M.; Ivić, I.; Nahod, M.-M. BIM implementation in building maintenance management. *Građevinar* **2019**, *71*, 889–900. [CrossRef]
165. Kolarić, S.; Mandičák, T.; Vukomanović, M.; Mésároš, P. The Influence of BIM Education Improvement on Raising BIM Awareness in Croatia and Slovakia. *Period. Polytech. Arch.* **2019**, *50*, 21–29. [CrossRef]
166. Funtík, T.; Makýš, P.; Ďubek, M.; Erdélyi, J.; Honti, R.; Cerovšek, T. The Status of Building Information Modeling Adoption in Slovakia. *Buildings* **2023**, *13*, 2997. [CrossRef]
167. Mayer, P.; Funtík, T.; Gašparík, J.; Makýš, P. Analysis of the Current State of Automation of Hazard Detection Processes in BIM in Slovakia. *Appl. Sci.* **2021**, *11*, 8130. [CrossRef]
168. Mandičák, T.; Spišáková, M.; Mésároš, P. Sustainable Design and Building Information Modeling of Construction Project Management towards a Circular Economy. *Sustainability* **2024**, *16*, 4376. [CrossRef]
169. Mésároš, P.; Mandičák, T. Exploitation and Benefits of BIM in Construction Project Management. *IOP Conf. Ser. Mater. Sci. Eng.* **2017**, *245*, 062056. [CrossRef]

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