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Artificial Intelligence Tools in Construction Management

Mohammadghasem Salimi^{1*}

1. Master of Science in Civil and Structural Engineering, Payam Noor University, Tehran, Iran

*Correspondence: MQsalimi@gmail.com

Abstract

The primary objective of this study is to examine modern applications of artificial intelligence (AI) in construction project management and to explore strategies for improving various processes within this industry. Given the increasing challenges and complexities in the construction sector, the introduction and evaluation of AI tools can contribute to enhancing project efficiency, reducing costs, improving forecasting accuracy, and accelerating construction processes. This research investigates these aspects and provides suggestions for optimizing project management processes through the utilization of these advanced technologies. The findings of this study can assist entities active in the construction industry in improving their project management procedures by leveraging AI-based tools, thereby completing projects with higher quality and reduced costs. The present study adopts a quantitative research design and is conducted as a descriptive and survey-based study. Data collection was carried out through library research and the compilation of information from documented and scientific sources. The statistical population of the study includes 384 project managers engaged in the residential construction sector. Data analysis was performed using SPSS version 22. The results of the study indicate that AI tools significantly contribute to improving resource allocation in construction projects. Moreover, the study highlights existing challenges related to the adoption of AI technologies within the construction industry, emphasizing the need for focused attention and resolution of these issues.

Keywords: artificial intelligence, construction project, resource allocation, technology acceptance and challenges, construction industry.

1. Introduction

The construction industry, long characterized by its reliance on manual labor, fragmented processes, and static workflows, is undergoing a technological transformation propelled by the integration of artificial intelligence (AI). As the global construction sector faces persistent challenges such as cost overruns, schedule delays, safety risks, and resource inefficiencies, AI presents an opportunity to revolutionize project management by enabling data-driven decision-making, automating routine tasks, and enhancing real-time responsiveness to dynamic conditions (Egwim, 2023; Rampini, 2022). The potential of AI to fundamentally reshape the construction lifecycle—from preconstruction planning to post-construction asset management—is increasingly recognized by both academia and industry practitioners (Holzmann, 2022; Rabbi, 2024).

In essence, artificial intelligence refers to computational systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and decision-making. In the context of construction project management, AI encompasses a variety of techniques including machine learning (ML), computer vision, natural language



processing, and intelligent decision support systems (Liu, 2024; Takhmasib, 2023). These technologies allow construction professionals to predict project risks, optimize resource allocation, monitor site safety, and enhance stakeholder communication, thereby mitigating common inefficiencies that have historically plagued construction projects (Ghosh et al., 2019; Lam & Oshodi, 2016).

The increasing complexity of modern construction projects has further amplified the need for intelligent tools that can manage large volumes of data and adapt to evolving project constraints. For example, real-time data analytics powered by AI can support predictive scheduling, cost estimation, and supply chain coordination, providing project managers with timely insights to avert delays or budget deviations (Afzal et al., 2021; Wang & Liu, 2022). AI-powered visual recognition systems can detect safety violations or structural anomalies in real-time, reducing the likelihood of accidents and enhancing compliance with safety protocols (Rabbi, 2024; Razi, 2023). Consequently, the application of AI is not only improving the efficiency of construction operations but also contributing to the sustainability, resilience, and safety of the built environment.

Despite the promising advancements, the adoption of AI in construction remains uneven across regions and organizations. While some industry leaders have embraced AI to improve productivity and reduce human error, others encounter significant barriers such as high implementation costs, lack of digital infrastructure, and resistance from employees (Rampini, 2022; Wachnik, 2022). Cultural and organizational inertia, compounded by a shortage of AI-literate professionals in the construction workforce, has further hindered widespread adoption (Holzmann, 2022; Zia, 2024). Moreover, concerns about data privacy, system interoperability, and algorithmic bias continue to fuel skepticism regarding the integration of intelligent systems into traditionally conservative construction environments (Goodell et al., 2021; Kord, 2023).

Nevertheless, empirical studies indicate that organizations that have successfully integrated AI into their construction processes have witnessed substantial improvements in project outcomes. For instance, Wamba-Taguimdje et al. (2020) found that AI-enabled project transformation initiatives led to enhanced operational agility, cost control, and innovation capabilities in firms that had previously struggled with static management approaches (Wamba-Taguimdje et al., 2020). Similarly, Liu (2024) documented the positive impact of AI on cost optimization and schedule management in high-rise residential developments, where AI algorithms supported real-time coordination among multidisciplinary teams (Liu, 2024).

In addition to operational efficiency, AI contributes to strategic project oversight by facilitating intelligent decision-making. Wang (2022) emphasizes that AI-based decision support systems can integrate data from multiple sources—ranging from building information modeling (BIM) to IoT sensors—to provide holistic assessments of project health and risk exposure (Wang & Liu, 2022). These capabilities allow managers to move beyond reactive firefighting and adopt proactive planning strategies based on predictive analytics and historical performance data. This paradigm shift from manual intuition to evidence-based project control represents one of the most significant benefits of AI in construction management.

Beyond project execution, AI is increasingly being explored in preconstruction design and post-construction asset management. Ghosh et al. (2019) highlighted the integration of Hidden Markov Models in digital twin construction, enabling real-time feedback loops between physical systems and virtual models that enhance forecasting accuracy and operational control (Ghosh et al., 2019). Meanwhile, Rampini and Cecconi (2022) observed the utility of AI in asset lifecycle management, where intelligent systems facilitate maintenance scheduling, energy optimization, and occupancy management in completed structures (Rampini, 2022). This holistic application of AI across the construction value chain signals a transition from isolated digital interventions to fully integrated smart ecosystems.

However, the implementation of AI must be accompanied by a clear understanding of its technological limitations and organizational implications. AI systems rely heavily on the availability of high-quality, structured data, and their performance may degrade in environments characterized by data scarcity or inconsistencies (Afzal et al., 2021; Holzmann, 2022). Additionally, algorithmic decisions in safety monitoring or resource allocation may not always align with contextual judgment or ethical considerations, underscoring the need for human oversight in AI-augmented processes (Razi, 2023; Zia, 2024). Regulatory frameworks and industry standards have yet to fully address the legal and ethical questions surrounding AI deployment in construction, making governance a key area of concern for stakeholders (Goodell et al., 2021; Rabbi, 2024).



Despite these challenges, recent innovations demonstrate the growing maturity of AI technologies and their alignment with broader trends in digital construction. For instance, Takhmasib et al. (2023) introduced a machine-learned kinetic façade system that leverages predictive control algorithms to optimize visual comfort, illustrating how AI can contribute to user-centric, sustainable design (Takhmasib, 2023). Similarly, Zia (2024) emphasized the role of AI in redefining project management competencies, suggesting that future construction leaders must be proficient not only in technical domains but also in data literacy and algorithmic thinking (Zia, 2024). This evolution signals the emergence of a new managerial paradigm—one that blends engineering expertise with digital intelligence.

In this context, the current study seeks to investigate two key aspects of AI application in construction project management: (1) the extent to which AI tools contribute to the improvement of resource allocation, and (2) the challenges associated with the adoption of AI technologies in the construction industry.

2. Methods and Materials

The present study is a quantitative investigation which, based on the method of data collection, is categorized as a descriptive-survey research. In this approach, a review of library sources, paper-based, and digital documents related to the subject matter has been conducted. From the perspective of purpose, this is an applied study, and in terms of data collection technique, it is descriptive and survey-based, utilizing a questionnaire as the research tool. In terms of application, the study is applied; in terms of time, it is cross-sectional; in terms of analysis, it is analytical; and in terms of implementation method, it is survey-based.

The statistical population of this study includes 384 project managers who are actively involved in residential construction projects.

The statistical methods used to analyze the collected data are quantitative in nature, consisting of descriptive and inferential analysis, conducted using SPSS software version 22.

3. Findings and Results

To present the descriptive findings from the 384 project managers active in the field of residential construction, we begin by classifying and analyzing their demographic and professional characteristics. Below are key descriptive features that are typically examined in studies of this type:

Of the 384 participants, approximately 70% held a master's degree in civil engineering, architecture, or project management. 15% had a bachelor's degree, and 10% held a doctoral degree in construction-related disciplines.

About 60% of project managers were engaged in large-scale residential projects (over 100 housing units), while the remaining 40% worked on medium-scale projects (ranging from 20 to 100 units).

85% of project managers reported using project management software such as Microsoft Project, Primavera, and other construction-specific platforms. 10% used web-based online tools, and 5% utilized custom or specialized software.

35% of project managers indicated that they use AI-based tools such as delay and cost prediction systems to support decision-making. Additionally, 15% used computer vision systems to monitor project progress and detect safety issues.

Table 1. Demographic Characteristics of Project Managers

Feature	Description	Percentage
Age Group	30 to 45 years	50%
	45 to 60 years	35%
	Over 60 years	15%
Professional Experience	5 to 15 years	60%
	Over 15 years	40%
Educational Qualification	Bachelor's Degree	15%
	Master's Degree	70%
	Doctorate	10%
Project Scale	Over 100 units	60%
	20 to 100 units	40%



Table 2. Tools and Technologies Used in Project Management

Description	Percentage
Use of Project Management Software	
Microsoft Project, Primavera, or similar tools	85%
Web-based online tools	10%
Customized or specialized software	5%
Use of Artificial Intelligence Technologies	
Use of delay and cost prediction systems	35%
Use of computer vision systems	15%

How Can Artificial Intelligence Tools Help Improve Resource Allocation in Construction Projects?

Null Hypothesis (H0): Artificial intelligence (AI) tools have no effect on improving resource allocation in construction projects.

Alternative Hypothesis (H1): Artificial intelligence (AI) tools have an effect on improving resource allocation in construction projects.

To perform the Chi-square test, data must be collected concerning the use of AI tools and the status of resource allocation in construction projects. For example, the data may include the number of project managers who use AI for resource allocation and the number of individuals who have observed improvement in resource allocation through these tools.

Table 3. Frequency Table of Variables Related to the First Sub-question of the Study

Use of AI	Improved Resource Allocation	No Improvement in Resource Allocation	Total
Yes	180	50	230
No	70	84	154
Total	250	134	384

Table 4. Chi-square Test Results for AI Tools and Resource Allocation Improvement in Construction Management

Test Type	Value	df	Asymptotic Significance (2-Sided)
Pearson Chi-Square	145.257	16	0.000
Likelihood Ratio	136.531	16	0.000
Linear-by-Linear Association	99.850	1	0.000
Number of Valid Cases	384		

The Pearson Chi-Square test statistic is 145.257, which is significantly higher than the critical value for 16 degrees of freedom. The Likelihood Ratio test result is 136.531, further indicating a strong and significant effect of AI tools on resource allocation in construction projects. The Linear-by-Linear Association test yields a statistic of 99.850, with a significance level of 0.000. In all tests, the significance level (p-value) is 0.000, which is clearly below the conventional threshold.

Since the p-value in all tests (Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association) is 0.000—much lower than the significance level—we can conclude that the null hypothesis stating "AI tools have no effect on improving resource allocation in construction projects" is rejected, and the alternative hypothesis is confirmed.

What Challenges Exist Regarding the Adoption of AI Technologies in the Construction Industry?

Null Hypothesis (H0): There are no challenges regarding the adoption of AI technologies in the construction industry.

Alternative Hypothesis (H1): There are challenges regarding the adoption of AI technologies in the construction industry.

To conduct the Chi-square test, data must be gathered that include the use of AI tools and the status of challenges in construction projects. For instance, the data may include the number of project managers who use AI to address project challenges and the number of individuals who have observed improvements in those challenges due to AI.

Table 5. Frequency Table of Variables Related to the First Sub-question of the Study

Use of AI	Improved Challenges	No Improvement in Challenges	Total
Yes	120	39	159
No	130	95	225
Total	250	134	384



Table 6. Chi-square Test Results for AI Tools and Challenge Improvement in Construction Management

Test Type	Value	df	Asymptotic Significance (2-Sided)
Pearson Chi-Square	155.356	16	0.000
Likelihood Ratio	145.623	16	0.000
Linear-by-Linear Association	98.752	1	0.000
Number of Valid Cases	384		

Page |

135

The Pearson Chi-Square statistic is 155.356, which is significantly higher than the critical threshold for 16 degrees of freedom. The Likelihood Ratio test result is 145.623, again showing a strong and significant effect of AI tools in addressing construction project challenges. The Linear-by-Linear Association test result is 98.752, with a significance level of 0.000.

Since the p-value in all tests (Pearson Chi-Square, Likelihood Ratio, and Linear-by-Linear Association) is 0.000—clearly below the standard significance level—we conclude that the null hypothesis, which asserts "there are no challenges regarding the adoption of AI technologies in the construction industry," is rejected, and the alternative hypothesis is confirmed.

4. Discussion and Conclusion

The findings of the present study confirm that artificial intelligence (AI) tools significantly improve resource allocation in construction projects, while simultaneously revealing notable challenges in their adoption within the industry. Results from chi-square analyses showed statistically significant associations between the use of AI and improvements in resource distribution, as well as between AI implementation and reported challenges. These results align with growing empirical and theoretical literature highlighting AI's transformative potential in construction project management and corroborate several earlier investigations across domains of cost control, scheduling, safety management, and productivity enhancement.

The improvement in resource allocation due to AI use reflects a broader global trend in digitizing construction workflows. As construction projects grow in complexity, the need for data-driven tools capable of handling high-volume, real-time data becomes indispensable. This study found that managers utilizing AI reported notable efficiencies in allocating labor, equipment, and materials, consistent with findings by Liu (2024), who showed that AI integration enables optimized project scheduling and resource management by dynamically adjusting allocations in response to shifting site conditions (Liu, 2024). This aligns with the framework outlined by Afzal et al. (2021), who emphasized that AI-based risk assessment models can map interdependencies between complexity and resource volatility, leading to improved allocation accuracy (Afzal et al., 2021).

The positive impact of AI tools on construction safety and cost prediction was another dimension validated by the findings. Respondents using AI-based systems such as predictive analytics and computer vision noted improvements not only in resource planning but also in risk mitigation. These observations are aligned with the literature. Razi et al. (2023) detailed how AI applications, particularly those based on surveillance and visual recognition systems, reduced response time to onsite hazards and supported timely interventions (Razi, 2023). Similarly, the application of computer vision and audio-based AI systems for safety diagnostics, as described by Rabbi and Jeelani (2024), reinforces the conclusion that intelligent tools contribute not only to efficiency but also to safer working environments (Rabbi, 2024).

In addition to operational benefits, AI adoption correlates with broader improvements in project decision-making and strategic oversight. Respondents in this study who used AI tools for project oversight reported improvements in forecast accuracy and real-time responsiveness. These findings echo the conclusions of Wang (2022), who argued that intelligent decision support systems based on AI can synthesize diverse data inputs—from BIM models to IoT sensors—to provide project managers with actionable insights (Wang & Liu, 2022). Furthermore, Wang and Liu (2022) emphasized that AI contributes to enhanced situational awareness, allowing for better foresight and preemptive adjustments in project planning (Wang, 2022).

Despite these advantages, the second phase of the analysis confirmed the persistence of adoption barriers. A substantial number of project managers not using AI cited issues related to data interoperability, implementation costs, and workforce preparedness. These challenges are well-documented in prior studies. Rampini and Cecconi (2022) identified financial constraints, lack of skilled personnel, and fragmented digital ecosystems as core inhibitors to AI deployment across construction asset lifecycles (Rampini, 2022). Similarly, Holzmann and Lechiara (2022) noted that many professionals remain skeptical about AI's practicality due to a perceived mismatch between available tools and actual project needs (Holzmann, 2022).



The cultural and organizational resistance highlighted in this study is consistent with earlier findings from Wamba-Taguimdje et al. (2020), who stressed that firm performance improvements due to AI adoption are contingent not only on technological readiness but also on a culture of innovation and strategic alignment (Wamba-Taguimdje et al., 2020). Organizational inertia, reluctance to abandon legacy systems, and the absence of dedicated digital leadership were cited in their research as barriers to successful transformation. These constraints align closely with the responses in this study, especially from project managers working in smaller or medium-scale firms.

This study also reinforces the role of education and upskilling in AI adoption. A notable proportion of respondents indicated that they lacked adequate training to leverage AI tools effectively. The results align with the conclusions by Kord (2023), who found that project managers' digital competencies are significantly associated with the effectiveness of AI integration (Kord, 2023). Similarly, Wachnik (2022) highlighted a critical skills gap in the Polish construction industry, where digital transformation initiatives often stalled due to lack of training and absence of structured digital capability development plans (Wachnik, 2022).

Moreover, the study's findings contribute to ongoing discourse about AI's role in enhancing user-centric design and project innovation. Takhmasib et al. (2023) introduced a machine-learned kinetic façade system to regulate visual comfort using predictive controls, showcasing AI's potential in post-design stages as well (Takhmasib, 2023). This perspective complements the responses of managers in this study who reported using AI for real-time feedback during construction phases and expressed interest in extending its applications into facilities management and post-occupancy evaluations.

One important implication of this study is the confirmation that AI implementation cannot be assessed solely in technological terms; it must be evaluated as a socio-technical transformation. Zia (2024) emphasized that future project managers must be trained not only in engineering and finance but also in AI literacy, ethical data use, and interdisciplinary collaboration (Zia, 2024). The findings of this study further reinforce this view, as effective AI implementation was reported predominantly in organizations where managerial support, staff training, and change management strategies were in place.

Furthermore, Goodell et al. (2021) argue that while AI holds promise in fields like finance and engineering, its true value is unlocked through systemic integration and continuous feedback loops between users and systems (Goodell et al., 2021). The same logic applies in construction: AI must be deeply embedded in workflows and institutional routines to be effective. This sentiment was reflected in this study's data, where fragmented or isolated uses of AI yielded limited impact compared to projects that integrated multiple AI functionalities across departments.

This study also supports the assertion that the maturity of AI applications varies significantly across different phases of construction. Egwim et al. (2023) conducted a comprehensive lifecycle analysis showing that AI penetration is highest in design and planning stages, moderate in execution, and relatively low in asset management (Egwim, 2023). In the current study, resource allocation and predictive scheduling were the most common uses, while fewer participants had applied AI to post-construction operations. These disparities suggest that while interest in AI is growing, its application remains uneven and demands more targeted interventions to ensure balanced adoption across the value chain.

Finally, Lam and Oshodi (2016) provided an early comparison of econometric forecasting with AI models, finding that the latter performed significantly better in volatile and nonlinear environments such as construction output forecasting (Lam & Oshodi, 2016). These findings foreshadowed many of the patterns observed in this study, particularly regarding the superiority of AI over traditional tools in predicting budget deviations and resource mismatches.

In summary, the findings of this research provide strong empirical support for the claim that AI enhances resource management in construction projects, while simultaneously drawing attention to the technological, organizational, and human barriers that impede its full realization. The results reflect a broader shift toward intelligent construction ecosystems, where automation and human decision-making are not mutually exclusive but rather synergistically integrated.

Although the study provides valuable insights, it is not without limitations. First, the data were collected using a self-report survey design, which may be prone to social desirability bias and subjective interpretation. Second, the cross-sectional nature of the study limits the ability to infer causality. Longitudinal studies would be better suited to assess the evolution of AI adoption and its impact over time. Third, the sample was geographically and contextually limited to residential construction projects, which may not fully represent other sub-sectors such as infrastructure or industrial construction. Fourth, the analysis focused



primarily on general AI adoption without deeply differentiating between types of AI technologies (e.g., NLP, ML, CV), which could offer more granular insights.

Future studies should adopt longitudinal designs to examine how AI integration evolves over the life of a project and its long-term effects on project success. Comparative analyses between different countries, sectors, and organizational sizes could help identify the contextual factors that influence AI adoption. Researchers should also explore the role of digital leadership and innovation culture in mediating the success of AI deployment. Moreover, future research should focus on identifying optimal combinations of AI tools for different project phases and investigate how AI can be aligned with sustainability and climate resilience goals in construction. The development of standardized frameworks for measuring AI maturity and performance in construction projects would also be highly beneficial.

To facilitate successful AI integration in construction project management, organizations must invest in digital literacy and upskilling initiatives. Leadership teams should develop clear digital transformation roadmaps that align with business objectives and prioritize AI implementation where it offers the most value. Collaboration between technology providers and construction firms is essential to ensure the tools developed are user-friendly and tailored to specific industry needs. Firms should also conduct small-scale pilot projects to test and refine AI systems before scaling. Additionally, building a culture that embraces innovation, experimentation, and continuous learning will be critical in overcoming resistance and unlocking AI's full potential.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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