Artificial Intelligence Applications in Construction Management: Challenges and Opportunities

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Abstract: **The construction sector is undergoing an unprecedented qualitative transformation, driven by the rapid advancement of artificial intelligence technologies that open new horizons for improving project management, particularly in the areas of planning and resource allocation. In this context, this research aims to evaluate the effectiveness of AI applications by identifying and analyzing the available opportunities, most notably enhancing operational efficiency, supporting decision-making, and optimizing resource utilization, while also identifying the main barriers hindering their adoption in the construction sector. To achieve the research objectives, a questionnaire was designed involving 204 industry experts from the construction and artificial intelligence sectors, and the data were analyzed using structural equation modeling (PLS-SEM). The results showed that the operational efficiency improvement group ranked first among AI opportunities with the highest composite weight of 0.380, followed by quality improvement with a weight of 0.372, and then risk and safety with a weight of 0.336. Regarding challenges, the technical group topped the list of barriers with a weight of 0.391, followed by the organizational group with a weight of 0.382, and then the ethical and social group with a weight of 0.351. These findings reflect the key priorities that should be focused on to maximize the benefits of AI and address the most impactful barriers in the context of planning and resource management in construction projects. Based on these results, the study provides practical guidance for managers and developers to strategically align AI adoption with core industry needs.**

Keywords: **artificial intelligence, construction management, resource optimization, PLS-SEM, planning management.**

I. INTRODUCTION

The construction industry, valued at $10.7 trillion (13% of global GDP in 2023), is one of the largest and most complex sectors worldwide, with modern projects involving over 150,000 interdependent activities [1], [2]. Despite its scale, the industry continues to suffer from persistent challenges such as delays, cost overruns, and low productivity, with McKinsey estimating that up to $1.6 trillion could be saved annually if productivity matched that of other sectors [3]. Traditional project management methods, which rely on static tools and rule-of-thumb approaches, often fail to address these complexities, highlighting the urgent need for innovative solutions [4].

Artificial Intelligence (AI) has emerged as a transformative technology capable of reshaping construction project management. Recent studies show that AI can enhance project monitoring, optimize planning, analyze costs, and improve the allocation of resources such as labor, materials, and equipment [5], [6], [7]. Specifically, AI-driven planning and resource management tools can address the limitations of manual and rule-based systems, which frequently result in suboptimal decisions and project risks [4]. However, while research on AI applications in construction is growing, there remains a lack of systematic analysis of how these technologies create opportunities and what challenges may hinder their adoption in practice [8], [9].

This gap is particularly significant in the context of resource-constrained project scheduling, where AI could play a crucial role in reducing execution time, minimizing costs, and improving efficiency. Yet, industry adoption remains inconsistent due to barriers such as data limitations, high implementation costs, and resistance to technological change [10], [11].

To bridge this gap, this study focuses on identifying and evaluating the opportunities and challenges of adopting artificial intelligence in construction planning and resource management. The specific objectives are as follows: first, to review previous research to identify the challenges and opportunities of using artificial intelligence in construction planning and resource management, and to provide a comprehensive perspective on how artificial intelligence contributes to project efficiency. Second, to identify and evaluate opportunities for expanding the scope of artificial intelligence adoption, focusing on how these technologies can bring about a qualitative shift in resource allocation practices and project planning. Third, to identify and evaluate the main challenges hindering the adoption of artificial intelligence, including organizational, technical, and cultural barriers. Fourth, to achieve the research objectives and support its findings, data collected from the literature review will be integrated with empirical data (a questionnaire) from 204 participants working in the construction and artificial intelligence sectors, and this data will be analyzed using PLS-SEM.

By addressing these objectives, this study contributes to the literature by moving beyond the theoretical description of artificial intelligence tools and providing a structured assessment of both opportunities and barriers. Thus, this research offers insights into how to better guide the adoption of artificial intelligence in practice, particularly for small companies navigating the complexities of resource-constrained scheduling in modern construction projects.

II. LITERATURE REVIEW

To investigate the use of artificial intelligence for planning and Resource management, we conducted a systematic literature review to analyze existing AI applications and Technologies in planning and resource management, and identify the opportunities and challenges associated with their implementation in the planning phase to enhance resource management. This will be achieved through the following points:

- Data Sources: The search was conducted using reliable databases such as Scopus, Web of Science, Google Scholar, and IEEE Xplore, which were searched using keywords such as AI, construction project management, resource management, planning, machine learning, computer vision, robotics, automation, optimization, decision-making, opportunities, and challenges.
- Inclusion Criteria: Studies published between 2023 and 2025 were included if they addressed practical applications of AI in construction project management, planning, or resource management. For each article, data were extracted on the application area, methodology, technologies used, opportunities, and challenges.
- Selection Criteria: Only opportunities and challenges appearing in at least three studies were considered to ensure significance.

III. METHODOLOGY

The research methodology adopted in this study followed a structured approach based on sequential systematic steps. It began with a comprehensive review of relevant literature published between 2023 and 2025, focusing on two main axes: first, reviewing previous studies that addressed the challenges and opportunities of applying artificial intelligence technologies in construction planning and resource management; and second, identifying future opportunities for integrating artificial intelligence into construction project management, particularly in the planning and resource management phases, along with the challenges that may hinder its implementation. For data collection, a questionnaire was selected as the primary tool due to its ability to efficiently gather quantitative data from a geographically distributed sample of experts, thereby allowing for statistical generalization. The study targeted specialists in construction project management and artificial intelligence, and participants were selected according to pre-defined criteria, including experience ranging from zero to 15 years and above in the construction field or areas related to artificial intelligence, or combined experience in both fields. Prior to field application, a pilot study was conducted using the Delphi method, involving 10 experts each with over 10 years of experience, to ensure the clarity of the questionnaire items and to identify any necessary modifications.

Subsequently, 204 valid responses were collected for analysis. The data were analyzed using structural equation modeling (SEM) with Smart PLS 4 software, which was chosen for its suitability for predictive models, its ability to handle medium-sized samples, and its effectiveness in analyzing non-normally distributed data [12].

The methodology was structured into several sequential phases. The preliminary phase began with defining the research aim, which focused on evaluating artificial intelligence applications in construction management in terms of challenges and opportunities. This was followed by a systematic search across multiple academic databases, including Google Scholar, Scopus, Web of Science, and IEEE Xplore, to identify relevant studies. The analysis phase concentrated on extracting studies related to AI applications in planning and construction resource management. Subsequently, the identification and assessment phase involved reviewing previous research to identify challenges (n=13) and opportunities (n=15) from the literature published between 2023 and 2025. These identified factors were then classified and used to prepare two separate questionnaires: the first to evaluate the identified challenges and the second to evaluate the opportunities. This structured sequence ensured a comprehensive and systematic approach to data collection and analysis throughout the study.

1) Identifying (Challenges and Opportunities)

A. First: Opportunities

This study identified opportunities (15) based on the most recent research from the past three years, ensuring that each opportunity was cited in at least three previous studies as a minimum criterion, in order to guarantee their effective realization during implementation. Opportunities mentioned in fewer than three studies were excluded to ensure that the remaining opportunities more accurately reflect their potential impact and significance in construction project management. To facilitate handling these opportunities and determining their types of impact, their classification is presented in TABLE 1, organized into three main categories, namely:

TABLE 1: Summary of AI Opportunities in Resource Management from Selected Literature.

classification	I.D	Opportunities Factors	Authors
Risk & Safety	OP_RS1	Improving Safety through Hazard	[13], [8], [14]
	OP_RS2	Improved Risk Prediction and Mitigation	[15], [16], [4]
	OP_RS3	Better handling of uncertainties	[11], [7], [17]
Quality	OP_Q1	Enhance process control	[1], [11], [8]
	OP_Q2	Improve decision-making based on data-driven insights	[18], [19], [7]
	OP_Q3	Enhancing predictive maintenance	[11], [18], [16]
	OP_Q4	Sustainability Impact	[20], [10], [21]
	OP_Q5	Resource Optimization	[5], [17], [22]
Efficiency	OP_E1	Task and process automation	[23], [9], [11]
	OP_E2	Improved Project Planning and Optimal Scheduling	[9], [24], [20]
	OP_E3	Time Savings and Delay Reduction	[25], [26], [4]
	OP_E4	Easy access to relevant information	[21], [9], [27]
	OP_E5	Productivity and Operational Enhancement	[6], [28], [29]
	OP_E6	Interoperability and Collaboration Enhancement	[1], [17], [29]
	OP_E7	Accurate Budgeting and Lower Operational Costs	[24], [30], [14]

B. Second: Challenges

Potential challenges (13) that may arise from leveraging the previously identified opportunities were identified. To facilitate addressing these challenges and understanding their nature, they are presented in TABLE 2, organized into three main categories:

TABLE 2: Summary of AI Challenges in Resource Management from Selected Literature.

classification	I.D	Challenges Factors	Authors
Technical	CH_T1	Continuous updates to ensure accuracy	[30], [17], [7]
	CH_T2	Interpretability	[9], [18], [4]
	CH_T3	Infrastructure for Computing and Data Storage	[13], [21], [29]
	CH_T4	Data Management	[23], [31], [32]
	CH_T5	scalability of models	[29], [9], [7]
Organizational	CH_O1	Integration Difficulties	[19], [8], [20]
	CH_O2	cost issues	[5], [3], [33]
	CH_O3	Complexities of the operation	[34], [25], [11]

	CH_O4	Change Resistance	[28], [16], [2]
	CH_O5	Limited Awareness	[15], [31], [28]
Ethical & social	CH_ER1	Regulatory and standards	[24], [22], [26]
	CH_ER2	Ethical Bias	[27], [21], [3]
	CH_ER3	security and information sharing	[1], [14], [6]

2) Questionnaire Design

The review resulted in the identification of 15 exploitable opportunities and 13 challenges that may hinder their effective implementation.

Based on these findings, two questionnaires were designed using Google Forms: one to assess the opportunities and the other to assess the challenges. Each questionnaire was divided into three main sections. The first section introduced the researcher and the purpose of the questionnaire, while the second section focused on the respondents' demographic data. The third section contained items related to assessing the likelihood of occurrence and the degree of impact of using artificial intelligence in construction resource management, based on the respondents' knowledge and experience.

A five-point Likert scale was adopted, ranging from (1 = not important) to (5 = extremely important). Based on this range, the mean scores of the factors were classified into five categories, where a mean of (3) indicated moderate importance. The rationale for this evaluation approach lies in measuring both opportunities and challenges by calculating their priority based on the product of probability and impact scores, in order to assess the effectiveness of implementing artificial intelligence applications in construction project management.

Prior to the final distribution of the questionnaires, a pilot study was conducted using the Delphi method, involving a sample of ten experts, each with over ten years of experience in both construction projects and artificial intelligence, through semi-structured interviews [35]. The pilot study aimed to ensure the clarity and logical sequence of the questions, and to verify that the listed opportunities and challenges reflected actual indicators in the sector, while avoiding repetition or the inclusion of irrelevant items. Most experts indicated no comments on the opportunities model, while eight experts agreed that one of the challenges related to data management had been divided into two separate challenges: "difficulty in obtaining data" and "data incompleteness." They recommended merging them into a single challenge under the title "data management" to achieve greater coherence within the study framework. Data reliability was verified using Cronbach's alpha coefficient for each sub-scale of the two questionnaires, with values of 0.95 for the opportunities scale and 0.93 for the challenges scale. These values exceed the minimum acceptable threshold of 0.7, indicating a good level of internal consistency [36].

3) Data Collection

Given that this research focuses on construction project management, specifically planning and resource management through artificial intelligence applications, the selection criteria prioritized planning engineers, project managers, and AI specialists. However, the selection was not limited to each profession in isolation; priority was given to respondents who had practical experience in using AI technologies in construction project management, coupled with substantial professional experience.

Additional emphasis was placed on targeting professionals from technologically advanced countries, such as the United States and the United Arab Emirates. The targeting strategy also considered respondents from urban areas, where exposure to advanced construction technologies is typically higher. This was facilitated by using LinkedIn to identify individuals based on their documented experience and geographic location.

The questionnaire was sent to 250 specialists, and the total number of collected responses was 210, yielding a response rate of 84% over ten weeks, exceeding the recommended threshold of 30% required for conducting reliable statistical analysis.

To ensure data quality, a multi-stage process was followed. Upon reviewing the respondents' answers, some incomplete data were identified, prompting reminder messages to be sent to participants who had not completed the questionnaire or had not responded at all. Initially, responses were checked for completeness, and participants who provided incomplete or unclear answers were contacted for clarification or correction. While some participants updated their responses, others did not. Subsequently, incomplete, duplicate, and outlier responses were excluded, resulting in a final sample of 204 valid responses suitable for statistical analysis.

The sample survey comprised respondents with professional experience in both construction project management and artificial intelligence applications. These individuals represented a diverse range of organizations, including owners, consultants, designers, and contracting firms operating. This diversity was intentionally sought to enrich the quality and depth of the collected data and to capture a variety of perspectives on construction project management, planning, and resource allocation. Regarding years of experience, 76 respondents (37.2%) had between 0 and 5 years of experience, 61 respondents (29.9%) had between 5 and 10 years, 35 respondents (17.2%) had between 10 and 15 years, and 32 respondents (15.7%) had more than 15 years of experience. This distribution reflects a balanced representation across different experience levels, encompassing both early-career professionals and seasoned experts. In terms of job titles, the sample included a diverse range of engineering roles. Site engineers constituted the largest group with 37 respondents (18.1%), followed by project managers with 35 respondents (17.2%), planning engineers with 34 respondents (16.7%), technical office engineers with 29 respondents (14.2%), AI engineers with 26 respondents (12.7%), cost control engineers with 15 respondents (7.4%), quality control engineers with 15 respondents (7.4%), and construction software developers with 13 respondents (6.3%). This variety ensures that multiple perspectives on construction project management, planning, and resource allocation were captured. Regarding organizational affiliation, the sample consisted of contractors with 89 respondents (43.6%), consultants with 45 respondents (22.1%), owners with 44 respondents (21.6%), and designers with 26 respondents (12.7%). This diversity was intentionally sought to enrich the quality and depth of the collected data and to reflect the varied stakeholder perspectives inherent in construction projects.

4) Frame/Model (smart-PLS)

After verifying the validity of the data, SMART PLS4 was used to develop two main models: one for the opportunities of applying artificial intelligence in planning and resource management, and another for the challenges associated with these opportunities. The analysis employed a reflective–formative second-order model using the two-stage approach. Fig. 1 illustrates both stages of the analysis: the first stage, in which the lower-order constructs were assessed, and the second stage, in which the latent variable scores from the first stage were used to estimate the higher-order models.

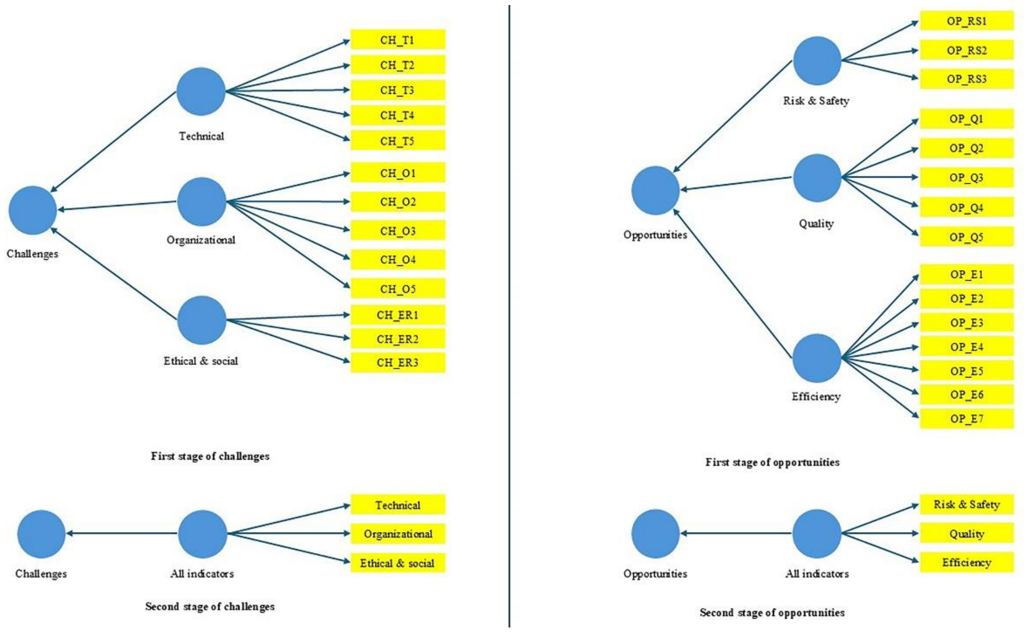

Fig. 1: The Two Models: Opportunities and AI Challenges

When applying a second-order reflective–formative model, the methodology requires a two-stage approach, where the overall contribution of each indicator to the higher-order construct is calculated as the product of its loading on the lower-order construct and the weight of the lower-order construct on the higher-order construct. This approach enhances model parsimony and predictive power, and it is particularly suitable in cases of complex models, small sample sizes, non-normal data, and formative constructs. Under such conditions, PLS-SEM is considered more appropriate than CB-SEM, which is commonly applied for confirmatory analysis but requires stricter assumptions [37].

A. PLS-SEM Model Development

The evaluation of Reflective-Formative measurement models (i.e., latent constructs) in PLS-SEM involves assessing convergent validity, discriminant validity, and internal reliability. Once the reliability and validity of the measurement model are established, the structural model can be examined [36]. TABLE 3 presents the results of convergent validity, showing that all constructs in the model meet the thresholds of Cronbach's alpha (CA) > 0.60, composite reliability (CR) > 0.60, and average variance extracted (AVE) > 0.50. The results indicated that the outer loadings (CA), (CR), and (AVE) were all within the accepted thresholds.

The results demonstrate that the measurement model is both consistent and convergent. Accordingly, the study model can be reliably used to evaluate each construct independently and appropriately, without confounding the results. When a construct exhibits a high number of external loadings, it indicates that the associated items are strongly interrelated.

TABLE 3: Convergent validity results.

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
	opportunities			
Efficiency	0.935	0.937	0.948	0.721
Quality	0.905	0.906	0.930	0.726
Risk & safety	0.793	0.794	0.879	0.707
	challenges			
Ethical & Regulatory	0.815	0.815	0.890	0.73
Organizational	0.900	0.900	0.926	0.714
Technical	0.878	0.879	0.911	0.673

B. Discriminant validity:

The Discriminant validity indicates that a construct is distinct from others and explains unique phenomena. It can be assessed using the Fornell–Larcker criterion and the HTMT ratio. In this study, all HTMT values (presented in TABLE 4) were below 0.90, confirming discriminant validity. According to TABLE 5, all constructs are also legitimate in terms of discriminant validity, since the square root of the AVE for each construct is higher than its correlations with other constructs for Fornell and Larcker. (Complete bootstrapping with 5000 iterations was used to determine the HTMT values) [12].

TABLE 4: HTMT analysis.

constructs	opportunities		
	Efficiency	Quality	Risk & safety
Efficiency			
Quality	0.880		
Risk & safety	0.831	0.896	
	challenges		
	Ethical & Regulatory	Organizational	Technical
Ethical & Regulatory			
Organizational	0.721		
Technical	0.848	0.809	

TABLE 5: Fornell and Larcker analysis.

constructs	opportunities		
	Efficiency	Quality	Risk & safety
Efficiency	0.849		
Quality	0.812	0.852	
Risk & safety	0.718	0.760	0.841
	challenges		
	Ethical & Regulatory	Organizational	Technical
Ethical & Regulatory	0.854		
Organizational	0.618	0.845	
Technical	0.719	0.721	0.82

C. Assessing the Structure Model:

For the Opportunities model, the VIF values for Risk and Safety (2.547), Efficiency (3.167), and Quality (3.624) were all below the commonly accepted threshold of 5 and close to the conservative cutoff of 3, indicating that multicollinearity is not a concern. The model fit index (SRMR = 0.048) was also below the recommended threshold of 0.08, demonstrating very good model fit [38], [39] Regarding the higher-order construct's weights, Risk and Safety (0.214, $p < 0.001$), Efficiency (0.507, $p < 0.001$), and Quality (0.359, $p < 0.001$) were all statistically significant, confirming their substantial contribution to the higher-order construct. The predictive relevance of the model was further supported by PLSpredict (k = 10). The Opportunities construct showed a strong influence on the dependent variable with an $R^2 = 0.989$, suggesting that 98.9% of the variance is explained by this predictor, confirming the robustness of the model [40].

TABLE 6: Outer Weights and Loadings of the Constructs

For the Challenges model			For the **opportunities** model		
ID	first stage (LF)	second stage (w)	ID	first stage (LF)	second stage (w)
CH_T1	0.818	0.391	OP_RS1	0.848	0.336
CH_T2	0.807	0.391	OP_RS2	0.850	0.336
CH_T3	0.811	0.391	OP_RS3	0.824	0.336
CH_T4	0.854	0.391	OP_Q1	0.815	0.372
CH_T5	0.809	0.391	OP_Q2	0.857	0.372
CH_O1	0.842	0.382	OP_Q3	0.850	0.372
CH_O2	0.853	0.382	OP_Q4	0.832	0.372
CH_O3	0.847	0.382	OP_Q5	0.903	0.372
CH_O4	0.855	0.382	OP_E1	0.823	0.380
CH_O5	0.828	0.382	OP_E2	0.855	0.380
CH_ER1	0.853	0.0351	OP_E3	0.902	0.380
CH_ER2	0.852	0.0351	OP_E4	0.850	0.380
CH_ER3	0.858	0.0351	OP_E5	0.862	0.380
			OP_E6	0.816	0.380
			OP_E7	0.834	0.380

For the Challenges model, the VIF values for Ethical and Regulatory (2.161), Organizational (2.174), and Technical (2.779) were also below the threshold of 3, indicating no multicollinearity issues. The SRMR value of 0.061 further confirmed a good model fit [38], [39]. The higher-order weights for Ethical and Regulatory (0.263, $p < 0.001$), Organizational (0.434, $p < 0.001$), and Technical (0.421, $p < 0.001$) were all significant, confirming their meaningful contributions. The PLSpredict analysis (k = 10), the construct Challenges exerted a very strong and statistically significant influence on the dependent variable, with an R^2 value of 0.994, indicating that 99.4% of the variance is explained, thereby reinforcing the explanatory strength of the model.

Since the model in this study is based on the formative approach (Formative – Mode B), the indicators were evaluated in two stages. In the first stage, the focus was on the loadings, which assess the strength of the association between the indicators and the first-order latent variables. In the second stage, after obtaining the latent variable scores, the weights [12] of the indicators were calculated, reflecting the relative importance of each indicator in forming the higher-order construct. Accordingly, the indicators were ranked from the most to the least influential, as presented in TABLE 6.

IV. RESULTS AND DISCUSSION

Two second-order models were developed to calculate the overall opportunity factor and the overall challenges of implementing artificial intelligence (AI) applications during the planning and resource management process in construction. The opportunities model consisted of 15 observable variables distributed across three latent dimensions. All variables used in the confirmatory factor analysis (CFA) in this study were measured on a five-point Likert scale.

The efficiency improvement group had the highest collective impact in this study, with a group weight of 0.380. The factor loadings reached 0.902, 0.862, 0.855, 0.850, 0.834, and 0.823 for time savings and delay reduction, productivity and project operations improvement, planning and scheduling enhancement, data accessibility, accurate cost prediction, operational cost reduction, task automation, interoperability, and collaboration, respectively. Among these, time savings and delay reduction recorded the highest loading at 0.90, reflecting the critical role of AI in optimizing resource distribution, which has been shown to achieve up to 30% faster project delivery through the use of autonomous equipment, including robotic excavators and cranes, as highlighted by [26]. This was followed by the quality improvement group with a weight of 0.372. The factor loadings reached 0.903, 0.857, 0.850, 0.832, and 0.815, respectively, for resource management improvement, decision-making enhancement, equipment maintenance prediction, sustainability impacts in terms of waste reduction, and process control enhancement. This was also confirmed by [4]. The highest loading was attributed to resource management improvement at 0.90, reflecting its critical role in optimizing resource allocation, consistent with our research that has demonstrated up to 25% improvement in resource utilization following the implementation of artificial intelligence in construction management. Finally, the risk and safety opportunities group recorded a weight of 0.336. The factor loadings reached .848, .850, and .824, respectively, for improving safety through hazard, improved risk prediction and mitigation, and better handling of uncertainties.

For the challenges model, 13 observable variables were distributed across three latent dimensions. All variables used in the CFA were measured on a five-point Likert scale. The technical challenges group had the highest collective impact in this study, with a group weight of 0.391. The factor loadings reached 0.854, 0.818, 0.811, 0.809, and 0.807 for training data issues, continuous updates to ensure output quality, data storage, computing infrastructure, model scalability, and interpretability, respectively. The results also indicated that the most influential factor in planning management was data-related problems, which represent a major challenge for the construction sector, given the reliance on non-digital records and data quality concerns. This finding aligns with [30], who emphasized that the cornerstone of building a robust AI model lies in the quality and reliability of the data, as inadequate data infrastructure remains a primary barrier to effective AI implementation in construction project management.

This was followed by the organizational challenges group with a weight of 0.382. The factor loadings reached 0.855, 0.853, 0.847, 0.842, and 0.823, respectively, for resistance to change, high initial cost, operational complexities, and difficulties integrating with existing legacy systems, as highlighted by (reference). Among these, resistance to change emerged as the most significant barrier to adopting unfamiliar technologies in construction management in Egypt, followed closely by the high initial costs associated with computing hardware and algorithms. This finding is consistent with [2], who emphasized that organizational resistance remains a critical obstacle to the successful implementation of emerging technologies in the construction industry. Finally, the ethical and social challenges group recorded a weight of 0.351. The factor loadings reached .853, .852, and .858, respectively, for regulatory and standards, ethical bias, and security and information sharing.

The results of this study extend and refine the existing body of knowledge on AI adoption in construction by moving beyond descriptive accounts of barriers and opportunities toward a more integrated understanding of their interplay, specifically within the context of construction planning and resource management. Previous research has consistently identified data quality and availability, high implementation costs, and skills shortages as major obstacles to digital transformation in construction. Our findings confirm the persistence of these barriers within the challenges model, where technical challenges particularly data-related problems recorded the highest collective impact, followed by organizational and ethical challenges. These results demonstrate that barriers are not isolated constraints; rather, they create a direct demand for solutions that AI is well-positioned to provide, particularly in enhancing planning accuracy and optimizing resource allocation [41], [42]. Conversely, the opportunities model revealed that efficiency improvement had the highest collective impact, followed by quality improvement and risk and safety opportunities. Notably, the highest factor loadings within these groups were associated with time savings and delay reduction, resource management improvement, planning and scheduling enhancement, and improved risk prediction and mitigation. These findings underscore the critical role of AI in addressing core challenges related to planning and resource management, where improved resource distribution was shown to contribute significantly to time savings and project delivery efficiency [43], [23]. Furthermore, the findings help explain why AI adoption in construction planning and resource management has been slow, despite widely documented benefits. Poor data quality undermines predictive accuracy in planning, which in turn reinforces skepticism about return on investment and fuels cultural resistance to adopting AI-driven resource management tools. This cycle helps account for the uneven pace of adoption observed in the industry, particularly in contexts such as Egypt, where reliance on non-digital records and traditional planning practices remains prevalent. Addressing these barriers requires strategies that do more than mitigate risks; they must convert constraints into strategic focal points for innovation, with a particular emphasis on improving data infrastructure for planning, building organizational capacity for resource management, and aligning technological investments with the specific needs of construction planning and resource allocation.

V. CONCLUSION

This study developed an evaluation model for implementing AI applications in construction planning and resource management using structural equation modeling in SmartPLS. The aim was to examine the overall opportunities and challenges associated with AI adoption in construction project management, specifically in planning and resource management, by analyzing the relationships between opportunity and challenge factors extracted from the literature alongside AI techniques and applications. The developed model enables construction stakeholders to measure and evaluate the resulting opportunities and challenges, with model fit results demonstrating strong alignment with actual data, encouraging implementation in Egypt.

The methodology followed a systematic approach, beginning with a comprehensive literature review, followed by expert interviews using the Delphi method. The analysis identified three latent dimensions and 15 observable opportunities, as well as three latent dimensions and 13 observable challenges. Two questionnaires were developed using a five-point Likert scale for both opportunities and challenges. After collecting responses from 204 participants, two models were proposed using SmartPLS, demonstrating strong relationships between observable and latent dimensions. Model fit indices confirmed the adequacy of both models.

The results revealed that the "Improving Project Operational Efficiency" cluster had the greatest impact among opportunities, while the "Technical Challenges" cluster had the greatest impact among challenges in the Egyptian context. The final modeling results showed that both models successfully predicted the overall opportunities and challenges of implementing AI applications in construction project management.

Practically, the two proposed models help stakeholders accurately identify and evaluate the opportunities and challenges influencing AI adoption in planning and resource management. This study contributes to the literature by examining the combined effects of opportunities and challenges through latent factors that cannot be captured using traditional analytical approaches.

Several limitations were identified. First, the indicators were derived based on technologies relevant to the study period and did not address each technology individually. Second, the study focused on measuring the impact of variables only. Future research may explore the impact of emerging AI technologies, such as generative AI and digital twins, on construction resource management.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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