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Analyzing Barriers to BIM and AI Integration in Construction Management: A Mixed-Methods Approach

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Abstract

Building information modeling (BIM) and artificial intelligence (AI), through their deep integration, are ushering in a new era for the construction industry. However, due to insufficient practical experience and exploration, construction companies still face significant challenges when adopting integrated BIM and AI technologies. This study aims to explore the integration of BIM and AI in depth by identifying and analyzing key barriers. Through systematic literature review and expert consultation, 16 major obstacles were identified. On this basis, a radial basis function neural network-enhanced weighted-influence non-linear gauge system (RBF-WINGS) model was constructed to calculate the weights of each barrier and deconstruct its non-linear interaction structure. The results indicate that data-related factors constitute the core category of barriers, while organizational culture and technological factors are the key secondary barriers. This study provides a theoretical basis for the development of China's construction industry and serves as a decision-making reference for government departments.

Keywords: BIM; AI; adoption barriers; neural network; WINGS

1. Introduction

The world is undergoing the fourth industrial revolution (Industry 4.0), which has been considerably transformed by the ubiquitous connectivity and data-driven decision-making enabled by big data and artificial intelligence (AI) [1]. The construction industry has also rapidly expanded its application of AI [2]. Recent research shows that applications of AI are increasingly penetrating the construction industry across its entire lifecycle [3–5]. This involves the synergistic deployment of digital and automated technologies to resolve complex engineering problems in building projects [6]. Nevertheless, as a globally recognized laggard in digital transformation, the construction industry has impeded optimal resource allocation and constrains multistakeholder collaboration [7]. Smart construction transcends mere technological tools for industrial efficiency. It represents systemic innovation to reconfigure production relations, foster high-quality productivity, and drive economic growth. According to the QYResearch analysis, the worldwide intelligent construction market is forecasted to expand at a compound annual growth rate of 12.0% in revenue generation between 2025 and 2031 [8].

The trends of digitization, automation, and the increased use of information and communications technology have together been envisioned as forming the main concept of

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the fourth industrial revolution. In Industry 4.0, the construction field must enhance its digitization and intelligence to improve efficiency [9,10]. The digital transformation of the architecture, engineering and construction (AEC) sector is driven by building information modelling (BIM). BIM-based projects feature 3D parametric models and object-based and data-rich information relating to attributes and datasets [11]. The BIM modelling process encompasses the tools and techniques applied throughout a building's entire life cycle to digitally document requirements relating to project performance, planning, construction, and operation [12–14]. Precisely because BIM offers the benefit of consolidating construction site information on a single platform [15], the process enables the creation of accurate information models and facilitates design analysis, simulation and interpretation, thereby enhancing its utility [16,17]. In the field of construction management, BIM 4D enables simulation by incorporating time as a dimension within the model. This allows teams to perform chronological and dynamic analyses, enabling the visualization of how a project evolves over time [18]. BIM 5D incorporates cost as a dimension, adding financial information to the model. This enables more effective cost management by combining real-time cost data with 3D and 4D representations and provides a comprehensive approach to the planning and execution of construction projects [19]. By providing semantic and geometric information, this multidimensional digital data offers potential benefits for digital design, construction and operations. Although BIM at this level can support tasks such as clash detection and progress visualization, its data processing remains constrained by predefined rules and static information structures, making it difficult to cope with the complexity and uncertainty of a dynamic construction site.

In this sense, this study argues that as the AEC industry integrates the requirements of BIM-driven digitalization and process automation, researchers and practitioners will face the challenge of handling vast amounts of data and understanding object–data relationships and interdependencies [16,19]. Consequently, these inherent constraints have spurred academic research into AI-driven algorithmic solutions [16,17]. Generally speaking, AI can be divided into three categories: Artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial superintelligence (ASI) [20]. ANI only demonstrates intelligence in specific tasks, such as virtual assistants and recommendation systems; AGI aims to enable machines to function like humans; ASI aims to create machines that surpass human capabilities across multiple domains [21]. AI works by collecting vast amounts of data for training, and then continuously optimizing its performance through machine learning (ML) and deep learning (DL) to improve the accuracy of its decisions and its ability to handle complex tasks [22]. This provides a much-needed boost to the AEC sector's capabilities in data management, processing and interpretation. In this context, the use of AI—particularly ML and DL—enables these data to be transformed into knowledge for a wide range of applications. ML methods develop models that predict future outcomes. Based on historical data, DL methods employ more automated neural pipelines that do not require complex feature learning and detection [11]. Unlike general artificial intelligence, these technologies do not need to simulate the full scope of human cognition; instead, they focus on identifying patterns in construction data, predicting risks and generating optimized decisions. AI has not only improved the accuracy and efficiency of projects, but has also strengthened the culture and leadership within the construction organization [21]. Integrating AI can enhance BIM collaboration efficiency and drive automation and intelligence in the construction field [23–25]. Notable benefits include improved data management and processing capabilities [26–29], automation and optimization of design and construction phases [30,31], enhanced facility management and operational efficiency [32,33], refined cost and schedule management [18], and risk-informed decision making support [10].

At present, the technical foundation of BIM is digital information management, which involves generating data-rich models for use throughout a project's lifecycle [30]. AI is paving the way for intelligent systems that translate visionary models into reality to support decision-making [34]. The integration of BIM and AI is driven by the aim of maximizing the immense value of both technologies. This creates the possibility of easily accessing actionable information and automatically generating profound insights for complex projects with minimal manual effort. Consequently, the combination of these two powerful technologies is bound to evolve in the future, serving as a digital assistant to enhance productivity, quality, and safety in construction projects [35]. As the digital engine of the construction industry, BIM-AI will drive rapid development in the AEC sector. Firstly, the BIM-AI-integrated system enables seamless data sharing between digital building infrastructure. Furthermore, the AEC sector has derived significant benefits from the generation and effective management of BIM data, as enhanced data accessibility—achieved through the use of AI models—is crucial for innovation [18]. BIM-AI-driven engineering digitization can bridge the digital transformation gap across the construction management life cycle [35]. Collectively, BIM-AI is transforming the AEC industry through multimodal knowledge graph technology, enabling a shift from static information models to dynamic intelligent systems.

While these benefits are promising, the AEC industry, which has been recognized as one of the least digitized sectors globally, faces more significant challenges in BIM-AI integration than other industries, owing to entrenched resistance to change, low automation levels, and structural complexity [36]. The key barriers include the high cost of hardware and software for BIM-AI integration, the requirement for customized deployment of hardware and software resources, and the need for continuous investment to track technological trends [37]. In addition, AI implementation poses the risks of data security breaches and compromised data quality in BIM models [37]. Moreover, BIM-AI adoption is hindered by conventional organizational mindsets and cultural inertia [38]. Critically, as BIM-AI integration remains in its nascent stage, there is a shortage of empirical evidence and academic consensus on its methodological frameworks, undermining stakeholder trust [35,39]. More importantly, although previous research has examined the integration of BIM and AI, most studies have focused on technical aspects, with limited attention paid to the management of such integration. Due to limited background knowledge, insufficient practical experience and a lack of understanding of the complexities involved, construction organizations continue to face significant obstacles. It is worth noting that current academic research has not yet comprehensively examined the barriers to the application of BIM-AI in construction. Although some studies briefly touch upon these barriers in their discussion of future research trends or present them through systematic reviews, these approaches are limited. Most existing research focuses on qualitative analysis or system design, rather than exploring the dynamic interactions between integration barriers.

Based on the above analysis, this study aims to identify the barriers to the integration of BIM and AI in construction management and to examine the interrelationships between them. To address this gap in the existing literature, three research objectives (ROs) have been formulated, as outlined below:

RO1: Identify barriers to BIM-AI integration in construction management.

RO2: Calculate the weights of barrier factors using a radial basis function (RBF) neural network-enhanced weighted influence non-linear gauge system (RBF-WINGS) model.

RO3: Examine the causal effects of barrier factors on BIM-AI integration in construction management by identifying the core variables and non-linear relationships.

This study provides one of the first systematic attempts to analyze the barriers to BIM-AI adoption and their interdependencies in the construction industry. By identifying and

prioritizing these barriers, the study offers a structured overview of the key impediments to BIM-AI integration and provides actionable insights for both academics and practitioners.

2. Literature Review

2.1. Integration of BIM and AI in the Construction Field

BIM and AI have become transformative tools in modern infrastructure [40]. The integration of BIM and AI is reshaping the AEC industry [41]. BIM-AI marks a revolutionary advancement in this field by enhancing efficiency and enabling innovative decision-making processes [42]. Previous research on the integration of BIM and AI in the AEC industry mainly focused on the following three main aspects.

First, researchers have clarified the current level, future evolution path, and main constraints of BIM-AI integration by combining systematic literature review with industry practice analysis. For instance, through a systematic literature review, Alves et al. (2025) [11] identified seven core areas of BIM and AI application in the construction industry. By detailing and mapping the functions of BIM and AI, their study provides comprehensive guidance for AEC professionals, offering a practical roadmap for integrating BIM and AI technologies within the construction industry, taking into account available capabilities. Salah & Alabdullatief (2025) [43] noted in a systematic review that, although AI applications are expanding in the construction industry, their full potential remains underutilized due to limited large-scale implementation. They also identified key future research directions, such as leveraging AI to enhance BIM for improved scheduling accuracy, predictive analysis, and resource optimization. Alwashah et al. (2025) [44] employed a mixed-methods review to investigate emerging trends, applications, and research gaps in the application of generative AI in the construction industry. The study highlighted that integration with BIM represents a key area where generative AI has the potential to transform construction processes. Waqar et al. (2024) [45] make the case that BIM is essential for improving the success of construction projects from a project controls standpoint. They further suggest that investigating the interaction between BIM and AI presents fertile ground for pioneering research. In addition, research by Pan & Zhang (2023) [35], Khan et al. (2024) [39] and Ajirotutu et al. (2024) [40] all outlined both the potential and the challenges of applying BIM-AI in the AEC industry.

The second area explores the integration framework and system design of BIM and AI from a technical perspective. Mousavi et al. (2022) [46] proposed a novel damage prediction framework for non-structural building systems by combining BIM and AI. Urbieta et al. (2023) [47] proposed a novel AI algorithm-based method for generating architectural and structural drawings using parsing BIM models, thereby automating the processing of structural and architectural blueprints. Chong et al. (2025) [48] examined the application value of a dynamic optimization framework that deeply integrates BIM and AI into schedule management, thereby significantly improving the efficiency and decision-making capability of scheduling. Liu et al. (2025) [49] integrated natural language processing with BIM using augmented reality, which enables on-demand extraction of construction knowledge and provides inspectors with a knowledge base for quality inspection. Hsieh et al. (2026) [50] integrates AI image recognition and BIM technology to develop a prototype system that achieves automation and visualization of construction progress control.

Thirdly, in order to further focus on specific application scenarios, some standards and typical examples that can be followed have been formed around the integration of BIM and AI. For example, in the field of collision detection, Shehadeh et al. (2024) [51] employed an improved XGBoost algorithm (MXGBoost) to enhance the effectiveness of collision detection and classification in complex BIM models. Borkowsk & Kubrat (2026) [52] used a set of AI components to process collision detection results and data from BIM models, schedules

(4D), and cost estimates (5D), thereby managing the entire conflict resolution process. In terms of teamwork, Dong et al. (2024) [53] propose a BIM-AI construction coordinator. As users communicate with the coordinator and provide feedback, the assistant can collect and annotate this data, thereby fine-tuning the current model to make it better suited to specific construction tasks. In terms of construction management, Lin et al. (2025) [54] utilized AI-enabled BIM to optimize project scheduling, quality control and safety management. The results showed that, compared with traditional construction management methods, the AI-driven approach reduced project duration by 23.7%, improved quality scores by 31.2% and reduced safety incidents by 45.8%. In the context of three-dimensional reinforcement placement, Zhang et al. (2026) [55] developed an intelligent automated reinforcement placement algorithm by integrating BIM and AI, which effectively resolved the challenges of reinforcement placement at complex junctions and significantly improved construction efficiency and design accuracy. In the context of building maintenance and refurbishment, Wong et al. (2025) [56] use the renovation of a Catholic church in Hong Kong as a case study and draw on experience from ten similar projects to explore the integration of BIM and AI in practice. The findings indicate that these tools can significantly improve data organization, proactive planning, compliance, stakeholder collaboration and overall project efficiency.

2.2. Barriers to BIM and AI Integration

Despite the significant potential benefits of BIM-AI integration in the construction industry, barriers to its adoption persist. This subsection presents the key integration barriers identified through a review of existing literature, industry reports, and expert perspectives.

2.2.1. Management and Collaboration Barriers

Numerous stakeholders influence BIM-AI integration in the AEC industry. Stakeholders serve as "resource providers" and "risk sources" for projects and as "co-creators" of project value and "guardians" of sustainability [21]. Communication and mismanagement of project information pose significant challenges, and coordination and collaboration issues among diverse stakeholders have persisted in the AEC industry [57,58]. Furthermore, BIM-AI implementation requires substantial expertise and a skilled workforce. When issues arise, it is often difficult to trace accountability across collaborative teams, and no standardized protocols exist to resolve such conflicts. Khan et al. (2024) [39] noted that poor stakeholder management undermines construction project success and hinders the transition to BIM-AI in the industry. Given that BIM-AI integration relies heavily on collaboration and information management, Pan & Zhang (2023) [35] emphasize that ensuring trust and contractual transparency among project participants remains an unresolved challenge, as does balancing human agency with algorithmic decision making.

2.2.2. Organizational Culture Barriers

BIM-AI integration can be envisioned as AI serving as a personal assistant in BIM software. However, efforts to integrate new technologies or drive digital transformation often encounter internal resistance [59], such as hierarchical entrenchment, cognitive biases, collaborative inertia, and lack of change resilience, which prevents BIM-AI technologies from realizing their full potential. Ajirotutu et al. (2024) [40] have noted that organizational resistance to change further complicates BIM-AI integration, as stakeholders often resist embracing new technologies because of traditional mindsets. Furthermore, BIM-AI integration is still in its infancy, and the lack of standardized information, clear drivers, enabling frameworks, best practice guidelines, and validated research hinder construction organizations from implementing these technologies effectively [60,61]. Finally, limited stakeholder awareness of BIM-AI's value proposition has hindered its widespread adoption in construction projects.

2.2.3. Data-Related Barriers

Ajirotutu et al. (2024) [40] and Cassandro et al. (2024) [61] identified data interoperability and standardization as the primary BIM-AI integration challenge. Because data and information-sharing standards remain undefined [62], data exchange between systems becomes cumbersome, limiting integrated functionality. The use of unstructured data formats poses a substantial impediment to interoperability, particularly in the context of importing BIM models into digital twin platforms [63]. Although standardized data schemas have been proposed to enhance interoperability, their implementation remains inconsistent within the industry. Sacks et al. (2020) [36] have demonstrated that AI-compatible BIM representations are a significant barrier. Ceccon & Villa (2021) [64] have noted that a standardized framework is required for global BIM-AI integration and sharing. Before implementing BIM-AI integration, data must be adequately prepared. However, data volume is not always guaranteed [9]. Substandard data quality can yield erroneous outputs [65], thereby eroding confidence in the integration solutions. In addition, applying AI algorithms to BIM data raises concerns regarding data protection and the potential misuse of sensitive project information [39].

2.2.4. Policy and Regulatory Barriers

Kassem & Succar (2017) [66] found that the uneven development of BIM policies in different countries and regions has led to difficulties in standardizing practices globally. BIM's inherent capacity to deliver data-rich 3D visualizations and reliable project data makes it well-suited for integration with AI, enabling rapid information retrieval and analysis across the entire construction project lifecycle [35]. However, the application of AI requires enabling capabilities (e.g., cybersecurity) to support its implementation [67], and implementing strong cybersecurity measures to protect BIM and AI systems from malicious activities is a major challenge [68]. The absence of regulatory clarity regarding ethical AI governance deters construction firms from adopting BIM-AI integration [69]. Moreover, the lack of standardized agreements for cross-system data exchange exposes organizations to liability disputes and security vulnerabilities, underscoring the urgent need for a comprehensive legal infrastructure [39].

2.2.5. Technical Barriers

Construction projects inherently involve multiple stakeholders, diverse materials, complex processes, dynamic environments, and the company's capacity constraints. Moreover, the BIM-AI system interface may pose usability challenges for users without a strong technical background [48]. This results in low overall adoption levels, in addition to the complexity and scalability challenges of BIM-AI integration, reducing organizational technological skills [36,68,70]. AI can be integrated into BIM using machine-learning algorithms. However, the dynamic nature of construction projects complicates this integration, and Wu et al. (2021) [71] have noted BIM's inherent difficulties in merging with other technologies. Successful BIM-AI integration requires deploying custom hardware and software resources [9,69]. Interoperability-triggered compatibility problems impede early BIM-AI integration in projects, hindering the initial phases [24,61,71].

2.2.6. Financial Barriers

The high costs associated with BIM in construction firms are significant barriers [16,72]. Furthermore, AI integration requires customized coding and computational skills, necessitating substantial funding to train design and construction employees [36,69]. Successful BIM-AI integration requires high-performance computing equipment, specialized software, and AI algorithm development tools, which are expensive to procure and license. For many

architectural firms, high upfront software installation costs are a significant deterrent [39]. Furthermore, the low level of maturity of BIM-AI integration capabilities requires continuous investments to keep pace with technological advancement [37]. In addition, the return on investment for BIM-AI solutions remains uncertain; despite potential benefits, value distribution conflicts may arise among stakeholders (e.g., mismatches between technical inputs and benefit attribution). These financial complexities discourage key construction industry stakeholders from adopting integrated BIM-AI solutions.

3. Construction of Barrier Indicator System and Research Methods

3.1. Developing an Adoption Barrier Indicator System for BIM-AI Integration

3.1.1. Background to the Adoption of a System of Barriers

According to the "2025–2030 China Smart Construction Industry Market Survey Analysis and Development Outlook Report", the compound annual growth rate of the construction market remains above 25%, whereas the trend of technological integration continues to advance, and it is expected that the penetration rate of AI assistants will be more than 50% by 2025 [73]. This study established an adoption barrier indicator system for BIM-AI implementation in the AEC industry, aligning with construction development objectives and synthesizing prior research on BIM-AI integration. This framework aims to (1) systematically identify integration impediments, (2) guide strategic development priorities for BIM-AI in the construction management, and (3) provide a theoretical foundation for barrier mitigation and quality-driven advancement.

3.1.2. Adoption of Measures Established by Barrier Indicators

Currently, construction management is in the critical phase of pilot phase deepening and localized scaling-up. We found that no standardized indicator system currently exists for BIM-AI adoption barriers in the AEC industry. Therefore, this conceptual study is based on the following: (1) cross-professional expert discussions in related industries, (2) relevant industry reports, and (3) a systematic and comprehensive literature review.

The indicator system for BIM-AI adoption barriers in the construction field should be grounded in the current level of industry development and address the primary challenges faced by the sector. In this study, we developed a comprehensive indicator system to assess the barriers to BIM-AI integration in the construction field based on the principles of scientific rigor, simplicity, relative independence, objectivity, and data availability in the selection of indicators, as well as integrating insights from both domestic and international research.

First, compilation of authoritative AEC industry reports from both domestic and international sources, identify the current "key challenges" and 'practical difficulties' highlighted in the report. For example, Deloitte's "China Infrastructure Industry 2024 Annual Review and Outlook" [74], published in August 2025, noted that BIM is gradually integrating with AI technology to drive the intelligent and digital transformation of the construction industry; however, challenges remain, including data silos and fragmented standards, a skills gap and inadequate training, as well as cost pressures. The "HKU and Deloitte China AI Adoption Index 2026" [75], published by Deloitte in February 2026, highlights that the main barriers to AI adoption in enterprises include low return on investment, high technical barriers, obstacles to cross-departmental collaboration and cultural inertia, and limited understanding of AI capabilities. In April 2026, Tencent Cloud officially released the "White Paper on AI+ Smart Building BIM Full-Scene Application Solutions" [76]. The report identifies the following barriers to BIM-AI integration: data silos, high technical barriers, low return on investment, resistance to organizational change, and a lack of standards. The China Research Network has published an analysis titled "Current Status and Development Trends of the BIM Industry" [77], which notes that by 2026, BIM technology will have

moved beyond the scope of traditional 3D modelling to form an integrated innovation ecosystem combining 'BIM and next-generation information technology', including AI technology. However, significant challenges remain, including low technical standards, data and privacy risks, and substantial upfront investment costs.

Furthermore, based on a literature review and conceptual definition of BIM-AI integration, and taking into account the current state of BIM-AI's practical application in construction projects, this study categorizes the barriers to integrating BIM-AI into construction management into six categories, as shown in Table 1 below.

Table 1. Barriers to BIM-AI integration.

Category of Barriers	Items	Data Sources
Management and collaboration barriers	Collaboration and information management; trust and contractual equivalence among project participants; lack of trust; blurred roles; inefficient workflows; the demand for technical specialists and interoperability; organizational and process change.	[35,39,57,58,78–80]
Organizational culture barriers	A negative culture; low motivation; organizational resistance to change; lack of standardized information and clear driving factors; limited understanding; lack of training; institutional weaknesses (e.g., corruption); knowledge gap.	[40,60,61,78,79,81–84]
Data-related barriers	Issues with geometric data extraction and limitations of IFC format conversion; poor data quality; data protection and the potential misuse of sensitive project information; lack of sufficient information; information gaps and uncertainty regarding AI outputs among clients; data fragmentation.	[9,36,39,40,61–65,79,81,84–89]
Policy and regulatory barriers	Uneven development of policies; inadequate cybersecurity measures; the absence of regulatory clarity regarding ethical AI governance; liability disputes and security vulnerabilities.	[35,39,66,68,69,87,88]
Technical barriers	Interoperability; software restrictions; the overall adoption rate is relatively low; custom hardware and software resources need to be deployed; low organizational technical skills; algorithm development.	[9,24,36,48,61,68–71,78,79,84,87]
Financial barriers	High initial software installation costs; the return on investment remains uncertain; conflicts over the distribution of value; the costs of purchasing and licensing equipment are high; debt and unstable finance; high service costs; the technical costs are too high.	[16,36,37,39,40,69,72,78,79]

Based on the above analysis, experts from various fields such as building management, BIM technology, artificial intelligence development, and building cost estimation gathered together through Tencent Meeting for structured discussions. Qualitative techniques, such as the nominal group technique, were employed to enable the experts to review the consolidated list of indicators—derived from the literature and reports—on a case-by-case basis: assessing whether the indicators were clearly formulated (simplicity), whether they

overlapped with other indicators (independence), whether they genuinely reflected barriers to BIM-AI integration (scientific validity), and whether they were feasible to measure in practical evaluations (data availability). The expert discussions also served to eliminate indicators that, whilst theoretically valid, could not be objectively measured at the current stage or were overly trivial, and to propose adjustments to the hierarchical structure, thereby ensuring the logical consistency and practicality of the framework.

Finally, the indicator database—comprising literature, reports and expert opinions—was applied to the five guiding principles (scientific rigor, simplicity, relative independence, objectivity and data availability) for calibration and refinement, resulting in the development of an indicator system for assessing barriers to BIM-AI adoption. In accordance with the design principles of the indicator system, application barriers were categorized into six dimensions: management and collaboration barriers, organizational culture barriers, data-related barriers, policy and regulatory barriers, technical barriers, and financial barriers. This specific indicator system comprises six secondary factors and 16 tertiary factors. This framework is based on a rigorous review of the literature and has been refined through industry practice and input from a diverse range of experts; it possesses a systematic theoretical foundation and practical application value.

Three indicators were selected for the management and collaboration barrier category: project manager issues, cooperation and trust issues, and efficiency of cross-sectoral collaboration. Two indicators were included in the organizational culture category, namely readiness to change acceptance and new technology awareness. Three indicators were included in the data barrier category: data interoperability and standardization, data security and privacy, and amount of data. Two indicators were defined for policy and regulatory barriers, namely policy support and industry regulation strictness. The technical barrier category consists of three aspects of BIM-AI integration: BIM-AI integration compatibility, technological level, and complexity and scalability. The financial barriers comprise three dimensions: initial investment costs, operation and maintenance costs, and return on investment (ROI). For the target factor, we selected the perceived success of BIM-AI integration projects as an evaluation index reflecting BIM-AI integration in the construction field (as shown in Table 2). In addition, the method flowchart is shown in Figure 1.

Table 2. Indicator system for BIM-AI integration adoption barriers.

Classification of Indicators	Level 1 Indicators	Secondary Indicators	Data Sources
	Target indicators	Y1 perceived success of BIM-AI integration projects	Expert ratings
Management and collaboration barriers	Project manager issues	A1 Management decision making effectiveness	Expert ratings
	Cooperation and trust issues	A2 Level of trust in cross-team collaboration	Expert ratings
	Efficiency of cross-sectoral collaboration	A3 Cross-departmental collaboration efficiency	Expert ratings
Organizational cultural barriers	Change acceptance	A4 Willingness to digitally transform the construction industry	Expert ratings
	New technology awareness	A5 Level of understanding of smart construction technology	Expert ratings

Table 2. *Cont.*

Classification of Indicators	Level 1 Indicators	Secondary Indicators	Data Sources
Data-related barriers	Interoperability and standardization	A6 Level of implementation of data standardization	Expert ratings
	Security and privacy	A7 Maturity of data security and privacy protection	Expert ratings
	Amount of data	A8 Data integrity and accuracy	Expert ratings
Policy and regulatory barriers	Policy support	A9 Clarity of construction policy support	Expert ratings
	Industry regulatory strictness	A10 Strength of regulatory enforcement	Expert ratings
Technical barriers	BIM-AI integration compatibility	A11 Degree of inter-system compatibility	Expert ratings
	Technical level	A12 BIM-AI technology application maturity	Expert ratings
	Complexity and scalability	A13 System expansion flexibility	Expert ratings
Financial barriers	Initial investment cost	A14 Financial feasibility of integrated technology implementation	Expert ratings
	Operation and maintenance costs	A15 Operation and maintenance financing	Expert ratings
	Return on investment	A16 Analysis of financial benefits of technology application	Expert ratings

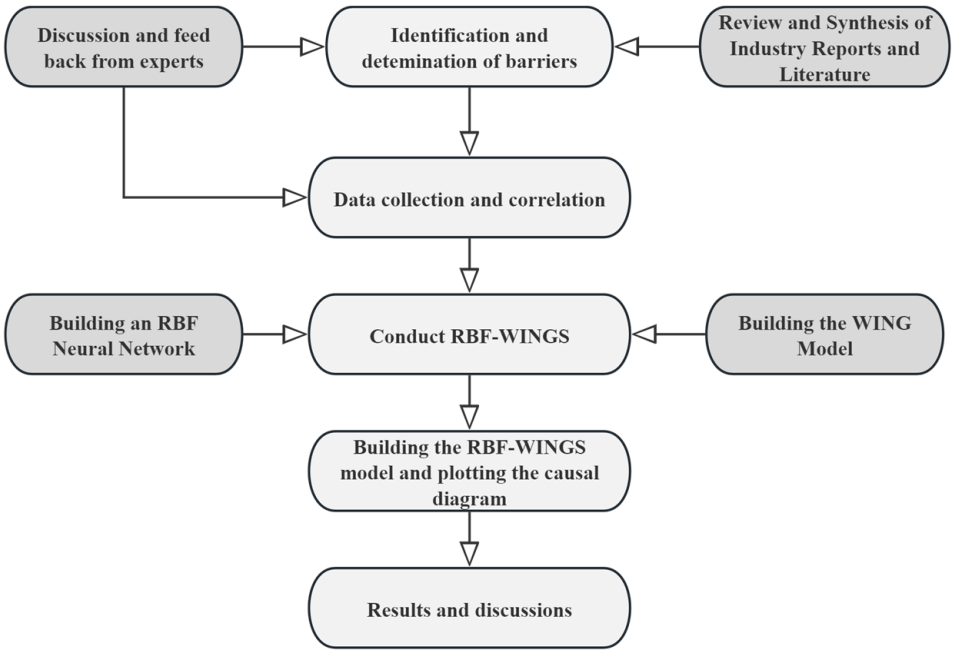


Figure 1. Research method flowchart.

3.2. Analytical Procedure Using RBF-WINGS

This study used the RBF-WINGS method. This method was initiated by processing the influencing factors through RBF neural network training. Subsequently, the connection weights derived from the converged network structure were used to establish a direct strength–influence matrix for quantifying the inter-factor interactions. Finally, the relationship between the factors can be scientifically analyzed, as well as the most important factor and its causal relationships [90]. RBF-WINGS was used to address the limitations of conventional linear weight calculation methods, which makes it difficult to capture complex non-linear relationships and accurately quantify the degree of influence of each barrier on BIM-AI integration in the construction field and their interactions [91].

3.2.1. Model Principles and Advantages

WINGS is a novel methodology for quantitative problem-solving in composite systems characterized by component interdependencies [92]. It is based on interpretive structural modeling (ISM) and decision-making trial and evaluation laboratory (DEMATEL) frameworks; it introduces the innovative concept of internal strength, which is absent in DEMATEL. This pivotal enhancement significantly expands the modeling capability and applicability [92], establishing WINGS as a comprehensive standalone method or modular component within complex analytical systems.

The steps for WINGS are as follows:

Step 1: Construct the direct strength-influence matrix $D = [d_{ij}]_{n\times n}$ between $e1,\ e2, \cdots\cdots enD = [d_{ij}]_{n\times n} D = [d_{ij}]_{n\times n}$, where e indicates the influencing factor indices in the index system. Elements on the diagonal of matrix D represent the strength of the factors; for $i = j$, dij represents the internal strength of the factors; for $i \neq j$, $dijdidj$ represents the direct influence of factor $eiaiai$ on factor ej.

Step 2: Normalize matrix D to form the direct strength–influence matrix C:

$$C = \frac{1}{s} D \tag{1}$$

$$s = \max\left(\max_i \sum_j d_{ij}, \max_j \sum_i d_{ij}\right) \tag{2}$$

Step 3: Calculate the total strength–influence matrix T:

$$T = tijn \times n = C + C^2 + C^3 + \cdots = C(I - C)^{-1} \tag{3}$$

where I is a unit matrix and tij represents the total influence of factor i on factor j.

Step 4: Compute the impact degree, receptivity degree, engagement level, and positional value of each factor.

$$R_i = \sum_{j=1}^{n} t_{ij} \tag{4}$$

$$C_j = \sum_{i=1}^{n} t_{ij} \tag{5}$$

where Ri represents the total impact and Cj represents the total receptivity. Meanwhile, for $i = j$, $Ri + Cj$ is the total engagement and $ri + cjri + cjri - cjri - cjRi - Cj$ indicates the position of the component in the system.

Engagement degree measures the importance of factors within the system; the higher the stickiness value, the more significant the role of a factor in the system [90]. Position measure describes the extent to which a factor influences other factors in the system; when its value is greater than zero, the factor is classified as an influencing factor, indicating

that it has a substantial impact on other system factors; in contrast, a value less than zero indicates that the factor is predominantly influenced by others, and is referred to as an influenced factor [93].

However, the conventional WINGS model has accuracy limitations when processing high-dimensional non-linear data. To address this issue, we introduced an RBF neural network that integrates both linear and non-linear transformations within a unified architecture. It can adaptively learn the implicit features of the input data, making it suitable for handling the problem of weight computation in multifactor-coupled systems. The model consists of a three-layer structure comprising an input layer, intermediate layer, and output layer. This framework facilitates the direct non-linear projection of input vectors onto a latent representation, followed by linear transformation onto the output space. The final network output comprises a weighted linear combination of hidden unit activations, as established by Wang et al. (2021) [90].

When analyzing the relationship between obstacles or influencing factors, commonly used methods in academia include ISM, DEMATEL, and their derivative methods. However, each of these three methods has its limitations in addressing the specific issues of this study. ISM uses a binary reachable matrix to establish a hierarchical structure between factors. Although ISM can reveal multi-level hierarchical relationships, its binary attributes cannot capture differences in the strength of influence between factors. In BIM-AI integration barrier analysis, different barriers exert substantially different degrees of influence on the system, and ISM cannot distinguish such differences. DEMATEL captures the strength of the influence between factors through a scale and can identify causal relationships. However, DEMATEL only considers the interdependence between factors and ignores the internal strength of each factor. The traditional WINGS method effectively overcomes the above limitations by incorporating the internal strength of factors and the strength of the influence between factors into a unified framework. The core innovation of WINGS lies in the recognition that the overall degree of influence between factors is determined by mixed relationships, rather than simply adding up the intensity of influence.

RBF-WINGS further improves on traditional WINGS by using data-driven learning instead of subjective expert assignment to construct a direct strength–influence matrix. Traditional WINGS relies entirely on experts to subjectively assign values to the strength and paired effects of factors themselves, inevitably introducing subjective bias. RBF-WINGS learns non-linear weight relationships from expert rating data through radial basis function neural networks. While retaining the advantages of the WINGS method, this provides a more structured and data-driven transformation of expert judgments into weights.

Based on the above comparative analysis, this study chooses the RBF-WINGS method mainly for the following considerations. (1) There are complex non-linear interaction relationships between BIM-AI integration barriers, and the neural network components of RBF-WINGS can effectively capture such non-linear relationships. (2) Decision makers not only need to know which obstacles are most important (engagement) but also which obstacles drive other obstacles and which are driven outcomes (position). WINGS can provide both types of indicators simultaneously. (3) BIM-AI integration is still in the exploratory stage, with limited large-scale empirical data, though RBF neural networks are suitable for small sample learning due to their local approximation characteristics. (4) RBF-WINGS reduces the reliance on direct subjective weighting, although the model still depends on expert-provided evaluation data.

3.2.2. RBF-WINGS Computation Steps

The RBF-WINGS model is shown in Figure 2. The specific steps are as follows:

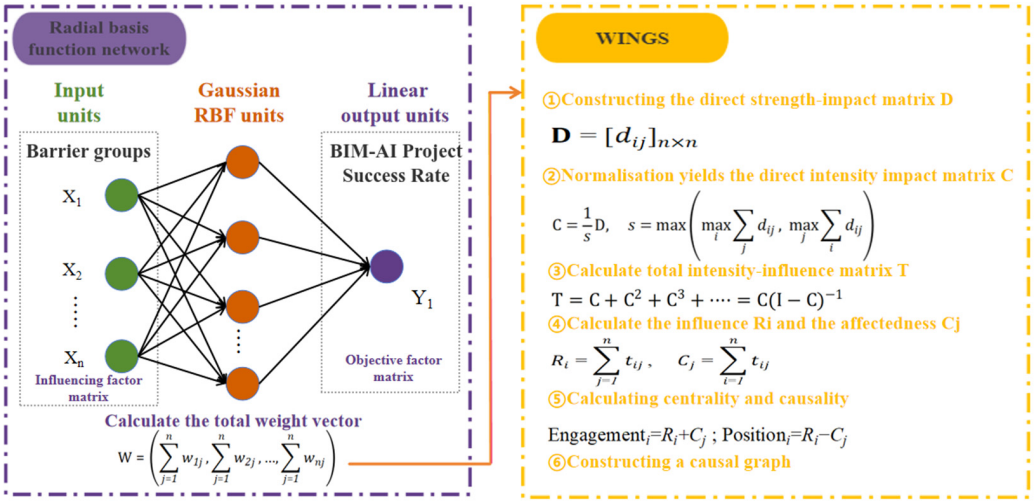


Figure 2. Flowchart of an RBF-WINGS model.

Step 1: Construct the obstacle factor matrix $x = xijm \times n$ and the target factor matrix $x = xijm \times nx = xijm \times ny = (yit)m \times kxt = (xit)m \times 1xt = (xit)m \times 1$; then, normalize to obtain x and $xtxt$. m is the sample size of a single obstacle factor; n is the number of obstacle factors; and k is the number of target factors. $i = 1,\ 2, \cdots\cdots m; j = 1, 2, \cdots\cdots n$; $t = 1, 2, \cdots\cdots n; t = 1, 2, \cdots\cdots n; t = 1, 2, \cdots\cdots k$.

Step 2: Construct an RBF neural network with n input neurons.

Step 3: Configure the RBF neural network with input vector xxx and expected output y. Initialize the following training parameters: error tolerance, maximum iterations, and learning rate. Iteratively train the network while adjusting the thresholds and weights until convergence is achieved. Finally, compute the weight matrix wij.

Step 4: Calculate the total weight vector.

$$i = 1, 2, \cdots m; j = 1, 2, \cdots n; t = 1, 2, \cdots nt = 1, 2, \cdots nt = 1, 2, \cdots k.$$

Step 5: Calculate the direct strength–influence matrix of the WINGS model

$$D = \left[d_{ij}\right]_{n \times n} = 11d12 \cdot\cdot d1nd21d22 \cdot\cdot d2n :::: dn1dn2 \cdot\cdot dnnn \times n.$$

For $i = j$, $dii = wi$; $for\ wj = 0, dij = 0$; $for\ wj = 0$, $dij = wiwji, j = 1, 2, \cdots n$ dij is the obstacle of factor i on j. $D = \left[d_{ij}\right]_{n \times n}$.

Step 6: Calculate the normalized direct strength-influence matrix C. $C = \frac{1}{s}D$, $s = \max\left(\max_i \sum_j d_{ij}, \max_j \sum_i d_{ij}\right)$.

Step 7: Calculate the total strength–influence matrix T. $T = C + C^2 + C^3 + \cdots = C(I - C)^{-1}$.

Step 8: Calculate the impact Ri and receptivity Cj, as well as the $Ri + Cj$ engagement and the $ri - cjri - cjRi - Cj$ position.

Step 9: Develop causal network diagram mapping factor interdependencies to identify the dominant drivers.

3.3. Data Collection

This study employed expert judgement as the primary data source to evaluate the barriers to BIM-AI integration in construction management. Given the exploratory nature of BIM-AI convergence in the AEC sector, and the current scarcity of large-scale empirical databases on this emerging topic, expert-based assessment is methodologically justified for identifying the relative salience and causal interdependencies among the barrier factors. The requisite informants were therefore defined as professionals and scholars possess-

ing demonstrable expertise and practical exposure to BIM, AI, digital construction, and construction project management.

The expert selection criteria were as follows: (1) participants had at least five years of professional, research, or consulting experience in construction management, BIM implementation, AI-enabled construction technologies, or digital construction; (2) participants had participated in BIM-related, AI-related, smart construction, or digital transformation projects, research, or consulting activities; and (3) participants were familiar with the practical barriers faced by construction organizations in BIM-AI integration or digital transformation. Only experts who met these criteria and provided complete responses were included in the final analysis.

Participants were identified and invited using purposive sampling. To ensure the relevance and diversity of expert opinions, we invited professionals and scholars from construction enterprises, consulting firms, universities, and other organizations related to smart construction. These experts were selected because they had relevant work, research, or consulting experience in BIM implementation, AI-enabled construction, digital construction, or construction management. A total of 35 experts were contacted, and 17 provided valid responses. The expert rating data were collected using a mixed online–offline approach. Specifically, structured expert consultations and electronic questionnaires were used to collect expert ratings on the strength of the identified barriers and the influence relationships among them. The experts evaluated the barriers according to the WINGS verbal scale, including "no intensity", "low intensity", "medium intensity", "high intensity", and "very high intensity". These ratings were then transformed into numerical values and imported into the RBF-WINGS model to construct the direct strength–influence matrix. Before data collection, all participants were informed of the purpose of the study, the voluntary nature of their engagement, and the confidentiality of their responses. Table 3 presents the demographic and professional characteristics of the participating experts.

Table 3. Demographic and professional characteristics of the participating experts.

Expert ID	Organization Type	Professional Role	Years of Experience	Familiarity with BIM	Familiarity with AI
E1	Construction enterprise	Project manager	13	High	Medium
E2	Construction enterprise	BIM manager	11	Very high	Medium
E3	Construction enterprise	Senior engineer	15	High	Medium
E4	Consulting firm	BIM consultant	10	Very high	High
E5	Technology-related organization	AI construction specialist	8	Medium	Very high
E6	University	Associate professor	14	High	High
E7	University	Researcher	8	High	High
E8	Consulting firm	Cost engineer	12	Medium	Medium

Table 3. *Cont.*

Expert ID	Organization Type	Professional Role	Years of Experience	Familiarity with BIM	Familiarity with AI
E9	Design institute	BIM engineer	10	Very High	High
E10	Construction enterprise	Digital construction manager	16	High	High
E11	University	Lecturer	7	High	High
E12	Consulting firm	BIM implementation specialist	11	Very High	High
E13	Technology-related organization	AI application engineer	7	Medium	Very high
E14	Construction enterprise	Project engineer	8	High	Medium
E15	Design institute	BIM coordinator	17	Very High	Medium
E16	Construction enterprise	Technical director	19	High	High
E17	University	Professor	18	High	High

WINGS, as a successor to DEMATEL, inherits all of the strengths of its predecessor: it can handle complex issues involving reaction factors and its mathematical operations are clear and straightforward [91]. This study analyzed feedback data from 17 experts. It should be noted that the sample size of experts was determined in accordance with the principle of information saturation rather than the law of large numbers in statistical sampling. Although there is no consensus in the existing literature regarding the ideal number of experts on a review panel, Hogarth, (1978) [94] concluded that a panel should consist of between 6 and 25 members. In the field of multi-criteria decision-making, there are no strict, uniform rules regarding the number of experts to be involved; typically, the number ranges from 5 to 10. Exceeding 10 may actually compromise the quality of decision-making due to significant divergence of opinion, as the method relies on experts' pairwise judgements of the relationships between factors; too many factors would result in a judgement matrix that is too large to be practical. Furthermore, previous studies have employed WINGS analysis with five experts [95] and DEMATEL analysis with ten experts [96], and have reached valid conclusions.

The decision to select 17 experts as the final sample for this study was based on the following considerations: (1) all 17 experts met strict selection criteria—at least five years of relevant professional or research experience, and prior involvement in BIM/AI-related projects or consultancy activities; (2) the experts were drawn from five types of organizations—construction firms, consultancy firms, universities, design institutes, and technology-related organizations—ensuring the diversity and representativeness of their views (see Table 3); (3) the 17 valid responses were considered adequate for this exploratory study, as the expert panel covered a diverse range of professional backgrounds and organizational types, including construction enterprises, consulting firms, universities, design institutes, and technology-related organizations. In multi-criteria decision-making applications that rely on expert judgments for pairwise comparisons, panel sizes within this range are commonly regarded as sufficient for capturing the diversity of perspectives while maintaining the analytical tractability of the method. The expert evaluations were

reviewed for completeness and logical consistency, and no major contradictions were observed across the aggregated judgments that would compromise the robustness of the subsequent analysis. Accordingly, the 17-expert sample was considered sufficient for constructing the strength–influence matrices in this exploratory study. Nevertheless, we acknowledge that a larger and more geographically diverse sample would further strengthen the generalizability of our findings—a point we address in the Section 6.

4. Results and Analysis

RBF-WINGS Analysis Results

The barrier factors to BIM-AI integration in the construction industry were analyzed based on data from 17 experts and using code written in the Python 3.7 programming language. An RBF neural network with an input layer (16 neurons) and a hidden layer was used with 17 samples of BIM-AI integration barrier indicators in the construction field. The hyperparameters were initialized at a learning rate of 0.005, minimum error of 0.05, and maximum iterations of 5000. The post-training convergence yielded a stabilized network topology. This framework enabled the computation of the total intensity–influence matrix using the RBF-WINGS methodology, followed by synthesis of the matrix and derivation of engagement/position metrics. Please refer to Table 4, Figures 3–5.

Table 4. Engagement and position of BIM-AI integration barriers.

Barriers	Engagement	Position
A1 Management decision-making effectiveness	2.482	−0.186
A2 Level of trust in cross-team collaboration	3.185	0.254
A3 Cross-departmental collaboration efficiency index	1.534	0.006
A4 Willingness to digitally transform the construction industry	5.392	−0.662
A5 Level of understanding of smart construction technology	4.992	−0.03
A6 Level of implementation of data standardization	5.979	0.505
A7 Maturity of data security and privacy protection	4.997	0.127
A8 Data integrity and accuracy	6.388	0.561
A9 Clarity of construction policy support	3.709	0.482
A10 Strength of regulatory enforcement	2.809	0.053
A11 Degree of inter-system compatibility	4.194	−0.462
A12 BIM-AI technology application maturity	4.844	−0.386
A13 System expansion flexibility	5.327	−0.005
A14 Financial feasibility of integrated technology implementation	2.98	0.391
A15 Operation and maintenance financing	2.876	−0.23
A16 Analysis of financial benefits of technology application	3.808	−0.417

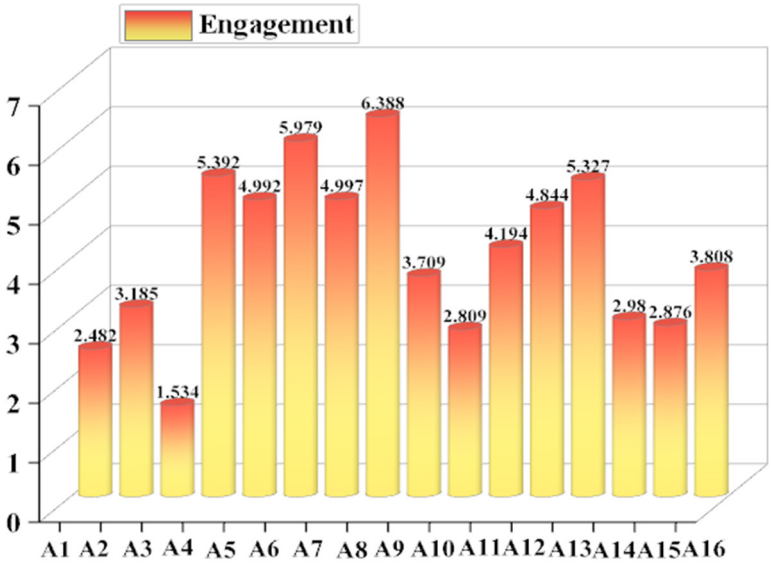


Figure 3. Engagement of barriers in BIM-AI integration.

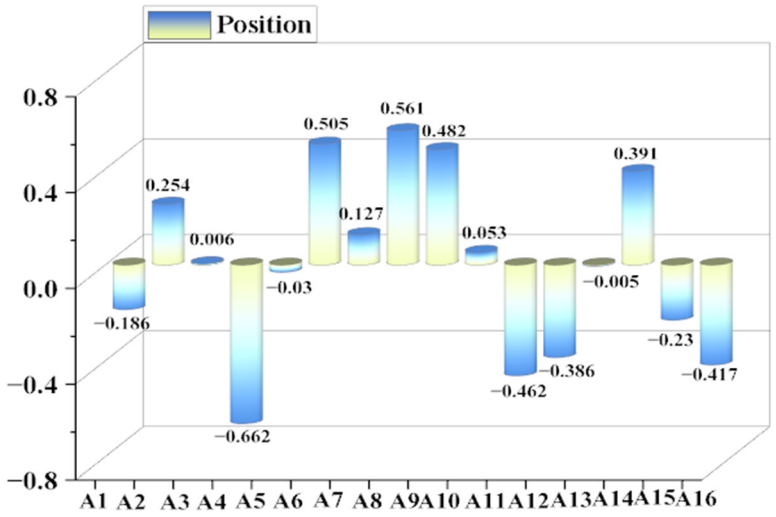


Figure 4. Position of barriers in BIM-AI integration.

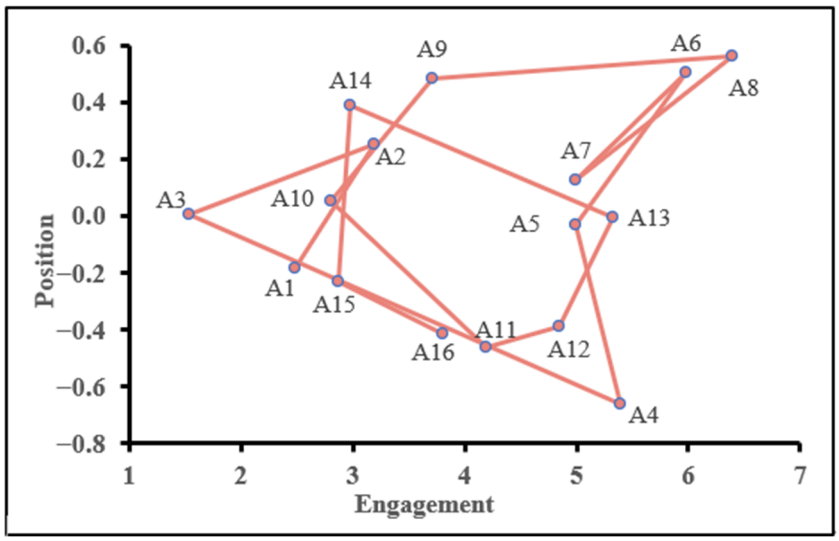


Figure 5. Relationship among barriers to BIM-AI integration.

In response to the risk of overfitting that may arise in RBF neural networks under small-sample conditions, this study adopted the following control measures during model construction: Firstly, automatic optimization of the network architecture, where the number of neurons in the hidden layer of the RBF neural network was automatically determined using a clustering algorithm—too many neurons in the hidden layer can lead to overfitting, while too few can result in underfitting. This study optimized the hidden layer structure by combining error monitoring during the network training process, thereby controlling model complexity whilst ensuring training accuracy. Second, the setting of training hyperparameters, where, for the training of the RBF network, this study specified hyperparameters such as the learning rate (0.005), minimum error threshold (0.05), and maximum number of iterations (5000). These settings were used to control the training process, avoid unstable fitting, and reduce the risk of overfitting under small-sample conditions. Third, RBF neural networks are a type of local approximation network; as such, their hidden layers utilize radial basis functions as activation functions, responding only to local regions of the input space. Compared with global approximation networks (such as BP neural networks), RBF networks exhibit faster convergence rates and superior generalization capabilities for small sample sizes. The simplicity and efficiency of RBF networks have been widely recognized in tasks such as small-sample classification. Fourth, robustness testing, where, as a robustness check, we compared the results obtained from the baseline Gaussian RBF specification with alternative neural-network activation specifications, including Sigmoid and ReLU (see Table 5 and Figure 6 for details). The results show that the engagement (R + C) and position (R-C) values calculated using the three activation functions (Gaussian, Sigmoid, and ReLU) are highly consistent, and that the ranking of the importance of each hindering factor remains largely unchanged. These robustness test results indicate that the model's conclusions do not depend on the choice of a specific activation function, thereby indirectly confirming that the model is not overly sensitive to specific parameter settings due to overfitting.

Table 5. Results of robustness test.

Barriers	Gaussian Function		Sigmoid Function		ReLU Function	
	r + c	**r − c**	**r + c**	**r − c**	**r + c**	**r − c**
A1 Management decision-making effectiveness	2.482	−0.186	2.457	−0.184	2.512	−0.186
A2 Level of trust in cross-team collaboration	3.185	0.254	3.188	0.257	3.165	0.255
A3 Cross-departmental collaboration efficiency index	1.534	0.006	1.543	0.007	1.552	0.01
A4 Willingness to digitally transform the construction industry	5.392	−0.662	5.389	−0.659	5.412	−0.667
A5 Level of understanding of smart construction technology	4.992	−0.03	4.992	−0.03	4.899	−0.03
A6 Level of implementation of data standardization	5.979	0.505	5.988	0.499	5.989	0.488
A7 Maturity of data security and privacy protection	4.997	0.127	4.995	0.125	4.899	0.124

Table 5. *Cont.*

Barriers	Gaussian Function		Sigmoid Function		ReLU Function	
	r + c	**r − c**	**r + c**	**r − c**	**r + c**	**r − c**
A8 Data integrity and accuracy	6.388	0.561	6.385	0.558	6.325	0.557
A9 Clarity of construction policy support	3.709	0.482	3.710	0.485	3.698	0.479
A10 Strength of regulatory enforcement	2.809	0.053	2.811	0.057	2.799	0.055
A11 Degree of inter-system compatibility	4.194	−0.462	4.192	−0.460	4.195	−0.458
A12 BIM-AI technology application maturity	4.844	−0.386	4.849	−0.386	4.849	−0.386
A13 System expansion flexibility	5.327	−0.005	5.322	−0.006	5.325	−0.005
A14 Financial feasibility of integrated technology implementation	2.98	0.391	2.985	0.395	2.98	0.392
A15 Operation and maintenance financing	2.876	−0.230	2.875	−0.228	2.874	−0.235
A16 Analysis of financial benefits of technology application	3.808	−0.417	3.805	−0.412	3.802	−0.413

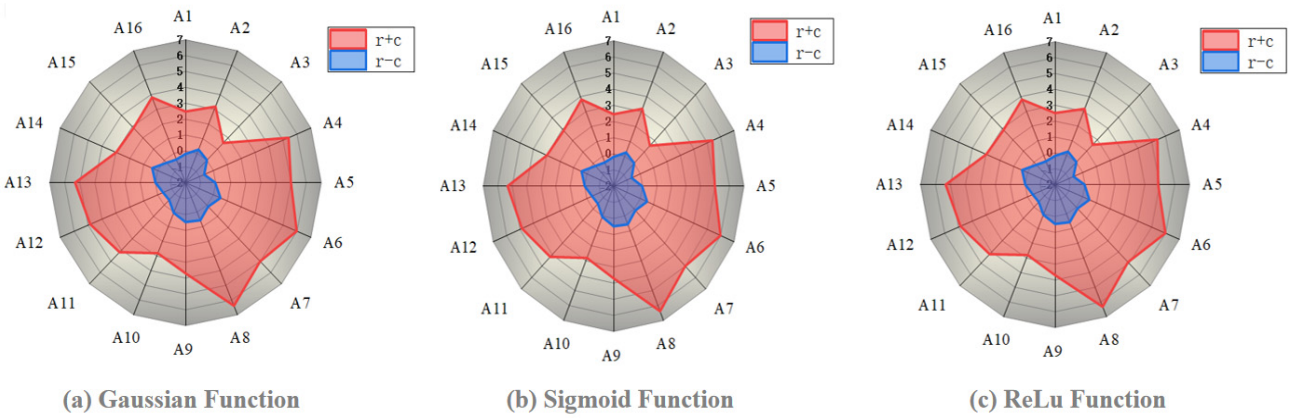


Figure 6. (R + C) and (R − C) values of barriers under different activation functions.

It should be clarified that the role of the RBF neural network here is to assist in weight calculation, rather than to make predictions independently. Consequently, the primary purpose of the model is to explain the structural relationships between factors, rather than to maximize predictive accuracy; this reduces, to some extent, the reliance on large sample sizes. The function of the RBF in this study is to learn the non-linear mapping relationships between factors through neural network training, taking the barrier factor matrix as input and the target factor (Y1 perceived success of BIM-AI integration projects) as output; the converged network connection weights are then utilized to construct the direct strength–impact matrix of the WINGS model. This application scenario differs fundamentally from traditional RBF predictive modelling. This study does not require the RBF network to possess strong generalization capabilities for new samples; rather, it requires the network to capture the non-linear relationships within the observed data to support subsequent WINGS causal structure analysis.

Consequently, traditional prediction performance metrics such as RMSE, MAE, and R^2 are not suitable for evaluating the role of RBF networks in this study. The core contribution of this study lies in utilizing the data-driven learning capabilities of RBF neural networks to overcome the limitations of the traditional WINGS method, which reduces the reliance on direct subjective weighting, although the model still depends on expert-provided evaluation data. Owing to their local approximation properties and strong ability to fit non-linear relationships, RBF neural networks have been successfully applied to weight determination and integrated evaluation problems in multi-criteria decision-making. RBF neural networks can effectively determine the weightings of objective evaluation parameters in relation to subjective evaluation results; under small-sample conditions, the RBF training method exhibits good robustness and generalization ability with regard to small datasets and noisy data. These characteristics make RBF particularly suitable for the small-sample (17 experts) weight learning task in this study.

As presented in Table 4, Figures 3–5, the eight barrier factors hindering BIM-AI integration in the construction field with position measure values > 0 are as follows (in descending order): (1) A8: data integrity and accuracy; (2) A6: level of implementation of data standardization; (3) A9: clarity of construction policy support; (4) A14: financial feasibility of integrated technology implementation; (5) A2: level of trust in cross-team collaboration; (6) A7: maturity of data security and privacy protection; (7) A10: strength of regulatory enforcement; and (8) A3: cross-departmental collaboration efficiency index. These factors significantly influence other barriers in the system, indicating that the remaining factors were predominantly affected by them.

The three barriers in the data category are among the top eight, with data integrity and accuracy (A8) identified as the most critical factor, followed by the level of implementation of data standardization (A6). This indicates that data-related barriers directly impede BIM-AI integration in the construction field.

Furthermore, while all of the barriers in the organizational culture category had engagement degree scores greater than 4, their overall average score was lower than that of the data category, suggesting that organizational culture barriers represent a secondary but significant barrier to BIM-AI integration.

The technology category barriers had lower average engagement degrees than the first two categories; however, each factor within this category had a score above 4. Therefore, technology-related barriers also pose significant challenges to BIM-AI integration in the construction field.

Among these eight primary barriers, three had engagement degree scores > 4, namely data integrity and accuracy (A8), level of implementation of data standardization (A6), and maturity of data security and privacy protection (A7). Notably, these three barriers belong to the data category, indicating that data-related barriers not only directly impede BIM-AI integration in the construction field, but also indirectly influence other factors.

To perform robustness validation, we utilized Sigmoid and ReLU activation functions under identical architectural configurations. The resultant intensity–influence matrices generated using the RBF-WINGS methodology were synthesized to obtain engagement/position metrics, with comparative outcomes across activation functions, as presented in Table 5 and Figure 6. As a robustness check, we compared the results obtained from the baseline Gaussian RBF specification with alternative neural-network activation specifications, including Sigmoid and ReLU. The results were mostly consistent, with their importance rankings remaining substantially unchanged. The computational outcomes showed good agreement across all three activation functions, demonstrating that RBF neural network models constructed using different activation functions can effectively identify the factors that hinder BIM-AI integration in the construction field.

5. Discussion and Implications

5.1. Discussion

This study combines RBF neural networks with the WINGS method—using RBF networks to learn non-linear mapping relationships between factors from expert rating data and utilizing the WINGS method to quantify the strength of direct and indirect influences between factors—thereby overcoming the limitations of existing research on the BIM-AI integration of barriers. This enables the present study to identify which barriers are system-driving factors and which are system-resulting factors, a distinction that has not been revealed in previous research. Furthermore, this study goes beyond the isolated listing of barriers or static categorization and summarization commonly found in previous research, revealing causal chains and feedback loops between barrier factors—for example, data integrity and accuracy (A8) not only directly affect the effectiveness of AI model training but also indirectly reinforce organizational resistance to change by undermining stakeholders' trust in AI outputs. This explains why data-related factors rank highest in terms of engagement indicators, thereby revealing the systemic evolutionary logic underlying the barriers to BIM-AI integration. Finally, based on the RBF-WINGS results, this study proposes a hierarchical causal model of barriers to BIM-Al integration. In this model, data-related barriers are positioned as foundational drivers, organizational culture and technical barriers function as intermediate mechanisms, and management and collaboration barriers as well as financial barriers are largely reflected as consequential factors. However, the causal roles of some categories are heterogeneous. For example, clarity of construction policy support (A9), financial feasibility of integrated technology implementation (A14), and level of trust in cross-team collaboration (A2) also show positive position values and should therefore be treated as important enabling drivers rather than purely consequential factors. This model consolidates a disparate list of barriers into a systematic framework with causal logic, providing a theoretical foundation for subsequent research.

The data-related factors identified as core barriers to BIM-AI integration in construction management align with the findings of Alves et al. (2025) [11], who argued that future research should prioritize enhancing dataset quality and diversity in BIM-AI applications to address current limitations in terms of the amount and quality of data. This aligns with the view of Zwaag et al. (2023) [97], who emphasized that all of the benefits of BIM and AI integration can only be realized if the BIM model possesses the capability to standardize its data. Furthermore, because BIM-AI integration is highly reliant on data-driven algorithms (Pan & Zhang, 2023) [35], the success of BIM-AI fundamentally depends on data quality and standardization. However, construction project data are highly project-specific and must be accumulated over time. Unlike algorithmic technologies that can be rapidly improved through R&D investment, data assets must be gradually accumulated through long-term project execution. The long construction period, high investment, and slow effectiveness of this "data infrastructure" make it the most fundamental bottleneck restricting BIM-AI integration.

More importantly, data-related barriers not only constitute obstacles on their own, but also indirectly affect other categories of obstacles through causal chains. For example, a low level of implementation of data standardization (A6) directly weakens the degree of inter-system compatibility (A11), thereby reducing BIM-AI technology application maturity (A12); insufficient data integrity and accuracy (A8) weakens the reliability of AI outputs, lowers the level of trust in cross-team collaboration (A2), and undermines management's determination to drive digital transformation (A4). This cause–effect chain explains why the engagement of data factors far exceeds other categories—it is both a direct obstacle and an amplifier for other obstacles. For instance, 62% of participants in a roundtable on the

adoption of digital and artificial intelligence in the construction industry indicated that they were at the initial stage of data deployment [98].

Organizational culture barriers, including willingness to digitally transform the construction industry (A4) and level of understanding of smart construction technology (A5), and technical barriers, including degree of inter-system compatibility (A11), BIM-Al technology application maturity (A12), and system expansion flexibility (A13), all have engagement values above 4, indicating that they are important secondary barriers. However, their positional degrees are all negative values (A4: −0.662, A5: −0.03, A11: −0.462, A12: −0.386, A13: −0.005), indicating that these factors are more influenced than driven in the system. This discovery reveals a blind spot in previous research: many studies consider "organizational cultural inertia" and "insufficient technological maturity" as primary barriers to BIM-AI integration. But the causal analysis of this study suggests that these factors are largely the result of data and policy factors—when data infrastructure is weak and policy support is unclear, organizations naturally lack the willingness to transform and technology is difficult to mature. This discovery has important guiding significance for practice: intervention measures should prioritize data and policy factors, rather than directly targeting organizational culture. For instance, a construction industry survey (adapted from Accenture's cross-industry research) found that 68% of middle-level managers perceived AI as a threat to their decision-making authority, whereas 53% of frontline supervisors admitted difficulties in interpreting AI-generated operational recommendations [99].

Finances are significant barriers to BIM-AI integration in the construction field, as highlighted by Khan et al. (2024) [39] and Rangasamy et al. (2024) [100]. Successful BIM-AI integration requires deploying customized hardware and software infrastructure, exerting financial pressures on firms with constrained cash flows. During operation and maintenance, challenges arise from the inevitable costs incurred for continuous BIM model updates, AI training requiring massive labeled datasets, and expensive manual labeling and calibration processes. Moreover, a critical concern is whether such a substantial investment can yield favorable returns. Current evidence shows that many AI projects in construction incur high costs but deliver suboptimal ROI, with returns often falling short of expectations. For instance, a Gartner report noted that only 13% of respondents are "very confident" in calculating the return on investment for AI, 37% are moderately confident, and 36% and 4% have lower confidence [101]. Essentially, financial barriers to BIM-AI integration represent a fundamental conflict between the costs of technological upgrading and the structural inertia of conventional industries.

Policies and regulations represent critical barriers to BIM-AI integration in the construction field. They have a dual impact on BIM-AI integration. Notably, BIM-AI integration introduces cybersecurity risks, particularly in terms of digital storage and processing of sensitive building data. Construction projects, which often contain proprietary information, are prime targets for cyberattacks because of the high value of their data assets. For example, in a number of large infrastructure developments, the integration of BIM model data among design institutes, contractors, and supervisory units has been constrained by stakeholders' reluctance to share original models, primarily due to unresolved intellectual property and privacy concerns arising from the absence of clear data sovereignty regulations. Policy and regulatory barriers to BIM-AI integration fundamentally reflect the lack of alignment between institutional systems and technological innovation in the construction industry's digital transformation.

Management and collaboration barriers represent obstacles to BIM-AI integration in construction management. While BIM has already transformed team collaboration dynamics, the introduction of AI introduces new uncertainties, with the building of stakeholder trust in AI-driven recommendations emerging as a critical challenge. Furthermore,

the participants' reluctance to share core data, stemming from ambiguous data ownership, intellectual property concerns, and undefined risk liabilities, hinders BIM-AI system learning and optimization. Finally, although BIM-AI integration can significantly enhance efficiency, poor cross-departmental collaboration often becomes a critical bottleneck in implementation.

In this study, quality, amount, and standardization of data are foundational as robust data form the basis for deep learning model training. BIM-AI integration in the construction field is inherently data-driven; therefore, data directly influence the technical maturity of integration. The low level of technical maturity, in turn, reinforces organizational inertia and resistance to change. Organizational culture and financial constraints are inextricably linked as the AEC industry often prioritizes short-term cost reduction over long-term value creation. This mindset hinders investments in BIM-AI, which requires sustained commitment. Data security and privacy concerns directly affect stakeholder management and collaboration. Ambiguities in data sharing, including the risks of privacy breaches among participants with diverse roles, undermine cross-functional efficiency, management decision effectiveness, and inter-team trust. Finally, the implementation and coverage of policies and regulations influence all other factors, with successful policies playing a pivotal role in coordinating and guiding the adoption of technology.

5.2. Implications

Based on the analysis of the RBF-WINGS model, the following suggestions are proposed for integrating BIM-AI into construction management.

First, data infrastructure should be consolidated to address interoperability and quality bottlenecks. Data-related factors constitute the core category of barriers identified in this study, among which the level of implementation of data standardization (A6) and data integrity and accuracy (A8) have the highest engagement among all 16 barriers, and are all system-driven factors. Therefore, the primary strategy for BIM-AI integration should focus on the construction of data infrastructure. At the level of IFC interoperability, it is urgent to develop a mature IFC-to-AI toolchain, including standardized processes for geometric information extraction, semantic enhancement, and format conversion, while promoting the continuous evolution of IFC standards for temporal data and dynamic attribute support, fundamentally solving the primary obstacle of "language barrier". At the level of design coordination, enterprises should promote the openness and standardization of API interfaces between BIM software, support plug and play integration of AI modules, and establish a unified data dictionary and naming convention to reduce semantic loss in data conversion from the source. At the on-site monitoring level, AI training methods based on synthetic data should be developed to reduce reliance on real on-site annotated data. At the same time, the government or industry associations should take the lead in establishing a publicly available dataset of de-identified construction sites to lower the threshold for small and medium-sized enterprises to obtain data.

Second, the technology deployment architecture should be optimized to support scenario-driven intelligent applications. On the premise of a solid data foundation, technical strategies should be deployed differentially around the characteristics of specific application scenarios, in response to technical factors (A11, degree of inter-system compatibility; A12, BIM-AI technology application maturity; and A13, system expansion flexibility) as secondary obstacles but equally critical practical challenges. In the digital twin scenario, it is recommended to deploy edge computing servers on the construction site to realize the localization and real-time analysis of BIM model and sensor data, reduce cloud delay, and establish a standardized data pipeline from BIM to digital twin to ensure the consistent updating of geometric and nongeometric information, so that digital twin can

truly move from "visual display" to "predictive analysis". In AI assisted decision-making scenarios, emphasis should be placed on "human–machine collaboration" rather than "machine substitution"—the decision recommendations output by AI should be presented to engineers in a visual and interpretable manner, and the AI reasoning process should be made transparent through tools such as SHAP value analysis to cultivate technical trust; enterprises should also simultaneously promote the digital re-engineering of management processes to avoid the inefficient mode of "arming old processes with AI". In on-site monitoring scenarios, it is necessary to focus on addressing the issue of insufficient real-time processing capabilities for heterogeneous data. Edge AI can be used to achieve real-time risk identification and warning at construction sites, while controllability of operation and maintenance financing (A15) are kept within an acceptable range.

Finally, management collaboration mechanisms should be restructured to support organizational and process adaptation. The implementation of technology and data ultimately depends on the adaptation and transformation of management systems and organizational culture, while management collaboration factors (A1, management decision-making effectiveness; A2, level of trust in cross-team collaboration; and A3, cross-departmental collaboration efficiency index) are mostly manifested as system outcome factors in this study, and their improvement depends on breakthroughs in data infrastructure and technology deployment. In the integrated scenario of facility management, it is recommended to adopt a phased implementation strategy—starting from scenarios with clear investment returns such as energy management and preventive maintenance, accumulating experience, and gradually expanding to the entire facility management field, while establishing clear data security and maturity of data security and privacy protection (A7) to eliminate the data-sharing concerns of facility managers. In the design coordination scenario, the cross-disciplinary collaboration process should be reshaped by embedding AI assisted design review, collision detection, and solution optimization into daily design coordination meetings, making "human–machine collaboration" a standard configuration for design decision-making rather than an additional link. At the project management level, executives need to incorporate BIM-AI integration into the top-level agenda of enterprise digital transformation, establish special budgets and KPI assessment mechanisms, establish cross departmental BIM-AI innovation centers, and connect the management chain of "strategic planning resource allocation on-site execution". Ultimately, the core of managing collaborative strategies lies in achieving a triple transformation—from an experience-driven to a data-driven decision-making culture, from departmental barriers to a platform collaboration organizational structure, and from one-time investment to continuous iteration investment philosophy. Only in this way can BIM-AI integration move from pilot exploration to large-scale implementation.

6. Conclusions and Limitation

This study systematically investigated the barriers to the adoption of BIM-AI integration in the construction field. Sixteen key barriers were identified, analyzed, and categorized into six dimensions through an extensive literature review, industry reports, and expert elicitation. Using the RBF-WINGS model, the causal relationships between these barriers were scientifically analyzed to extract the most critical barriers and their interdependencies. The results indicate that engagement is highest among data-related barriers, suggesting that they constitute the most significant category of barriers. Specifically, these include A6: level of implementation of data standardization; A7: maturity of data security and privacy protection; and A8: data integrity and accuracy. These factors not only directly impede BIM-Al adoption in the construction field but also indirectly affect other barriers. Furthermore, engagement is also concentrated at the technical and organizational

culture levels, indicating that organizational culture and technical factors are key secondary barriers. These include A4: willingness to digitally transform the construction industry; A5: level of understanding of smart construction technology; A11: degree of inter-system compatibility; A12: BIM-Al technology application maturity; and A13: system expansion flexibility. This study provides actionable guidance for AEC industry practitioners and policymakers, particularly in formulating targeted strategies to address the identified barriers to BIM-Al integration.

However, this study also has some limitations. First, the identification and selection of barriers relied mainly on literature reviews, industry reports, and expert opinions, which inevitably resulted in subjective bias. In addition, this study drew mainly on experts from China, indicating that the findings may be specific to the Chinese construction industry and may not be directly applicable to other countries or regions without modifications. Therefore, caution should be exercised when applying these findings in different contexts. Future research could extend the data collection to multiple countries or regions for comparative analysis to provide a broader understanding of the commonalities and differences in barriers across cultures and regulatory environments. Finally, because BIM-AI integration in the construction field is still at a nascent stage and expert resources are limited, this study did not conduct large-scale empirical data collection. The analysis was based on expert-rating data from 17 experts, which may limit the generalizability of the findings. Future studies could expand the expert sample, include participants from more regions and organization types, and further validate the identified barriers using larger-scale empirical data. As BIM-AI applications continue to grow, future research should use methods such as regression analysis or experiments to further determine the drivers, barriers, and critical success factors for the successful integration of these technologies in the construction field.

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