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MODELLING INTER-RELATIONSHIPS OF BARRIERS TO SMART CONSTRUCTION IMPLEMENTATION

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Abstract. Smart construction technology offers fresh avenues for advancing the field of civil engineering. It seamlessly integrates across the entire life cycle of civil engineering projects, encompassing planning, design, construction, and maintenance, thereby fundamentally reshaping the landscape of civil engineering development. Nonetheless, it is essential to recognize that, presently, smart construction's developmental stage remains relatively nascent. Its progression is subject to a myriad of adoption barriers, and the complex dynamics of their interactions remain insufficiently understood. Therefore, this study aims to (1) explore the barriers to the adoption of smart construction; (2) analyze the impact level of each barrier; and the interaction mechanism between the barriers (3) propose effective strategies to promote the development of smart construction. This study commences by identifying 16 major impediments to the adoption of smart construction through a comprehensive synthesis of existing literature and expert interviews. Subsequently, Euclidean similarity analysis is employed to harmonize varying expert assessments. Following this, the Decision-Making Trial and Evaluation Laboratory model is utilized to ascertain the degree of influence associated with each barrier. Further, the Interpretive Structural Model is employed to establish a hierarchical framework that illuminates the interdependencies among these barriers. Additionally, the Matrice d'Impacts Croisés Multiplication Appliqués à un Classement method is invoked to elucidate the roles and statuses of each barrier. Finally, strategies are proposed based on the results of the analysis. This study offers practical strategies for overcoming barriers and driving the adoption of smart construction, filling a critical gap in understanding by identifying key barriers and providing actionable insights, thus significantly advancing the field and empowering stakeholders for successful implementation and dissemination.

Keywords: adoption barriers, decision-making trial and evaluation laboratory model, inner mechanisms, interpretive structural model: smart construction.

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1. Introduction

The architecture, engineering, and construction (AEC) industry, renowned for its vast scale, substantial economic contribution, and significant resource utilization confronts formidable challenges stemming from its relatively low level of informationization and intelligence (Cheng et al., 2020). Notably, a McKinsey & Company report highlighted that the construction industry invests less than 1% of its revenue in research and development (R&D), which is significantly lower compared to other industries. As depicted in Figure 1, digitalization levels in the construction industry are notably trailing. Recognizing the need to increase productivity and improve the intelligence of the industry (Agarwal et al., 2016), various regions and stakeholders have made smart construction promotion a paramount development priority in recent times (Regona et al., 2022). Across numerous nations, intelligence has emerged as a central theme guiding future development trajectories, with concerted efforts directed toward the digitalization of the construction sector (Turner et al., 2021). The infusion of emerging technologies into the construction landscape holds the promise of revolutionizing the industry, envisaging enhanced processes, cost reduction, and bolstered safety measures.

Referring to the integration of advanced technologies and processes into the construction industry to improve efficiency, safety, and sustainability, smart construction is an important embodiment of Industry 4.0. Advanced technologies include Building Information Modeling (BIM) (Hu et al., 2018), 3D printing (Zheng et al., 2023), the Internet of Things (IoT) (Yang et al., 2020), artificial intelligence (AI)

(Yan et al., 2023a), prefabrication and modular construction (Masood et al., 2022), robotics (Zhu et al., 2021), big data (Jiang et al., 2023), digital twins (Yevu et al., 2023), blockchain (Li et al., 2021), cloud computing (Jiang, 2020), etc. These cutting-edge technologies facilitate innovative linkages across various dimensions of construction activities, ultimately enhancing industrial processes, products, and services. Recent years have witnessed substantial research efforts in the realm of smart construction, primarily focusing on the integration of diverse intelligent technologies into different phases of building construction. Scholars have conducted macro-level analyses of smart construction development, outlining key technologies and forecasting future trends. Štefanič and Stankovski (2019) systematically reviewed representative literature to underscore the potential of emerging smart technologies in construction monitoring, process management, and disaster early warning systems. Yang et al. (2018) introduced an emerging IT acceptance model to evaluate adoption behaviors and formulate acceptance strategies for smart construction systems. Masood and Roy (2022) conducted a comprehensive review of prefabricated building technology, establishing a classification system based on product types. This systematic classification aids scholars and practitioners in understanding the nuances of prefabricated building technologies, thereby fostering their increased adoption. While significant strides have been made in understanding the trends and potential for adoption of smart construction and information technologies, it is imperative to acknowledge that smart construction is still in its infancy. Numerous barriers hinder its development, and the complex interactions within this domain remain poorly understood. Thus, a meticulous examination of determinants affecting smart construction is indispensable for their effective integration into engineering practices.

Hence, a systematic and scientifically rigorous approach is imperative to dissect the adoption barriers hindering the advancement and proliferation of smart construction. Hwang et al. (2022) conducted an extensive literature review and pilot interviews with industry experts, followed by a survey and post-survey interviews to delve into the challenges and strategies associated with adopting smart technologies in the construction sector. The Interpretive Structural Model (ISM) methodology aids in pinpointing the pivotal factors or variables influencing the system and categorizing and prioritizing them, thereby facilitating a deeper comprehension of the relationships among different system components. Similarly, Xiahou et al. (2022) employed ISM to scrutinize the adoption barriers in smart construction site development, identifying 17 barriers from management, technology, and organizational perspectives. The application of DEMATEL-ISM provided novel insights into sustainable development within the construction industry, offering valuable guidance for governmental policies, construction enterprises, and other stakeholders. In another study, Ghansah et al. (2021) conducted a quantitative questionnaire survey involving 227 project management and design team participants to probe potential barriers to project management when integrating smart building technology in developing countries. Subsequent analysis using one-sample t-tests and exploratory factor analysis shed light on the collected data. While these studies employed scientific methodologies to dissect barriers to smart construction development, there remains a dearth of research addressing the magnitude of these barriers' impact and the underlying mechanisms governing their interactions. Thus, there is a pressing need for further exploration in this domain to better inform strategic interventions and propel the advancement of smart construction practices.

This study endeavors to fill this gap by conducting a comprehensive analysis of adoption barriers and the underlying mechanisms impacting the development of smart construction. It aims to explore the primary barriers to

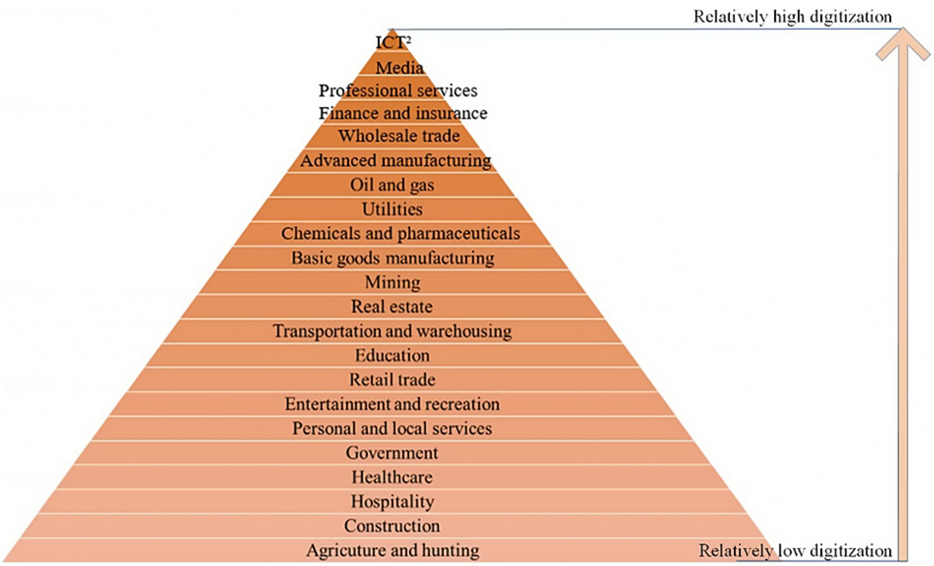


Figure 1. Industry digital rankings (Agarwal et al., 2016)

smart construction adoption and elucidate their interrelationships. Additionally, the study seeks to propose potential solutions to surmount these barriers. To address these objectives, a multifaceted methodology was employed. Initially, a Systematic Literature Review (SLR) and expert interviews were conducted to identify the principal barriers. Subsequently, Euclidean Distance Analysis was utilized to mitigate discrepancies in expert scoring. Following this, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) model was applied to identify key influencing factors and visualize causal relationships among various barriers. Moreover, the ISM-MICMAC model was employed to analyze hierarchical relationships and interaction mechanisms among the barriers. This study comprehensively analyzes smart construction and its associated influencing barriers, thoroughly uncovering the development barriers of smart construction and their internal mechanisms. Through systematically examining these internal relationships, we identify key development barriers and analyze their driving and dependent relationships, clarifying their characteristic attributes and providing theoretical guidance for decision-making in smart construction development. In response to these significant barriers, this paper proposes practical and feasible recommendations and measures, offering stakeholders viable strategies for promoting and disseminating smart construction technologies.

The article is structured as follows. Section 2 analyzes the commonly used methods of internal mechanism analysis and describes the rationale for selecting the proposed methods. Section 3 describes the methodology for barrier identification, elimination of scoring discrepancies, internal relations, and internal mechanism analysis. Section 4 then demonstrates the process of data analysis. Section 5 discusses the results obtained and gives strategies and recommendations for barrier improvement. Finally, Section 6 presents conclusions and future work.

2. Analysis of research methodology

Commonly used approaches for system hierarchization and adoption barriers determination include the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), the decision-making trial and evaluation laboratory (DEMATEL), the interpretive structural model (ISM), Total Interpretive Structural Model (TISM), and Matrice d'Impacts Croisés Multiplication Appliqués à un Classement (MICMAC), etc. (Shanker & Barve, 2021). The AHP method, with the advantages of being flexible, systematic, and direct, has been widely used in practical research to determine barrier weights. Lyu et al. (2020) combined the AHP method and triangular fuzzy number-based hierarchical analysis (TFN-AHP) into a geographic information system (GIS) to assess the flood risk of the Shenzhen metro system by determining the weights of the evaluation indexes. Das et al. (2022) developed a risk resilience framework to determine the adoption barriers that affect the global supply chain in the period of novel coronavirus outbreaks, using the AHP method based on the relative weights to determine the risk of flooding and the risk of floods. The AHP method was used to hierarchically rank the adoption barriers based on their relative weights. ANP was developed by Saaty (1996) based on AHP for solving more intricate decision problems. TOPSIS is often used to evaluate the advantages and disadvantages of programs and is capable of identifying the optimal versus the worst among a limited number of programs. Karim and Karmaker (2016) developed a decision support system for the machine evaluation process. The framework will be implemented via the integrated approach of AHP and TOPSIS to guide the decision-maker in selecting the appropriate machine. The AHP method is applied to determine the weights of the identified sectors and subsectors and the TOPSIS method is utilized to rank the eligible alternatives. Finally, the article validates the feasibility and reasonableness of the above method through an example. Solangi et al. (2021) integrated the AHP method with the TOPSIS method for the barriers to the development of renewable energy technologies in Pakistan. The VIKOR method is capable of obtaining compromise solutions in complex decision-making environments and ranking them by comparing the proximity of the evaluation results to the ideal solution. Rostamzadeh et al. (2015) proposed a comprehensive evaluation criterion for green supply chain management practitioners using the fuzzy VIKOR method. Safari et al. (2016) used the fuzzy VIKOR method to achieve prioritization of enterprise architecture risk factors. Total Interpretive Structural Modeling (TISM) represents an advancement over ISM, offering enhanced capabilities for analyzing relationships among system factors (Gardas et al., 2019). By accommodating a broader array of factors and enabling quantitative evaluation, TISM is better suited for the analysis of complex systems and decision support. In summary, AHP and ANP are mainly used to rank the adoption barriers and do not consider internal relationships. It requires a large amount of data and expert knowledge to complete the analysis, making it less suitable for simpler systems (Sevkli et al., 2007). The advantage of TOPSIS is that it can incorporate multiple factors into the evaluation, but it requires well-defined ideal and anti-ideal solutions, which may not be easy to determine in some cases (Jin, 2023). VIKOR is mainly used to solve problems with multi-criteria decision-making and also does not take into account the interrelationships between the barriers. In addition, its candidate program rankings may be affected by extreme values (Kim & Ahn, 2019).

Compared with the above methods, the DEMATEL method can better identify adoption barriers. The ISM method can better reveal the logical hierarchical relationships among barriers. The MICMAC method is usually used to determine the interactions among barriers by calculating the drivers and dependencies of the adoption barriers after the structural hierarchy model is established. Sindhu et al. (2016), to study the solar power generation in the rural areas in India universalization barriers, the ISM method was combined with the MICMAC method, which was used to identify the interrelationships between the barriers and to obtain the ranking of the identified barriers, based on which the next development strategy was clarified. Masood et al. (2023) used ISM and MICMAC to identify the performance drivers of prefabricated house building (PHB) firms and establish the interrelationships of performance dimensions as a way to develop key strategies to remain competitive in the housing market. Bux et al. (2020) used the ISM-MICMAC method to conduct a comprehensive analysis of the barriers to the implementation of CSR and used the ISM method to establish a structural model of the barriers and to differentiate between the CSR responsibility implementation barriers. Finally, the MICMAC method was analyzed to judge the impact of barriers and the ability to rely on them. He et al. (2021b) used DEMATEL and ISM to establish a multilevel hierarchical model to study the influence of different factors on highway vehicle fuel consumption, to determine the magnitude of the influence ability of different factors as well as the relationship between factors, and to provide a reference for the construction of a better economic highway. Liu et al. (2021) in the study of e-commerce supply chain elasticity of the adoption barriers, for the complex system, the use DEMATEL-ISM method to analyze the degree of integrated influence between the adoption barriers, causal relationship and logical hierarchy, based on which it is proposed to improve the adaptability of the supply chain is the top priority. Vishwakarma et al. (2022) used the DEMETAL-ISM-MICMAC method to study the barriers to supply chain management in the apparel and textile sector. This integrated approach allows for a thorough study of the relationships between factors or dimensions. However, the method has a certain degree of subjectivity and results may vary depending on the views and biases of the researchers involved in constructing the model and analyzing the data.

Given the strengths of each method outlined above, combining ISM with DEMATEL and MICMAC offers a comprehensive approach to analyzing adoption barriers in smart construction. DEMATEL can help in identifying the barriers, ISM can establish the logical hierarchy among them, and MICMAC can reveal their interactions and relative importance. This integrated approach allows for a thorough analysis of the relationships between factors or dimensions, helping practitioners and policymakers devise effective strategies to overcome these barriers and promote adoption in the industry.

3. Methodology

In this study, an adoption barrier analysis model based on DEMATEL-ISM-MICMAC under the Euclidean elimination method is proposed, as shown in Figure 2. Firstly, the main smart construction adoption barriers are identified through a systematic literature review (SLR) and expert interviews (EI). Secondly, Euclidean similarity analysis is applied to eliminate differences in scoring by different experts. Thirdly, the DEMATEL model is used to find out the degree of influence of each barrier, identify the key influences based on the centrality and causality of the adoption barriers, and visualize the causal relationship among different barriers. Fourthly, the ISM was used to establish a hierarchical structure to examine the coupling relationship between the barriers. Finally, MICMAC was used to clarify the role and status of each barrier.

3.1. Identification of adoption barriers by SLR-EI

SLR is a methodical and comprehensive approach to identifying, evaluating, and synthesizing existing research relevant to a particular research question or topic (Masood et al., 2022). We adapted the SLR proposed by Zhang et al. (2020) to conduct a detailed review of research on barriers to the development of smart construction. This review is based on scholarly articles sourced from reputable academic journals, spanning up to August 2023, situated

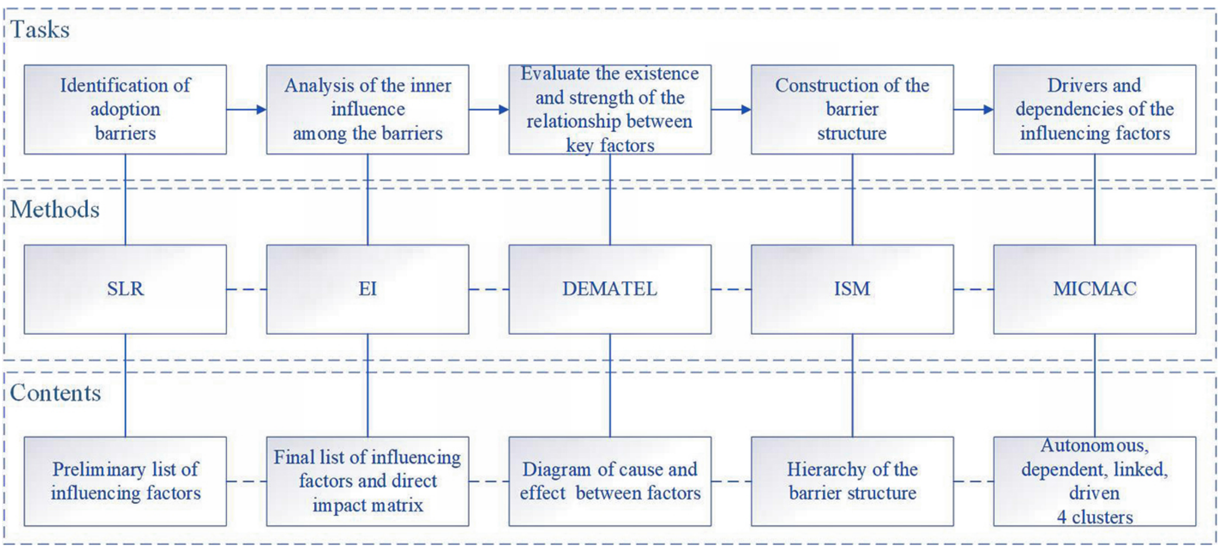


Figure 2. Schematic diagram of the analysis model of barriers affecting the development and popularization of smart construction

within the purview of the AEC industry. The objective is to elucidate the prevailing developmental trends and the contemporary state of smart construction. The chosen journals hold notable sway within the AEC field and are cataloged within either the Science Citation Index Expanded (SCIE) or the Engineering Index (EI) Compendex database. For literature acquisition, Science Direct, Google Scholar, and Web of Science served as the primary search engines. A systematic approach was employed, with two separate search iterations conducted to ensure a comprehensive and robust selection of articles. In the first search round, the articles were searched using a diverse combination of key phrases, including smart construction, intelligent construction, green building, barriers, adoption barriers, design, architecture, engineering, construction, and operation. Based on the findings of the first search round, a second search round was conducted by manually filtering the papers related to smart construction to remove irrelevant papers. The abstract of each paper was read by the authors to ensure that the application of the paper is within the field of smart construction. For example, several papers obtained from the first round of searching were about smart management rather than smart construction, which shall not be considered in this study. After two rounds of filtering, 82 journal papers were selected and classified into five categories: economic, social, policy, technical, and natural. The specific process is shown in Figure 3.

Based on the literature, an initial list of major barriers to the adoption of smart construction was identified. According to related studies, 15 experts is appropriate and sufficient for such qualitative analysis (Xu & Zou, 2020; Gardas et al., 2019). Fifteen experts were invited to evaluate the initial list of barriers. These 15 experts were required to be from academia and industry, respectively, with at least 5 years of work experience in the construction industry. Detailed information is shown in Table 1. First, the 15 experts were invited to review and refine the initial list of barriers. Comments were summarized and sent back to the experts for revision. This process was repeated until all experts agreed on all barriers and a final list of barriers was obtained. Once the final barriers were identified, a questionnaire was created and distributed to the experts to score the adoption barrier correlations to obtain a scoring matrix.

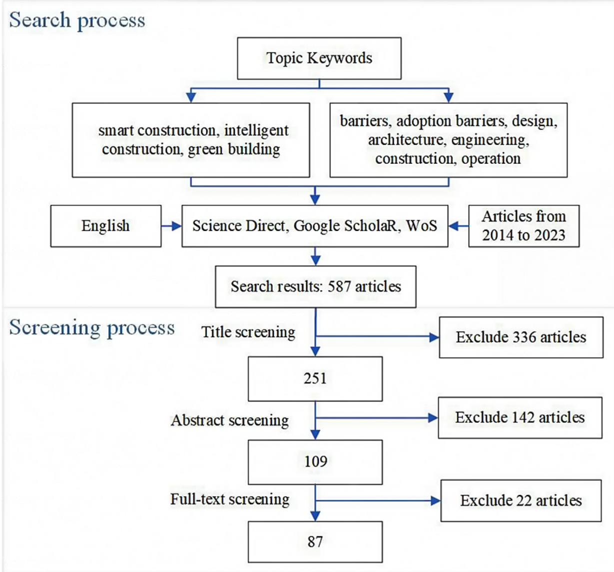


Figure 3. The process of SLR used for this study

3.2. Eliminating scoring differences by Euclidean similarity analysis

Past studies have mostly used the average-worth method to process the questionnaire results (Xiahou et al., 2022; Huo et al., 2023). During the expert scoring process, variations in scores can arise due to the personal preferences and cognitive habits of the scorers. These differences can manifest as differences in scoring leniency and interpretations of the scoring criteria. Therefore, this paper proposes to use the Euclidean similarity analysis method to get the similarity score matrix between experts (Liu et al., 2024). Then the weight calculation is carried out to comprehensively analyze their relative importance, eliminate the scoring differences, and get a more scientific direct impact matrix. The specific methods are as follows.

(1) Euclidean distance

Euclidean distance is used to measure the similarity between the rating patterns of different experts. There are two rating matrices of experts, denoted as E_i and E_j. The following formula was used to calculate the Euclidean distance between these two rating matrices:

$$D(E_i, E_j) = \sqrt{\sum_{r=1}^{u}\sum_{c=1}^{v}(E_i(r,c) - E_j(r,c))^2}, \quad (1)$$

where $D(E_i, E_j)$ denotes the Euclidean distance between expert i and expert j. $E_i(r, c)$ denotes the rating value of row r and column c in the rating matrix E_i, u and v denote a total of rows and columns of the rating table.

(2) Expert weight calculation

The similarity score was used to calculate the weight of each expert to reflect their importance in the similarity network. To calculate the weight W_i of expert i, the similarity scores of all experts are summed up:

$$W_i = \sum_{i=1, j\neq i}^{m} S\left(E_i, E_j\right) = \frac{1}{1 + D(E_i, E_j)}, \quad (2)$$

where m represents the number of experts and $S(E_i, E_j)$ denotes the similarity score between expert i and expert j. A larger score indicates a more similar rating pattern between the two experts.

(3) Normalized weight calculation:

$$N_i = \frac{W_i}{\sum_{k=1}^{m} W_k}, \quad (3)$$

where N_i denotes the normalized weight of the expert i and W_k denotes the weight of the expert k.

Table 1. Participants information and experience in the field

Participant	Background and Qualifications	Specialization	Experience (Years)
Expert 1	PhD in Civil Engineering, Previous role as Project Manager at a construction firm	Sustainable Construction	8
Expert 2	Master's in Architecture, Currently works as a Senior Researcher at a university	Building Information Modeling (BIM)	7
Expert 3	Bachelor's in Construction Management, Consultant at a construction consultancy firm	Project Management	4
Expert 4	PhD in Electrical Engineering, Associate Professor at a technical institute	Smart Building Technologies	10
Expert 5	Master's in Environmental Engineering, Chief Sustainability Officer at a construction company	Green Building Practices	15
Expert 6	Bachelor's in Mechanical Engineering, Safety officer at a multinational company	Prefabrication and Modular Construction	2
Expert 7	PhD in Architecture, Professor at a renowned architecture school	Sustainable Design	20
Expert 8	Master's in Construction Economics, Senior Consultant at a construction consultancy firm	Cost Estimation and Value Engineering	8
Expert 9	Bachelor's in Civil Engineering, Structural Engineer at a structural design firm	Structural Engineering	4
Expert 10	PhD in Construction Management, Director of Research and Development at a construction technology company	Innovation in Construction Processes	12
Expert 11	Master's in Urban Planning, Senior Planner at a municipal government agency	Urban Planning and Development Regulations	11
Expert 12	Bachelor's in Architecture, Architect at an architectural design firm	Architectural Design and Sustainability	2
Expert 13	PhD in Mechanical Engineering, Head of Research and Development at a construction materials company	Materials Science and Engineering	11
Expert 14	Master's in Construction Law, Legal Counsel at a construction law firm	Construction Contract Law	8
Expert 15	Bachelor's in Environmental Science, Environmental Consultant at an environmental consulting firm	Environmental Impact Assessment	2

(4) Scale aggregation

By weighting and averaging each expert's scoresheet, a comprehensive scoresheet was obtained to reflect the combined impact of different barriers. The following formula can be used to calculate the combined scoring matrix A:

$$A = \sum_{i=1}^{m} N_i * E_i, \tag{4}$$

where E_i is the rating matrix of the expert i and N_i is its normalized weight. Through the above calculations, the scoring information from different experts was successfully aggregated to generate a composite scoring matrix, which indicates the degree of combined influence between barriers to reflect the role of different experts' views and weights on the whole.

3.3. Analysis of inner relationships by DEMATEL

DEMATEL is considered to be an effective method for identifying the components of causal chains in complex systems (Si et al., 2018). It can obtain a visual structural model to assess the interdependence of barriers through matrix computation, which can integrate the cause and center indicators of the barriers to find the adoption barriers of a complex system and draw the barrier relationship image (Lee et al., 2013). The specific methodology is as follows.

(1) Direct influence matrix

Expert interviews in the form of questionnaires were conducted and experts were asked to rate the magnitude of the correlation between pairs of adoption barriers to determine the degree of direct influence between the barriers. The correlation between a pair of identical adoption barriers is specified as 0. The direct influence matrix $C\left(C = \left[c_{ij}\right]_{n\times n}\right)$ is obtained after collation:

$$C = \begin{bmatrix} 0 & c_{12} & \cdots & c_{1n} \\ c_{21} & 0 & \cdots & c_{2n} \\ \vdots & \vdots & & \vdots \\ c_{n1} & c_{n2} & \cdots & 0 \end{bmatrix}, \tag{5}$$

where $c_{ij}(i, j = 1, ..., n; i \neq j)$ represents the degree of impact of c_i on c_j, if $c_i = c_j$, then $c_{ij} = 0$.

(2) Normative impact matrix

Sum the values of each row of the direct impact matrix C, take the maximum value, and normalize the direct impact matrix C to obtain the standardized impact matrix

$D\left(D=\left[d_{ij}\right]_{n\times n}\right)$, $0 \le d_{ij} \le 1$.

$$D=\frac{c_{ij}}{\max\left(\sum_{j=1}^{n} c_{ij}\right)}. \tag{6}$$

(3) Comprehensive impact matrix

The comprehensive impact matrix was recorded as $T\left(T=\left[t_{ij}\right]_{n\times n}\right)$. The comprehensive impact matrix can be calculated using the following equation:

$$T=(D^1+D^2+\ldots+D^K)=\sum_{K=1}^{\infty} D^K = D\left(I-D\right)^{-1}, \tag{7}$$

where matrix I is the identity matrix.

(4) Degree of influence and degree of being influenced of barriers

The degree of influence f_i is obtained by adding the elements in each row of matrix T. The degree of being influenced e_i is obtained by adding the elements in each column, representing the impact of the corresponding elements in the row or column on all other elements of the matrix. The calculation formula is as follows:

$$f_i/e_j=\sum_{j/i=1}^{n} t_{ij},\ (i/j=1,\ldots,n). \tag{8}$$

(5) Center degree and cause degree of each barrier

The center degree of a barrier is obtained by adding its degree of influence and the degree of being influenced, which indicates the position of the barrier in the system and the size of its role. The center degree of a barrier is calculated by the following formula:

$$m_i=f_i+e_i,\ \left(i=1,\ldots,n\right). \tag{9}$$

The cause degree of a barrier is the result of subtracting the degree of influence from the degree of affected. If the cause degree is greater than 0, it means that the barrier has a strong influence on other barriers so it is called a cause barrier. If the cause degree is less than 0, it is called the result element. The cause degree of a barrier is calculated as follows:

$$n_i=f_i-e_i,\ (i=1,\ldots,n). \tag{10}$$

(6) Cause-result diagram

Cause-result diagram was drawn using the center degree and cause degree of each barrier as horizontal and vertical coordinates. The causal relationships were then simplified and the importance of each barrier was analyzed according to its position in the coordinate system.

(7) Overall impact matrix of the system

Record the overall impact matrix as $E\left(E=\left[e_{ij}\right]_{n\times n}\right)$, and the formula is as follows:

$$E = T + I. \tag{11}$$

3.4. Analysis of inner mechanism by ISM-MICMAC

The ISM method constitutes an interactive learning process with remarkable utility (Raut et al., 2017). In the realm of learning analysis, it excels in the integration of diverse and interrelated elements into a comprehensive system model. This modeling technique is particularly adept at scrutinizing the impact of one variable upon others. Widely embraced in systems engineering, the ISM method is a well-established approach for building hierarchical models. It facilitates the systematic construction of an entire barrier system, taking into account both direct and indirect relationships. Consequently, it proves especially suitable for exploring the intricate interconnections among barriers within a complex system (Tan et al., 2019).

On the other hand, the MICMAC method operates on the fundamental principle of matrix multiplication. It offers insights into the role and position of each influencing barrier within the system by computing driving and dependence forces. These calculations give rise to the four quadrants of linkage, independence, autonomy, and dependence (Singh & Gupta, 2020). The MICMAC method primarily serves as a tool for assessing the influence and interdependence of barriers in the system. The specific methodologies employed in this regard are outlined as follows.

(1) Reachable matrix

To facilitate the clear delineation of the hierarchy, it is necessary to introduce a threshold value λ to filter out the less influential barriers and delete them. The value of λ is generally based on the actual situation and the recommendations of experts. The matrix E is processed using λ to obtain the reachable matrix $K\left(K=\left[k_{ij}\right]_{n\times n}\right)$:

$$k_{ij}=\begin{cases}1, e_{ij}\ge \lambda\ \left(i,j=1,2,\ldots,n\right)\\ 0, e_{ij}\le \lambda\ \left(i,j=1,2,\ldots,n\right)\end{cases}. \tag{12}$$

(2) Classification of levels

The reachable level and the prior level of each barrier were determined. The reachable level is denoted as R, and the prior level is denoted as S. The formula is:

$$R(b_i)=\{b_i|f_{ij}=1\},\ (i=1,2,\ldots,n); \tag{13}$$

$$S(b_i)=\{b_i|f_{ij}=1\},\ (i=1,2,\ldots,n). \tag{14}$$

If the matrix barriers satisfy the following equation, it means that all corresponding elements in the prior level can find corresponding antecedents in the reachable level, and the corresponding elements are the bottom barriers and cross out row i and column i in the matrix K. The uncrossed-out advanced barriers are extracted to form a new matrix. The above steps are repeated until all obstacles have been crossed out:

$$R_i=R_i\cap S_i,\ (i=1,2,\ldots,n). \tag{15}$$

(3) Hierarchical structure

The hierarchy is created according to the order of barrier division. A multilevel-directed topology map between system elements is drawn according to the order of barrier division.

(4) Draw dependency and drive diagram.

The driving force D_i and dependence degree R_j of the matrix are calculated by following equations, where D_i denotes the driving force of the barrier on other barriers, and R_j denotes the degree of dependence of the barrier on other barriers. The i-row and j-column sums of the reachable matrix K, respectively:

$$D_i = \sum_{j=1}^{n} K_{ij}, \ \ (j = 1,\ldots,n); \qquad (16)$$

$$R_j = \sum_{i=1}^{n} K_{ij}, \ \ (j = 1,\ldots,n). \qquad (17)$$

4. Findings

4.1. Identified smart construction adoption barriers

Drawing upon a plethora of pertinent literary sources, this article seeks to synthesize and analyze the complex and multifaceted barriers that exert a profound impact on the trajectory of smart construction. This study draws upon the classification methodology proposed by Chen et al. (2023c) and extends it to provide a comprehensive analytical framework. We conduct a detailed analysis of the development and dissemination of smart construction within the domains of economic, social, policy, techniques, and natural. Through this analysis, we identify over twenty barriers that hinder the advancement and widespread adoption of smart construction. However, recognizing the importance of soliciting expert opinion and feedback, the author proceeds to invite fifteen accomplished and renowned experts to participate in a comprehensive and exhaustive questionnaire survey. Through this iterative process of refining and refining once again, the author ultimately distills the twenty initial adoption barriers into a parsimonious and sleek set of sixteen adoption barriers that are the most salient and germane to the topic at hand.

These sixteen adoption barriers are explicated in Table 2, which offers a clear and concise summary of the crucial components that drive the growth and uptake of smart construction.

4.1.1. Economic

Production cost (B1). The adoption of information technology has led to increasingly complex building structures and improved customer discernment, and effective control of production costs is essential in order to achieve sustainable development of smart buildings (Gong & Caldas, 2011; Abioye et al., 2021; Cheng, 2014).

Economic benefits (B2). The economic benefit barrier to smart construction's development lies in the need to ensure profitability, especially as the construction industry increasingly focuses on quality, productivity, efficiency, safety, sustainability, and financial gains in the era of Industrialization 4.0 (Iyer & Jha, 2005; Zhang et al., 2014; Ding et al., 2023).

Labor productivity (B3). The development of smart construction faces labor productivity barriers linked to inefficient supply chains, decentralized assembly construction trade, and challenges with the practical implementation of certain BIM software functions that may lead to time inefficiencies (Karthik & Rao, 2019; Ma et al., 2016; Jahanger et al., 2023; He et al., 2021a; Lee et al., 2017).

Energy consumption (B4). Energy consumption represents a barrier to the development of smart construction due to the increasing attention on resource and environ-

Table 2. Adoption barriers affecting the development and popularization of smart construction

Category	Critical barrier	Description
Economic	Production cost (B1)	High costs
	Economic benefits (B2)	Uncertainty in economic and social benefits
	Labor productivity (B3)	Lack of efficient supply chain
	Energy consumption (B4)	Impact on resources and environment
	Level of Market Environment (B5)	Market flexibility and openness
Social	Social recognition (B6)	Low public recognition
	Level of management mechanism (B7)	Incomplete and inefficient management mechanism
	Technical level of employees (B8)	Low level and lack of training
Policy	Industry-standard (B9)	Lack of unified guidance and standard processes
	Government support (B10)	Financial and policy support
Technical	Hardware support (B11)	Low reliability, low computing power
	Platform building (B12)	System differences and difficulties in data acquisition
	Algorithm support (B13)	Low reliability and high resource consumption
	Technology integration (B14)	There are differences in the level of technical integration
	Data management (B15)	Lack of strict data-sharing platforms and data security
Natural	Severe weather (B16)	Transportation delays, productivity fluctuations

mental concerns, the focus on green, healthy, and sustainable development, and the importance of energy-saving goals in green buildings (Zuo & Zhao, 2014; Ansah et al., 2019; Chen et al., 2023a; Mehmood et al., 2019; Tushar et al., 2018).

Level of Market Environment (B5). The level of market environment represents a barrier to the development of smart construction, with the maturity of the local construction market significantly influencing cost-effectiveness, the application of BIM technology, and the development and popularity of prefabricated buildings (Tan et al., 2019; Paiho et al., 2023; García de Soto et al., 2018; Hong et al., 2018).

4.1.2. Social

Social recognition (B6). Social recognition presents a barrier to the development of smart construction due to the lack of understanding, personal preferences, concerns about job displacement, resistance to change, and the influence of cultural and social norms (Navaratnam et al., 2022; Olofsson Hallén et al., 2023; Li et al., 2019).

Level of management mechanism (B7). A perfect management mechanism is the guarantee and foundation for the development of smart buildings. However, due to the lack of an effective management evaluation mechanism, there is a certain degree of difficulty in evaluating the maturity of smart management of buildings, which hinders its development to a certain extent (Chen et al., 2023b; You & Feng, 2020; Leśniak et al., 2021).

Technical level of employees (B8). The promotion and application of IT and the quality of construction projects will be affected by the under-skill level of practitioners, the lack of appropriate technical support, systematic vocational training, and difficulties in communication and coordination among construction personnel (Olanrewaju et al., 2022; Dong, 2017; Alaloul et al., 2020; Chen et al., 2024; Yilmaz et al., 2023).

4.1.3. Policy

Industry-standard (B9). The lack of industry-standard guidelines and policies is an obstacle to the development of smart construction, especially when it comes to the implementation of BIM. The need for standardized processes and regulations is highlighted to facilitate the transfer and exchange of information between users (Huang et al., 2021; Chen et al., 2022; Anastasiades et al., 2021; Too et al., 2022; Zhang et al., 2017).

Government support (B10). Government support, encompassing industrial support, scientific research project backing, and promotional efforts, plays a pivotal role in the development of smart construction, influencing the enthusiasm of the construction industry for adopting intelligent information technology and the successful implementation of key technologies like BIM (Jalaei et al., 2022; Oluleye et al., 2023; Abanda et al., 2017; Yang & Chou, 2018; Huh et al., 2023; Jiang et al., 2021; Zabin et al., 2022; Chegu Badrinath et al., 2016; Dong & Martin, 2017).

4.1.4. Techniques

Hardware support (B11). Hardware support such as robotic arms, robots, 3D printers, and mapping equipment is expected to improve the efficiency and quality of smart construction, but high costs, technical standards, and maintenance and data security issues are likely to remain barriers to development (Song & Wu, 2022; Kumar et al., 2015, 2018; Zhao et al., 2020).

Platform building (B12). Platform building for smart construction is hindered by insufficient technology and technical support, limiting its development, while system interoperability can help overcome information silos and enable the integration of smart construction data (Sun & Liu, 2022; Chen et al., 2021).

Algorithm support (B13). Algorithm support is a critical cornerstone in the field of smart construction, as algorithms are essential for the proper functioning of computer systems, network management, and improving project efficiency, safety, and cost control through precise construction process calculations (Yan et al., 2023b; Wu & Lu, 2022; Yu & Zuo, 2022).

Technology integration (B14). The development of smart construction relies on the integrated application of technologies such as artificial intelligence, internet big data, internet of things, BIM, blockchain, and cloud computing throughout the construction process, emphasizing the collaboration between information science and technology and construction industrialization (Song, 2022; Tian et al., 2021).

Data management (B15). The smart construction process generates a huge system of data, and data management becomes an important evaluation barrier affecting the level of smart construction (Wang et al., 2022; Zhao, 2022).

4.1.5. Natural

Severe weather (B16). During the actual construction building process, construction participants may face severe weather such as rain, snow, wind high temperature, and high humidity. Severe weather conditions pose a barrier to the development of smart construction, as they lead to transportation delays, productivity fluctuations, and physical and psychological challenges for construction workers. These problems can be solved by using smart technologies including wearable sensors and digital twin technology for safety and efficiency optimization (Jiang et al., 2022; Karthick et al., 2023; Jia et al., 2022; Chiarelli et al., 2017; Wang et al., 2019; Yi et al., 2016; Liu et al., 2020).

4.2. Causality analysis of adoption barriers based on DEMATEL

Based on the list of adoption barriers in Table 2, 15 practitioners and research scholars in the construction field were invited to score the strength of the relationship between the adoption barriers. The scoring criteria include very little influence (0 points), low influence (1 point), medium influence (2 points), high influence (3 points), and very high influence (4 points). The questionnaires were collected after scoring by the experts and a total of 15 direct impact matrices were obtained. To standardize the direct influence matrix and eliminate the phenomenon of individual differences in expert scoring, the 15 direct influence matrices were subjected to Euclidean distance analysis to eliminate the scoring differences (two decimal places were retained). The direct influence matrix was obtained, as shown in Table 3. Table 4 shows the expert weights calculated by the method in Section 3.2.

The comprehensive impact matrix (Table 5) was calculated by the DEMATEL method. The degree of influence, the degree of being influenced, the center degree, and the cause degree are shown in Table 6.

Based on the results of calculating the center degree and cause degree in Table 6, Matlab was used to draw the cause-effect diagram of the adoption barriers affecting the development and popularization of smart construction with (9, 0) as the origin (Figure 4).

Table 3. Direct impact matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1	0.00	4.21	2.66	2.86	2.61	2.61	2.20	2.69	2.72	2.65	3.28	3.34	3.13	3.14	3.20	2.75
B2	2.14	0.00	2.51	2.12	3.00	3.73	2.85	2.59	2.60	2.79	3.01	3.25	2.91	2.85	2.98	2.81
B3	3.23	4.07	0.00	2.67	2.88	2.50	2.90	2.97	2.39	2.45	2.82	2.68	2.76	2.49	2.48	2.36
B4	3.16	3.07	2.35	0.00	2.37	2.58	2.26	1.83	2.76	2.82	2.11	2.03	2.03	2.18	1.91	3.72
B5	3.17	3.51	2.91	2.31	0.00	3.54	3.72	2.96	3.54	3.54	2.92	2.78	2.59	2.85	2.78	2.40
B6	2.23	2.88	2.31	1.71	3.19	0.00	2.91	2.87	3.19	3.29	2.77	2.77	2.71	2.59	2.45	1.45
B7	3.43	3.70	3.31	2.94	3.64	3.16	0.00	3.01	3.62	3.01	2.74	2.79	2.75	2.88	3.21	2.88
B8	3.38	3.64	4.39	2.62	3.65	2.99	2.42	0.00	2.25	2.52	2.53	3.54	3.35	3.22	3.21	2.07
B9	3.25	3.27	2.75	3.50	3.96	3.43	3.83	3.31	0.00	3.30	3.23	3.09	2.83	2.89	3.09	3.09
B10	3.52	3.59	3.16	2.71	3.61	4.15	3.21	3.19	3.25	0.00	3.68	3.68	2.96	3.22	3.09	2.82
B11	3.81	3.51	3.73	2.35	2.89	2.43	2.28	2.79	2.19	2.06	0.00	3.59	3.59	3.67	3.60	1.98
B12	3.38	3.45	2.83	2.10	2.71	2.11	2.66	2.31	2.06	2.12	3.41	0.00	3.58	3.60	3.87	1.78
B13	2.98	3.03	2.82	2.04	2.64	2.25	2.67	2.50	1.86	2.06	3.28	3.82	0.00	3.81	3.82	1.72
B14	3.57	3.30	3.04	2.62	2.88	2.50	2.59	2.51	1.98	2.20	2.82	3.33	3.39	0.00	3.66	2.16
B15	2.87	2.98	2.56	2.11	2.70	2.38	3.12	2.18	2.27	2.22	2.44	3.14	3.29	3.28	0.00	1.91
B16	2.45	2.37	1.72	3.73	2.50	3.11	2.38	1.65	2.92	3.45	1.65	1.97	1.78	2.04	1.79	0.00

Table 4. Weight of experts

Exp1	Exp2	Exp3	Exp4	Exp5	Exp6	Exp7	Exp8	Exp9	Exp10	Exp11	Exp12	Exp13	Exp14	Exp15
0.061	0.069	0.073	0.073	0.065	0.073	0.068	0.070	0.064	0.064	0.068	0.063	0.061	0.061	0.067

Table 5. Comprehensive impact matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1	0.28	0.37	0.31	0.28	0.31	0.30	0.28	0.28	0.28	0.29	0.31	0.32	0.31	0.31	0.32	0.26
B2	0.31	0.29	0.30	0.26	0.30	0.31	0.29	0.27	0.27	0.28	0.29	0.31	0.29	0.30	0.30	0.26
B3	0.33	0.36	0.26	0.27	0.30	0.29	0.29	0.28	0.27	0.28	0.29	0.30	0.29	0.29	0.30	0.25
B4	0.31	0.33	0.28	0.21	0.28	0.27	0.26	0.25	0.26	0.27	0.26	0.28	0.27	0.27	0.27	0.26
B5	0.34	0.37	0.32	0.28	0.27	0.32	0.32	0.29	0.30	0.31	0.31	0.32	0.31	0.31	0.32	0.26
B6	0.29	0.32	0.28	0.24	0.29	0.23	0.27	0.26	0.26	0.27	0.27	0.28	0.27	0.27	0.28	0.22
B7	0.36	0.39	0.34	0.30	0.34	0.32	0.26	0.30	0.31	0.31	0.32	0.33	0.32	0.32	0.33	0.28
B8	0.35	0.37	0.35	0.28	0.33	0.31	0.30	0.24	0.28	0.30	0.30	0.33	0.32	0.32	0.33	0.26
B9	0.37	0.39	0.34	0.32	0.36	0.34	0.34	0.32	0.26	0.33	0.33	0.35	0.33	0.34	0.34	0.29
B10	0.38	0.40	0.35	0.31	0.35	0.35	0.33	0.32	0.32	0.27	0.34	0.36	0.34	0.34	0.35	0.29
B11	0.34	0.36	0.33	0.27	0.31	0.29	0.28	0.28	0.27	0.28	0.25	0.32	0.31	0.32	0.32	0.25
B12	0.32	0.34	0.30	0.25	0.29	0.27	0.28	0.26	0.26	0.27	0.29	0.25	0.30	0.30	0.31	0.23
B13	0.31	0.33	0.30	0.25	0.29	0.27	0.27	0.26	0.25	0.26	0.29	0.31	0.24	0.30	0.31	0.23
B14	0.33	0.35	0.31	0.27	0.30	0.28	0.28	0.27	0.26	0.27	0.29	0.31	0.30	0.25	0.31	0.24
B15	0.30	0.32	0.28	0.24	0.28	0.27	0.27	0.25	0.25	0.26	0.27	0.29	0.28	0.29	0.24	0.23
B16	0.29	0.31	0.27	0.27	0.27	0.28	0.26	0.24	0.26	0.28	0.25	0.27	0.26	0.26	0.26	0.19

Table 6. Results of DEMATEL analysis

Barriers	f_i	e_i	m_i	n_i
B1	4.82	5.22	10.04	–0.40
B2	4.64	5.62	10.26	–0.97
B3	4.66	4.91	9.57	–0.25
B4	4.34	4.31	8.65	0.03
B5	4.97	4.86	9.82	0.11
B6	4.31	4.71	9.02	–0.40
B7	5.14	4.58	9.72	0.57
B8	4.97	4.37	9.34	0.60
B9	5.35	4.39	9.74	0.96
B10	5.40	4.53	9.93	0.87
B11	4.80	4.68	9.47	0.12
B12	4.53	4.95	9.48	–0.41
B13	4.48	4.73	9.22	–0.25
B14	4.61	4.81	9.41	–0.20
B15	4.31	4.89	9.19	–0.58
B16	4.22	4.02	8.24	0.20

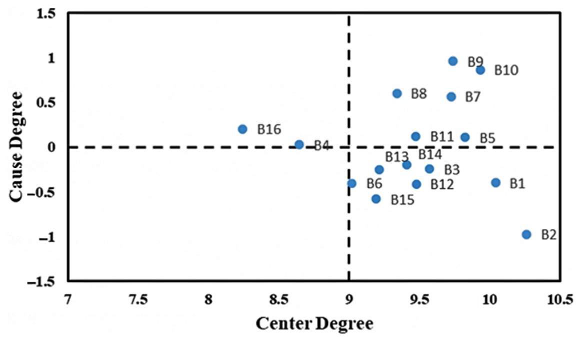


Figure 4. Cause-result diagram of adoption barriers influencing the development of smart construction

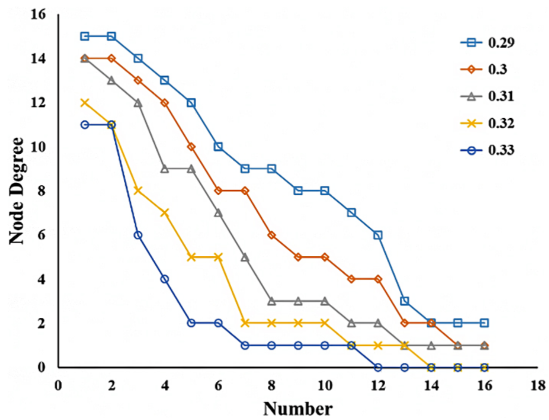


Figure 5. Scatter plot of node degree attenuation under different thresholds

4.3. Hierarchical structure analysis of adoption barriers based on ISM-MICMAC

To make up for the lack of consideration of the role of the barriers themselves in the matrix, the overall impact matrix is calculated by adding the comprehensive impact matrix and the unit matrix in Table 5. According to the overall impact matrix of the system, a threshold value is set to screen out the less influential barriers, retain the more influential barriers, and simplify the structure of the relationship between the barriers. The value of the threshold needs to be scientifically appropriate. If it is too small, more barriers will be retained and the structure will be too complicated. If it is too large, fewer barriers will be retained and the structure will be too simplified, making it difficult to accurately analyze the relationship between the barriers. This paper sets the thresholds as 0.29, 0.30, 0.31, 0.32 and 0.33, calculates the node degree of the barriers according to the accessibility matrix corresponding to different thresholds, and draws the node degree decreasing graph, as shown in Figure 5. After comparative analysis, it is found that when the threshold value is 0.32, the trend of the graph is more appropriate, Therefore, the threshold λ is determined to be 0.32. The reachability matrix was determined based on the overall impact matrix with thresholds, as shown in Table 7.

From the reachability matrix in Table 7, the reachability and precedence levels of the adoption barriers affecting the development and popularization of smart construction can be determined. The reachable and prior levels are brought into Eqn (15) for hierarchical division. The hierarchical decomposition is shown in Table 8. The above steps were repeated until all barriers were delineated, creating a total of six levels and modeling a multi-layer recursive structure based on the completion of the hierarchical delineation, as shown in Figure 6.

Based on ISM, the driving force and degree of dependence of each barrier were calculated, and the adoption barriers were categorized by MICMAC. The dependency-driving force relationship of the influential barriers of smart construction is plotted with dependency (R) as the horizontal coordinate and driving force (D) as the vertical coordinate (Figure 7).

Table 7. Reachability matrix

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16
B1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B3	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
B4	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
B5	1	1	1	0	1	1	0	0	0	0	0	1	0	0	0	0
B6	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
B7	1	1	1	0	1	1	1	0	0	0	0	1	0	1	1	0
B8	1	1	1	0	1	0	0	1	0	0	0	1	0	1	1	0
B9	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	0
B10	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	0
B11	1	1	1	0	0	0	0	0	0	0	1	1	0	0	1	0
B12	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B13	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0
B14	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0
B15	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
B16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

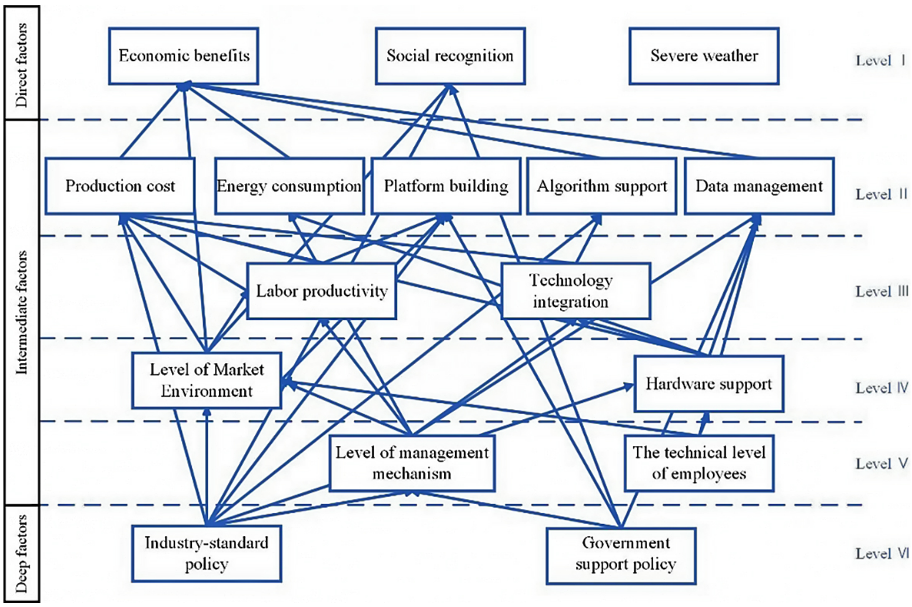


Figure 6. Hierarchical structure model

Table 8. The hierarchical decomposition

Level	Barrier
Level I (Appearance Level)	B2, B6, B16
Level II	B1, B4, B12, B13, B15
Level III	B3, B14
Level IV	B5, B11
Level V	B7, B8
Level VI (Root Layer)	B9, B10

5. Discussion

5.1. Results of the analysis framework

In the DEMATEL method, when the cause degree of adoption barrier is greater than 0, it indicates that the barrier has a large influence on other barriers and is a cause barrier in the system. When it is less than 0, it indicates that the barrier is susceptible to the influence of other barriers and is a result barrier in the system. Therefore, according to Figure 2, the 16 adoption barriers can be divided into cause barriers and result barriers. 8 more important adoption barriers can be identified from the 16 adoption barriers, which are ranked in descending order of their influencing ability according to the size of the center degree, as economic efficiency (B2), the level of development of the market environment (B5), the cost of production (B1), the government's support policy (B10), the degree of perfection of the management mechanism (B7), industry-standard (B9).

As can be seen in Figure 6, the system of barriers to smart construction development presents a 6-level distribution state under the ISM method, in which there are 2 barriers at the root level, 11 barriers at the intermediate

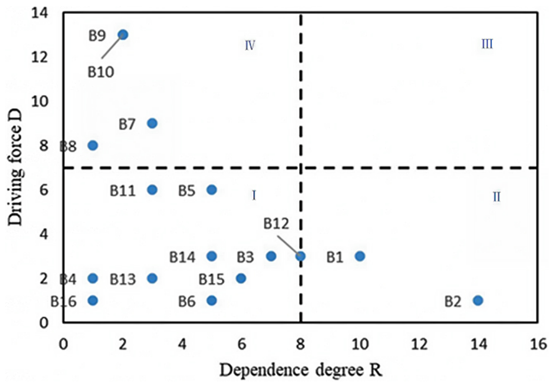


Figure 7. MICMAC classification of barriers influencing smart construction

level, and 3 barriers at the appearance level. Among them, government support policies (B10) and industry-standard (B9) are in the root layer (L6), which has a profound impact on other barriers and is the most fundamental barrier affecting the development of smart construction. The degree of perfection of management mechanism (B7) and technical level of employees (B8) are in the 5th level (L5), and these barriers directly or indirectly affect the other factors through the intermediary effect, which can be regarded as the bottom level barriers affecting the development of smart construction. Production cost (B1), labor productivity (B3), the level of market environment development (B5), hardware support (B11), platform construction (B12), data management (B15), energy consumption (B4), algorithmic support (B13), technology integration (B14) is in the intermediate tier (L2-L4). These barriers are affected by level 5 and level 6 barriers and at the same time act on level 1 barriers, and there is a complex interaction between the barriers, which belong to the intermediate level barriers affecting the development of smart construction. Economic benefits (B2), social acceptance (B6), and severe weather (B16) are located in Tier 1. Among them, economic benefits (B2) and social acceptance (B6) need to work through the intermediate layer and the root layer barriers, and severe weather (B16) exists as an independent barrier, which belongs to the surface layer of direct barriers, and it is the most direct barrier affecting the development of smart construction.

The MICMAC method categorizes the barriers into 4 clusters of autonomy, dependence, association, and driving based on the degree of driving and dependence. As shown in Figure 4, it is found that: Quadrant I belongs to the autonomy obstacles, with B3, B4, B5, B6, B11, B13, B14, B15, and B16, which are 9 obstacles with low dependence and driving force, and although they are relatively independent, they have a direct influence on the development of smart construction, and they are the influencing obstacles that should not be neglected. Quadrant II belongs to dependent barriers, with B1, B2, and B12 having high dependence and low driving force, which are dependent variables and should be controlled by focusing on the changes of other barriers in the development of smart construction. Quadrant III belongs to the associated barriers, with high driving force and high degree of dependence, indicating that this barrier has a considerable impact on the development of intelligent construction, but is also vulnerable to the influence of other barriers, with instability. Quadrant IV belongs to the driving barriers with B7, B8, B9, and B10, which are four barriers with low dependence and high autonomous driving force, less influence on other barriers, and show strong proactive characteristics, which are the root barriers to smart construction development, and greater control of these barriers will bring greater benefits.

Based on the analysis results of the three methods, there is a comprehensive understanding of the various obstacles in the development of smart construction. From the perspective of the DEMATEL method, factors such as economic benefits (B2), the level of market environment (B5), and government support (B10) have been identified as the most influential factors, playing important roles in promoting the development of smart construction. The ISM method reveals the hierarchical structure of obstacles to smart construction development, emphasizing the importance of fundamental barriers such as government support (B10), industry-standard (B9), and the level of the management mechanism (B7). The analysis of the MICMAC method further emphasizes the relationship between driving force and dependency, pointing out the critical role of significant barriers with high autonomous driving force.

In summary, to effectively overcome the various obstacles in the development of smart construction, it is necessary to use a combination of methods to propose targeted solutions. The focus should be on strengthening government support policies, promoting industry standardization, improving the perfection of management mechanisms, optimizing economic benefits, promoting the development of the market environment, and enhancing the technical proficiency of employees. Additionally, attention should be paid to effectively controlling obstacles with high driving force and dependency to ensure the smooth progress of smart construction development. By considering various factors comprehensively and implementing integrated measures, it will help break through the obstacles in the development of smart construction and promote the industry towards a more sustainable and intelligent direction.

5.2. Comparison analysis of different years of work experience of experts

The expert scoring method is a commonly used simple and intuitive quantitative estimation method, which has a certain degree of subjectivity. In this paper, the Euclidean distance method eliminates the impact of scoring differences between different experts, but it cannot avoid the differences in the evaluation of barriers due to the different years of experience. To verify the impact of different years of experience on this paper, the expert scoring group verification is divided into three groups (less than 5 years, 5–10 years, and more than 10 years). 5 people are invited in each group and the collected results are analyzed by ISM. The hierarchical analysis graph is shown in Figure 8. It is illustrated from the results of the three groups that work experience does not have a significant impact on cognitive level.

Both Group 1 and Group 3 delineated the developmental barriers to smart construction into six levels, whereas Group 2 categorized them into seven levels. Remarkably, the apparent level barriers and root level barriers identified by all three groups exhibit a notable degree of consistency with the previously analyzed factors. These results suggest that the findings of this study remain robust and independent of the respondents' varying years of work experience, thus underscoring the scientific validity and credibility of our conclusions.

5.3. Development strategies and recommendations

The E-DEMATEL-ISM-MICMAC method illuminates the intricate web of interconnections among impediments affecting the advancement of smart construction. This approach aims to target the progress and proliferation of smart construction, proposing corresponding strategies that can provide valuable guidance for the subsequent phases of smart construction development and the realization of economic advantages. Among the barriers hindering the advancement of smart construction, as identified through DEMATEL analysis, the level of development of the market environment (B5), production cost (B1), government support (B10), the degree of improvement of management mechanism (B7), and industry standards (B9) stand out as fundamental influencers that propagate other obstacles. These foundational obstacles constitute the deep-rooted constraints on smart construction's development. The foundational layer of the model, as deduced from ISM-MICMAC calculations, notably includes government support (B10) and industry standards (B9), in alignment with the findings of the DEMATEL analysis. These barriers emerge as the most pivotal and interrelated, demanding primary attention. Consequently, the primary focus should be directed toward enhancing market development within the industry, curbing production costs, bolstering government support policies, and establishing standardized industry benchmarks, all intended to elevate the level of smart construction. Nevertheless, the influence of less prominent factors should not be disregarded. Hereinbelow, we present specific strategic recommendations:

(1) Market Development: Prioritize efforts to augment the level of market development within the smart construction industry, fostering a conducive environment for its growth.

(2) Production Cost Optimization: Implement cost-reduction measures to enhance cost-efficiency in smart construction processes, thus facilitating its wider adoption.

(3) Government Support: Advocate for and implement policies that extend substantial support from governmental bodies to incentivize and advance smart construction initiatives.

(4) Industry Standards Establishment: Work towards establishing standardized benchmarks within the industry to provide a solid framework for the growth and harmonization of smart construction practices.

These recommendations collectively form a comprehensive strategy for addressing the multifaceted challenges faced by the development of smart construction, thereby paving the way for its enhanced development and widespread adoption.

5.4. Research implications

The E-DEMATEL-ISM-MICMAC method illuminates the intricate web of interconnections among impediments affecting the advancement of smart construction. This approach not only identifies fundamental barriers but also provides strategic recommendations with significant academic, managerial, and social implications. By targeting the progress and proliferation of smart construction, the proposed strategies offer valuable guidance for subsequent phases of development and the realization of economic advantages.

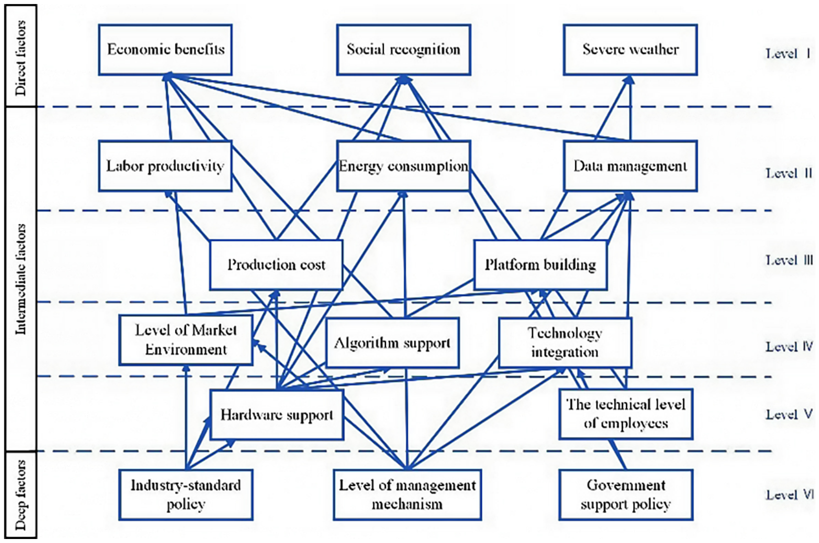
Academically, the method contributes to a deeper understanding of the complex interrelationships between barriers to smart construction adoption. Through DEMATEL analysis, foundational obstacles such as the level of market development, production cost, government support, improvement of management mechanisms, and industry standards are identified as fundamental influencers. These findings establish a theoretical framework for understanding the structural dynamics of smart construction barriers.

Managerially, the study's strategic recommendations provide actionable insights for industry stakeholders. Prioritizing efforts to augment market development, optimize production costs, secure government support, and establish industry standards forms a comprehensive strategy for overcoming barriers to smart construction adoption. Implementation of these recommendations can facilitate smoother project execution, improved resource allocation, and enhanced collaboration among stakeholders, ultimately driving transformative changes in the industry.

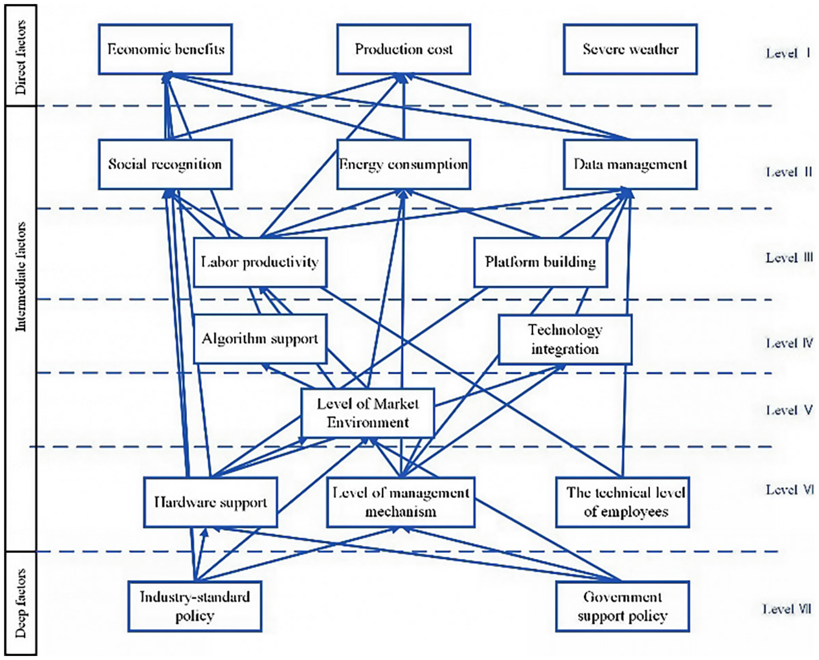
Socially, the study's implications extend to broader societal benefits derived from the widespread adoption of smart construction technologies. By addressing barriers to innovation and technology integration, promoting sustainability principles, and ensuring regulatory compliance, the proposed strategies contribute to the creation of more efficient, sustainable, and resilient built environments. This aligns with broader societal goals of mitigating environmental impact, enhancing quality of life, and fostering economic development.

In conclusion, the application of the E-DEMATEL-ISM-MICMAC method and its associated strategies holds significant promise for advancing smart construction adoption, with implications spanning academia, management

Less than 5 years



5–10 years



More than 10 years

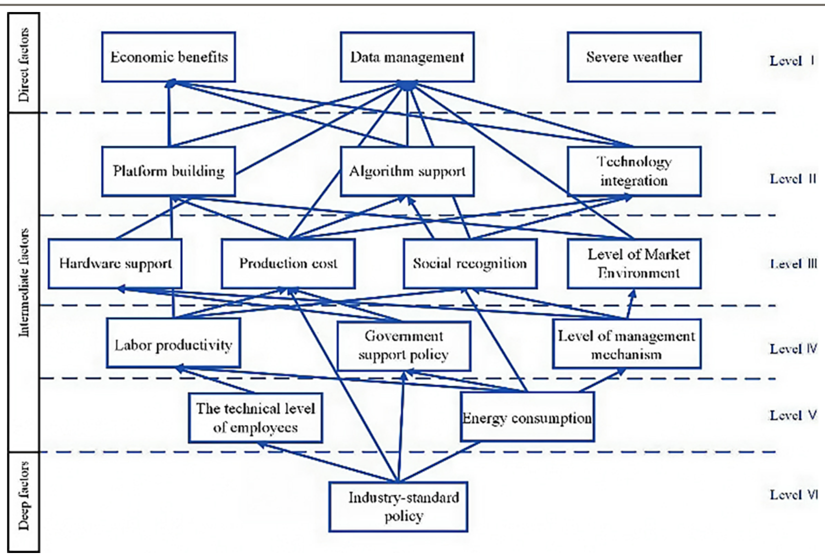


Figure 8. Hierarchy diagram of different work experiences

practices, and societal well-being. By addressing barriers and promoting the adoption of smart construction technologies, stakeholders can collectively work towards building a more sustainable and resilient future.

6. Conclusions

In conclusion, this study presents an integrated evaluation model utilizing Euclidean distance, DEMATEL, and ISM-MICMAC techniques to comprehensively examine obstacles to the adoption of smart construction. Firstly, our use of Euclidean distance to standardize expert scores ensures robustness in our analysis, laying a strong foundation for subsequent evaluations. Secondly, DEMATEL categorizes and ranks barriers based on their causal and central degrees, providing valuable insights into the structural dynamics of smart construction impediments. Thirdly, ISM-MICMAC investigates the internal hierarchical relationships among these barriers, analyzes their driving and dependence relationships, and clarifies their attribute characteristics, offering theoretical guidance for decision-making in smart construction development. Our findings reveal that industry standards and government support policies constitute fundamental barriers to smart construction development, with market environment development posing a primary hurdle. Additionally, economic benefits, platform construction, data management, and social acceptance are identified as immediate barriers, highlighting areas for focused intervention.

The practical suggestions and measures delineated in this paper represent a crucial contribution, as they offer stakeholders tangible strategies for overcoming significant obstacles and driving the advancement and widespread adoption of smart construction technologies. By meticulously investigating the intricate interplay of barriers at the micro-level and constructing a comprehensive analytical model, our study not only identifies the key challenges but also provides actionable insights into how these challenges can be effectively addressed. This comprehensive approach fills a critical gap in the current understanding of the multifaceted challenges inherent in smart construction, empowering stakeholders with the knowledge and tools needed to navigate and surmount these obstacles effectively. As such, our research significantly advances the field by not only shedding light on the complexities of smart construction but also by providing practical guidance for its successful implementation and dissemination.

Despite these contributions, certain limitations remain. An important limitation of this study is its focus on practitioners from China, which may limit the generalization of the findings to other countries. To address this limitation, future studies will aim to include participants from different countries, thus covering a wider range of national and cultural contexts. By integrating a more diverse sample, we can better capture the different challenges and opportunities facing the adoption of smart buildings globally. In addition, by comparing barriers in different countries, we can gain insights into how local environments influence the development and implementation of smart construction. This extended approach will enhance the robustness and applicability of our findings and contribute to a more comprehensive understanding of the factors influencing the development of smart construction globally.

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