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INTEGRATING AI-ENHANCED AND CONVENTIONAL MARKET SELECTION APPROACHES FOR THE CONSTRUCTION INDUSTRY: INSIGHTS FROM INDIAN FIRMS

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Abstract. International market selection (IMS) plays a pivotal role in shaping construction companies' global strategies. However, conventional IMS models generally fail to capture the distinctive challenges in the construction sector, such as the regulatory volatility, supply chain vulnerabilities, and site-specific operational constraints. To address these deficiencies, this study introduces a data-driven IMS framework specifically designed for the construction industry that incorporates financial, institutional, and industry-specific variables. The research adopts a two-phase analytical process: First, key IMS factors are identified and assessed through four methodological approaches, namely, logistic regression, partial least squares structural equation modeling, adaptive neuro-fuzzy inference systems (ANFIS), and the fuzzy ordinal priority approach. Second, the model is validated using 5,656 international market entry records for Indian construction firms from 2016 to 2023. The results demonstrate that the proposed artificial intelligence-enhanced framework significantly outperforms conventional models. Specifically, the ANFIS model achieved a prediction accuracy of 94.523% with an AUC-ROC of 0.874. This quantitative enhancement confirms that the integrated approach effectively captures nonlinear interactions and complex market constraints that conventional models generally neglect. Internal variables such as international experience and engineering productivity contribute positively to predictive accuracy. Meanwhile, external variables, particularly geographic distance and national risk, are demonstrated to be more difficult to model. Overall, the proposed framework provides a reliable foundation for strategic decision-making in global construction. It provides actionable insights for firms aiming to expand sustainably in uncertain international environments.

Keywords: international market selection model, international construction project, artificial intelligence, data-driven decision making, adaptive neuro-fuzzy inference system.

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1. Introduction

The international expansion of the construction industry is a critical factor in determining the sustainability and growth potential of companies within the sector (Elsayegh & El-adaway, 2021). The evaluation of emerging markets and diversification of global operations are regarded as key to achieving profit maximization and risk diversification (Tetteh et al., 2023). Unlike the domestic construction market, overseas expansion is advantageous for securing global competitiveness, and (owing to the project-based characteristic of the industry) mitigating macroeconomic risks and establishing a sustainable revenue structure through market diversification (Li et al., 2022). Accordingly, the entry into the international construction market involves aspects beyond business expansion and constitutes an essential strategic decision for securing financial stability, maintaining core technological capabilities, and formulating sustainable growth strategies (Deng et al., 2018). However, for successful entry into overseas markets, relying only on conventional empirical approaches or macroeconomic indicators is insufficient to capture the complexity of the rapidly evolving global construction environment. Traditionally, international market selection has relied on expert judgment and macroeconomic indicators, which have been widely used by firms in developing their entry strategies (Lee et al., 2023). However, these approaches often overlook the sector-specific intricacies of the construction industry, where the increasing influence of experienced practitioners imposes structural constraints on altering the fundamental variables that determine regional decisions. In response to these limitations, emerging approaches increasingly combine conventional analytical models with artificial intelligence methodologies, thereby enhancing the precision, adaptability, and real-world relevance of decision-making processes, particularly in complex and data-intensive sectors such as construction. Therefore, a more sophisticated data-driven decision support system is required because entering overseas markets is a major challenge and can act as a headwind for companies, making strategic decisions about which countries to enter and how to enter them is essential. Furthermore, as the existing IMS research focused on linear regression, there was a disregard for nonlinear variables, and the analysis was forced to proceed only at the level of a general model implemented based on traditional variables (Lee et al., 2023).

Therefore, international market selection (IMS) is a core process in formulating overseas market entry strategies for construction firms. It plays a critical role in identifying optimal markets and maximizing the organizational performance (Francioni & Martín, 2024). To support this process, various analytical approaches have been developed. These include environmental, social, and governance (ESG) frameworks (Zhou et al., 2024) and structural equation modeling (Li et al., 2020). Prior studies have examined the influence of factors such as market potential, competitive intensity, country risk, and firm experience on IMS, based on Cavusgil (1985, 1997), Dikmen and Birgonul (2004), Rahman (2003), Koch (2001), and O'Farrell and Wood (1994). However, existing studies have focused primarily on macroeconomic factors at the national level without adequately capturing industry-specific factors that critically influence the success of construction projects. Within the field of IMS, idiosyncratic construction factors – supply chain stability, project operational risks, and regulatory permitting procedures – have been largely neglected in analytical models. This omission results in a significant failure to encapsulate the context-specificity inherent in the construction industry (Hui et al., 2025). Furthermore, while recent scholarship on AI and digital transformation consistently underscores the critical importance of context-specific variables across diverse sectors (Alsakran et al., 2025), the scarcity of industry-defined parameters in the construction domain has inherently limited the applicability and evolution of the analytical models themselves. Therefore, more refined analyses reflecting the unique characteristics of the construction industry are required.

Recently, data-intensive industries have increasingly sought to integrate AI methodologies with traditional analytical models to enhance decision-making precision and adaptability. Within this evolution, explainable AI (XAI) is being leveraged to enable users to identify and interpret influential variables (Alsakran et al., 2025), whereas hybrid approaches are increasingly adopted to maximize predictive accuracy (Farghaly et al., 2020). Notably, adaptive neuro-fuzzy inference system (ANFIS) – a synthesis of fuzzy logic and neural networks – is frequently applied to resolve nonlinear problems involving ambiguous data (Eliwa et al., 2024), whereas the fuzzy ordinal priority approach (FOPA) facilitates systematic evaluation by reducing subjective bias in decision-making (Shafaghizadeh & Sajadi, 2023). Therefore, by conducting a comparative analysis between conventional analytical methods and fuzzy-based approaches designed to address ambiguity, grounded in variables that represent the nonlinear interactions and dynamic market shifts unique to the construction industry, this study can more comprehensively examine the nonlinear characteristics and multifaceted risk factors previously neglected by traditional IMS models. Ultimately, this represents a methodological transition that moves beyond existing static analytical frameworks to more precisely reflect real-world international market entry patterns.

This study aimed to extend existing IMS models by incorporating variables that reflect the unique characteristics of the construction industry and conducting a multifaceted analysis based on these factors. The paper begins with a literature review that broadly categorizes traditional factors and various IMS methodologies, such as logistic regression, structural equation modeling (SEM), ANFIS, and fuzzy-based ranking approaches. Following the description of the research design and data processing in the methodology section, an empirical analysis is presented using a dataset of 5,656 Indian construction firms (2016–2023) to assess the impact of industry-specific variables on model performance. The results section confirms the proposed model's validity by uncovering critical factors and market entry patterns. The paper concludes with a discussion that translates these AI-driven quantitative insights into practical contributions, offering an industry-specialized IMS framework for strategic decision-making in the global construction environment.

2. Literature review and development of theoretical framework

International expansion within the construction sector involves intricate interdependencies between variables and is highly susceptible to project-specific characteristics and volatile external conditions. Because successful decision-making rests upon two fundamental axes – the identification of deterministic drivers and the application of analytical methodologies to achieve optimal outcomes – a comprehensive approach that synthesizes these two dimensions is required (Nindartin et al., 2025). Hence, this section aims to clarify the theoretical framework of this research. First, it distinguishes the pivotal factors affecting market entry, including macroeconomic indices and industry-specific parameters. Thereafter, the progression of statistical and AI-driven models is evaluated for multidimensional analysis, facilitating a systematic methodology and the proposal of an integrated framework.

2.1. Influencing factors in international construction industry selection

The IMS process is a crucial component of global business strategies. It serves as a method for assessing the viability of selecting external regions or foreign markets as targets (Brewer, 2001). The process is predominantly utilized in industries with frequent interactions with foreign markets, such as banking, marketing, manufacturing, trade, and export. In its initial stages, the IMS process considers both company-specific variables (e.g., revenue and capital) and market variables of the target region (e.g., physical and social distance) (Brouthers & Nakos, 2005; Ojala & Tyrväinen, 2007; Rothaermel et al., 2006; Terpstra & Yu, 1988). The IMS process is typically categorized into qualitative models (which focus on identifying the process stages and factors influencing decision-making) and quantitative models (which emphasize country-market clustering and market ranking analysis) (Kumar et al., 1994).

Qualitative models assist IMS by identifying and eliminating candidate markets that fail to satisfy the criteria because of adverse regional factors such as economic development, political stability, and continuity of laws and policies (Cavusgil, 1985; Rahman, 2003; Wood & Robertson, 2000). Subsequently, the models assess the positive factors in potential markets to determine the feasibility of market entry (Cavusgil, 1997; Whitelock & Jobber, 2004; Robertson & Wood, 2001). These factors include entry barriers, market demand, and competitive advantages (O'Farrell & Wood, 1994). The final market selection is based on company-specific financial factors such as profit margins, return on investment (ROI), and payback period. This approach ensures compatibility between the company and target market by systematically eliminating adverse factors, reviewing positive factors, and calculating company-specific criteria (Koch, 2001). In contrast, quantitative models identify suitable markets by detecting markets with attributes like those found in the domestic market within the same industry, utilizing the economic indicators of the target countries. These models rely primarily on multiple regression analyses for their assessment (Gorg & Strobl, 2001; Olley & Pakes, 1992).

The influential factors for IMS can be divided into four categories: conditions, firm strategy, related industries, and construction. The condition category concerns the external situational conditions emerging from an international project, such as the labor fees, physical and cultural distances, and market size (Cavusgil, 1985; Dikmen & Birgonul, 2004; O'Farrell & Wood, 1994; Whitelock & Jobber, 2004; Robertson & Wood, 2001; Reid & Kurth, 1990). Internal conditions also influence IMS. Firm size, experience, and international experience are typical indicators used to describe a firm (Musso & Francioni, 2012; Andersen & Buvik, 2002; Erramilli, 1991; Brewer, 2001). The competition between bidding firms also influences selection. These factors include supply chain stability, competition intensity, and market (Cavusgil, 1997; Rahman, 2003; Robertson & Wood, 2001; Dikmen & Birgonul, 2004). An international project is sensitive to the governance situation and its perspectives on construction and budgets (Wood & Robertson, 2000; Rahman, 2003). A few construction-related factors that influence decision-making for IMS are construction permit progress (Cavusgil, 1985; Rahman, 2003), public participation in infrastructure, and national risk (Cavusgil, 1985; Wood & Robertson, 2000).

Ultimately, the factors influencing the IMS can be broadly categorized into external factors (such as the market environment and market entry barriers) and internal factors (such as the firm size and experience). Table 1 summarizes important factors such as market size, competitive

Table 1. Theoretical framework that influences IMS and respective sources

Category	Factors	Sources
Market Environment	Market size / Market potential	Cavusgil (1985, 1997); Dikmen and Birgonul (2004); Koch (2001); O'Farrell and Wood (1994); Rahman (2003); Robertson and Wood (2001); Whitelock and Jobber (2004); Wood and Robertson (2000)
	Permit progress	Cavusgil (1985, 1997); Rahman (2003)
	Logistics stability	Cavusgil (1997); Musso and Francioni (2012); Rahman (2003)
	Physical distance / Cultural distance	Dikmen and Birgonul (2004); Musso and Francioni (2012); O'Farrell and Wood (1994); Robertson and Wood (2001); Whitelock and Jobber (2004); Wood and Robertson (2000)
	Productivity	Dikmen and Birgonul (2004); Gorg and Strobl (2001); Koch (2001); Olley and Pakes (1992)
	Labor fees	Cavusgil (1985); Robertson and Wood (2001); Wood and Robertson (2000)
Market Competition and Entry Barriers	Competitive intensity	Cavusgil (1985, 1997); Dikmen and Birgonul (2004); Evirgen et al. (1993); Koch (2001); O'Farrell and Wood (1994); Rahman (2003); Robertson and Wood (2001); Whitelock and Jobber (2004); Wood and Robertson (2000)
	National risk	Cavusgil (1985); Rahman (2003); Robertson and Wood (2001); Wood and Robertson (2000)
Firm Capabilities and Experience	Firm size	Musso and Francioni (2012); O'Farrell and Wood (1994)
	Firm experience (Domestic and International)	Dikmen and Birgonul (2004); Koch (2001); Musso and Francioni (2012)
	International experience	Andersen and Buvik (2002); Brewer (2001); Dikmen and Birgonul (2004); Erramilli (1991)
	Engineer productivity	Dikmen and Birgonul (2004); Halligan et al. (1994); Thomas et al. (1990)

intensity, and entry barriers that companies must consider when entering a new market, as supported by previous research (Koch, 2001; O'Farrell & Wood, 1994; Whitelock & Jobber, 2004).

Market barriers such as legal constraints, cultural differences, and high tariffs represent the challenges a company may encounter when entering a new market. These barriers can prevent companies from establishing themselves (Wood & Robertson, 2000). Related to this is market receptivity, which examines the extent to which a market is accessible or welcoming to new products or foreign companies. A receptive market reduces the challenges and costs of entry. However, market risk, which includes political instability and economic uncertainty, can deter companies from entering markets (Cavusgil, 1985; Robertson & Wood, 2001). Musso and Francioni (2012) emphasized that evaluating these risks is essential for a company's long-term sustainability.

Other factors such as logistics stability affect the efficiency of businesses operating in the market (Musso & Francioni, 2012; Rahman, 2003). For example, good transportation and communication systems are critical to ensure the efficient movement of goods and services (Musso & Francioni, 2012; Rahman, 2003; Cavusgil, 1997). Moreover, political stability ensures a more predictable business environment that is safer for investments and growth (Wood & Robertson, 2000). Companies should assess physical and cultural distance because significant differences in language, norms, and geographic location can complicate business operations (Dikmen & Birgonul, 2004; Whitelock & Jobber, 2004).

Internally, the firm size and experience also play a role. Among these internal factors, engineer productivity significantly affects international project performance. Efficient utilization of engineering resources can improve schedule adherence, reduce design errors, and enhance cost control in unfamiliar market environments (Halligan et al., 1994; Thomas et al., 1990). Larger firms generally have more resources for handling the costs and complexities of entering new markets (Musso & Francioni, 2012). Similarly, more experienced companies are usually better equipped to navigate challenges because these have learned from past market entries (Dikmen & Birgonul, 2004; Koch, 2001). To summarize, the decision to enter a new market depends on the conditions of the market and the company's capabilities.

2.1.1. Market environment

Market environment variables serve as the foundational criteria for international market selection in the construction industry. Labor fees (LF) and productivity (PR) are among the most influential factors determining a project's cost efficiency. Countries with lower LFs and higher PRs provide substantial advantages in terms of budget management and schedule adherence (Amin, 1994; Reid & Kurth, 1990). This study applied a normalized index to assess the relative competitiveness of each country.

$$LF_j,\ PR_j = \frac{\left(I_{ij} - I_{ic}\right)^2}{V_i}, \tag{1}$$

where I_{ij} and I_{ic} represent the labor fees and productivity for category i in country j and India, respectively. V_i denotes the global variance.

Physical distance (PD) affects the logistics and communication costs. It is measured using bilateral distances from CEPII's GeoDist database. Cultural distance (CD) was conceptualized by Hofstede and operationalized by Kogut and Singh (1988). It captures managerial and communicative friction, particularly in multi-stakeholder construction projects. It is calculated using the extended Hofstede index across six dimensions:

$$CD_{cj} = \sum_{i=1}^{n} [\left(I_{ij} - I_{ic}\right)^2 / V_i] / n. \tag{2}$$

Market size (MS) is operationalized through the size of the construction market (rather than the GDP) using IHS Markit data and reflects the actual scope of project acquisition.

Logistics stability (LS) is assessed using the World Bank's Logistics Performance Index (LPI) and is critical for preventing delays and cost overruns.

The regulatory environment is evaluated through the construction permit process (PP) and extent of public participation in infrastructure (PPI). Both these are sourced from World Bank databases. These variables indicate the institutional maturity and openness of the market to international contractors.

2.1.2. Market competition and entry barriers

Competitive intensity (CI) is a key determinant for evaluating a firm's strategic fit within a market. Although highly competitive markets may reduce profit margins, these signal higher demand and opportunity. CI is calculated by averaging the presence of international firms over five years.

$$CI_j = \sum_{k=2019}^{2023} \sum_{i=1}^{n} X_{ijk} / 5, \tag{3}$$

where X_{ijk} = 1 if firm i operates in country j in year k, and zero otherwise.

National risk (NR) represents political, economic, and institutional uncertainties. It is assessed using S&P Global's sovereign risk scores (one–six). These reflect the potential disruptions to construction project execution, including delays, cost escalations, and operational setbacks.

2.1.3. Firm capabilities and experience

A firm's internal capabilities strongly influence its capability to enter foreign markets. Firm size (FS) is measured as the total revenue (2021–2023). It reflects financial stability, bidding capacity, and technical resources.

Firm experience (FE) and international experience (IE) are crucial for enhancing adaptability, project coordination, and stakeholder communication. IE is defined as the number of countries a firm has entered:

$$IE_i = \sum_{j=1}^{101} IMS_j, \tag{4}$$

where IMS_j = 1 if firm i has entered market j and zero otherwise.

A higher IE implies accumulated market knowledge and cross-cultural project management capacity. Both these are critical success factors in international construction ventures.

2.2. International market selection models

International Market Selection (IMS) is commonly conducted through two primary approaches: systematic and non-systematic methods (Papadopoulos & Denis, 1988; Andersen & Buvik, 2002). Systematic approaches generally utilize quantitative models to ensure objectivity, transparency, and reproducibility. However, in the construction industry, characterized by complex, project-based operations and rapidly changing external environments, traditional models often fall short in capturing nonlinear relationships and adapting to dynamic market conditions (Ahady et al., 2017; Bayhan et al., 2022; Okika et al., 2025).

Previous studies have introduced various analytical methods to support IMS decision-making, including logistic regression (Chen et al., 2017), structural equation modeling (Li et al., 2020), and fuzzy logic–based approaches (Utama et al., 2019; Zhou et al., 2024). Although these models provide structured insights into variable relationships, their applicability remains limited to contexts that require adaptability and real-time responsiveness (Kazar et al., 2022; Li et al., 2020).

To address these limitations, this study adopted an artificial intelligence-based approach that reflects the unique operational and environmental complexities of the construction industry. It did so particularly by enabling a large-scale, data-driven analysis of market conditions. Thereby, it has provided a significant methodological advancement over existing IMS frameworks.

2.2.1. Logistics regression (LR) model

LR is a statistics-based model with binary outcomes. It uses a logistic sigmoid function to model the probability that the dependent variable is one. The logistic function is an S-shaped curve that adopts any real-valued number and maps it to a value between zero and one. The odds and log odds are calculated for beta. The coefficients are calculated using maximum likelihood estimations to determine the parameter values that maximize the likelihood of the observed data. Then, a prediction is made using the fitted model with a threshold of 0.5 where the outcome is predicted as 1, and 0 otherwise (Chen et al., 2017).

$$P\left(y = 1x\right) = \frac{1}{1 + e^{-\left(\beta 0 + \beta 1x1 + \beta 2x2 + \cdots + \beta nxn\right)}}, \tag{4}$$

where $P(y = 1|x)$ is the probability that the outcome y is one (positive class) given the input features $x1$, $x2$,..., xnx_1, x_2, ..., x_nx1, $x2$,..., xn; β0 is the intercept (bias term); β1, β2,..., βn are the coefficients corresponding to each feature $x1$, $x2$,..., xn; and e is Euler''s number (approximately 2.718).

In the context of international construction project (ICP) decision making, logistic regression enables a data-driven evaluation of market entry feasibility by quantifying the probability of success (Chen et al., 2017; Okika et al., 2025). By analyzing the relationships between independent and dependent variables, this method identifies the key factors that influence IMS (Bayhan et al., 2022). Its capability to handle categorical variables and minimize overfitting risk makes it suitable for structured prediction tasks in construction management (Ahady et al., 2017). Moreover, by providing interpretable coefficients, logistic regression supports the prioritization of influential factors and provides practical insights for formulating international market entry strategies.

2.2.2. Partial least squares structural equation modeling

Partial least squares structural equation modeling (PLS-SEM) is a robust analytical approach capable of simultaneously modeling both measurement and structural components. This makes it particularly suitable for analyzing complex, multivariate systems such as those encountered in international construction project environments (Li et al., 2020). Unlike conventional structural models, PLS-SEM can effectively handle small sample sizes and non-normal data distributions, which are common limitations in empirical construction research (Hair Jr. et al., 2021).

The SEM method used in this study involved evaluating the relationships between constructs and indicators. The relationships between the constructs and their indicators were modeled using the following equation:

$$y = \lambda x + \epsilon, \tag{5}$$

where y is the observed variable, λ is the factor loading (representing the strength of the relationship between the latent variable and observed variable), x is the latent variable, and ϵ represents the error term or residual.

Moreover, its capability to capture nonlinear relationships among latent variables enables the identification of indirect effects and complex causal paths. These are particularly relevant for evaluating interdependent market- and firm-level factors in IMS (Sarstedt et al., 2017). Through path analysis, the PLS-SEM quantifies both magnitude and direction of these relationships. Thereby, it enhances the explanatory power of the models (Henseler et al., 2009). This facilitates informed decision-making in areas such as resource allocation, strategic risk management, and market-entry planning. Thus, PLS-SEM is an effective tool for improving predictive accuracy and supporting sustainable internationalization strategies in the construction sector (Rigdon et al., 2019).

2.2.3. Adaptive neuro fuzzy inference system (ANFIS) model

ANFIS is a hybrid model that integrates the learning capabilities of artificial neural networks (ANNs) with the reasoning mechanisms of fuzzy logic. This makes it highly suitable for decision-making in complex and uncertain environments such as ICPs (Utama et al., 2019). Applying a fuzzy inference system to an ANN framework, ANFIS maps inputs to outputs using fuzzy rule sets and continuously adapts its parameters through gradient descent to minimize the prediction error. This adaptability enables the model to capture nonlinear and multidimensional interactions among variables effectively, thereby enhancing its predictive accuracy (Jang, 1993).

In practical applications, such as in Utama et al. (2019), a Delphi survey was first conducted with experts to identify 21 critical decision-making criteria related to project scale, contract type, client reputation, and political stability (Polat et al., 2014). These were used to generate 110 simulated case scenarios. Each scenario was evaluated by experts as a "Go" or "Not Go" decision. The ANFIS model was trained in 70% of these cases and achieved over 88% prediction accuracy when validated using the root mean square error (RMSE) and correlation coefficient (R). This demonstrated its effectiveness in supporting complex decision-making processes (Ebrat & Ghodsi, 2014).

The formula for the ANFIS model consists of a membership function for fuzzy inputs, rule aggregation, weighted output, and RMSE calculations:

$$O_i = \mu_A(x_1),\ O_i = \mu_B(x_2), \quad (6)$$

where μ_A and μ_B are the membership functions for the fuzzy sets of the input variables x_1 and x_2.

$$\omega i = \mu_A(x_1) \times \mu_B(x_2). \quad (7)$$

The product of membership values is used to determine the "firing strength" of a fuzzy rule in the inference process:

$$Y_i i = \omega_i (p_i x_1 + q_i x_2 + r_i), \quad (8)$$

where p_i, q_i, and r_i are the parameters adjusted during training to optimize the relationship between the inputs and outputs.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2}, \quad (9)$$

where A_i is the actual value, F_i is the predicted value, and n is the number of observations.

In addition to its high predictive performance, ANFIS provides enhanced interpretability through fuzzy rule-based reasoning. This enables decision makers to understand the logic underlying the model's recommendations. It also supports real-time learning, thereby enabling flexible responses to evolving project environments. These characteristics make the ANFIS an effective tool for reducing project risks and enabling reliable data-driven decisions in international market-entry planning and construction project evaluation.

2.2.4. Fuzzy ordinal priority approach (FOPA) model

FOPA is a structured decision-making model that integrates fuzzy logic with ordinal priority theory to effectively address problems characterized by uncertainty, ambiguity, and subjective assessments (Zhou et al., 2024). Leveraging the strengths of fuzzy logic in handling imprecise information and applying ordinal rankings to reflect the relative importance of decision criteria, FOPA enables a systematic evaluation process that aligns with expert assessments (Ataei et al., 2020). This model is particularly well suited for ICP decision-making, where complex trade-offs among multiple (frequently conflicting) factors are common (Ebrat & Ghodsi, 2014; Utama et al., 2019). Through its capability to process fuzzy preferences and rank alternatives based on aggregated priority weights, FOPA provides a scientific and rational framework for generating optimized decisions that reflect both qualitative and quantitative aspects of project selection. Its integrative structure allows for the consideration of the interactive effects between decision variables. This makes it an effective tool for enhancing decision transparency and supporting successful project outcomes in highly uncertain international environments (Kahraman & Kaya, 2010). These steps operationalize the decision logic and include fuzzy membership assignment, priority ranking, and linear-programming-based optimization.

The algorithmic functions of FOPA are as follows: membership function of triangular fuzzy numbers, operations with fuzzy numbers, generalized mean importance ranking score calculation, normalization of data, and fuzzy linear programming model. A triangular fuzzy number $q = (l, m, u)$ is defined by three parameters: lower value l, middle value m, and upper value u. The membership function is given by

$$\mu(x) = \begin{cases} 0, & x < 1 \\ \frac{x-1}{m-l}, & l \le x \le m \\ \frac{u-x}{u-m}, & m \le x \le u \\ 0, & x > u \end{cases}. \quad (10)$$

For two triangular fuzzy numbers $A = (l_1, m_1, u_1)$ and $B = (l_2, m_2, u_2)$, the basic operations are:

- Addition:

$$A + B = (l_1 + l_2, m_1 + m_2, u_1 + u_2); \quad (11)$$

- Subtraction:

$$A - B = (l_1 - l_2, m_1 - m_2, u_1 - u_2); \quad (12)$$

- Multiplication:

$$A \times B = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2); \quad (13)$$

- Division:

$$A \div B = (l_1 \div l_2, m_1 \div m_2, u_1 \div u_2). \quad (14)$$

To obtain the score for a fuzzy number q = (l, m, u), q = (l, m, u), the generalized mean importance ranking (GMIR) score is calculated as follows:

$$R(q) = \frac{1+4m+u}{6}. \quad (15)$$

To normalize the data (including factors such as political stability and government credit), the following formulas are used depending on whether the factor has a positive or negative influence:

- Positive influence (higher values are better):

$$Y = \frac{a - \min}{\max - \min}; \quad (16)$$

- Negative influence (lower values are better):

$$Y = \frac{\max - a}{\max - \min}, \quad (17)$$

where a is the value to be normalized. Moreover, min and max are the minimum and maximum values of the dataset, respectively.

This study also transforms the fuzzy linear programming model into a more solvable form using the simplex method. This simplified model is expressed as follows:

$$\text{Max}(\text{Min})\left\{\sum_{j=1}^{n}\left(p_j, q_j, r_j\right)\otimes\left(x_j, y_j, z_j\right)\right\}. \quad (18)$$

This is subject to

$$\sum_{j=1}^{n}\left(a_{ij}, b_{ij}, c_{ij}\right)\otimes\left(x_j, y_j, z_j\right)(<=)\left(b_i, g_i, h_i\right), \quad (19)$$

where (x_j, y_j, z_j), (p_j, q_j, r_j), and (a_{ij}, b_{ij}, c_{ij}) are fuzzy numbers. $\otimes$ represents the fuzzy multiplication.

2.3. Research gap and framework development

A theoretical review of IMS reveals that current research has predominantly focused on general country-level variables, such as macroeconomic indicators, political stability, and market size. However, this approach fails to adequately capture the influence of sector-specific characteristics on market entry decisions and is particularly limited in explaining the operational and institutional idiosyncratic nature of the construction industry.

Specifically, construction operations and supply chain risks are not adequately considered. Wang et al. (2025) reported that logistics and supply chain stability exert a decisive influence on a firm's operational performance and competitiveness. Similarly, Oprach and Heintze (2019) indicated that the heterogeneous data structures, low levels of digitalization, and diverse stakeholder networks of the construction industry make accurately interpreting external market environments challenging. Furthermore, existing studies lack reflection on project difficulty and decision-making complexity. Hui et al. (2025) identified that construction projects involve high levels of decision-making difficulty owing to inter-team dependencies, high uncertainty, and organizational structural complexity. Taiwo et al. (2024) also emphasized that the industry's unstructured information, multi-contractual frameworks, and high-risk decision processes necessitate more sophisticated analytical methodologies.

Beyond these industry-specific challenges, a significant research gap remains in the integrated analysis of internal organizational capabilities and external environmental risks. In the broader field of international business, concepts such as organizational ambidexterity, dynamic capabilities, and intellectual capital have been identified as pivotal drivers of performance in foreign market entry (Kolte et al., 2022; Festa et al., 2021, 2022). However, the IMS field has yet to fully develop an integrated approach that examines the interplay between these internal capabilities and external risk factors. Previous studies have predominantly restricted internal capabilities to the level of individual variables, failing to provide a profound analysis of the structural relationships they form with industrial environmental factors.

These conceptual limitations in variable selection inevitably extend to the analytical models employed. While recent scholarship on AI and digital transformation repeatedly underscores the vital role of context-specific variables across diverse industries (Festa et al., 2026; Hui et al., 2025; D'Amico et al., 2024), IMS research in construction has largely failed to incorporate these industry-specific nuances. Consequently, a methodological gap persists; while other sectors actively utilize advanced techniques – ANFIS regression, deep learning, efficient feature selection, and knowledge structuring – to process nonlinear and multidimensional data (Badawy et al., 2021; Farghaly & Abd El-Hafeez, 2023; Eliwa et al., 2024), IMS studies still rely on static and linear frameworks. This results in a theoretical and conceptual gap in explaining the complex interrelationships among variables unique to the construction industry.

To address the identified gap, this study proposes a comprehensive research framework derived from a review of relevant theories. Figure 1 presents a visual diagram representing the factors and their hypothetical influence on the IMS process. The influential factors are categorized into **external market environment** (e.g., labor fees, logistics stability) and **internal firm capabilities** (e.g., firm size, experience). The influential factors included labor fees (LF), PD, CD, MS, MP, CI, FS, FE, firm IE, LS, construction PP level, PPI, and NR. As the previous studies have emphasized the need for further studies with additional factors, this study expands the body of knowledge by adding construction-specific factors: supply chain stability (LS), construction permit progress (PP), and public participation (PPI). This integrated framework was developed to test the hypothesis that firm-specific capabilities moderate the impact of construction-specific market barriers on entry decisions.

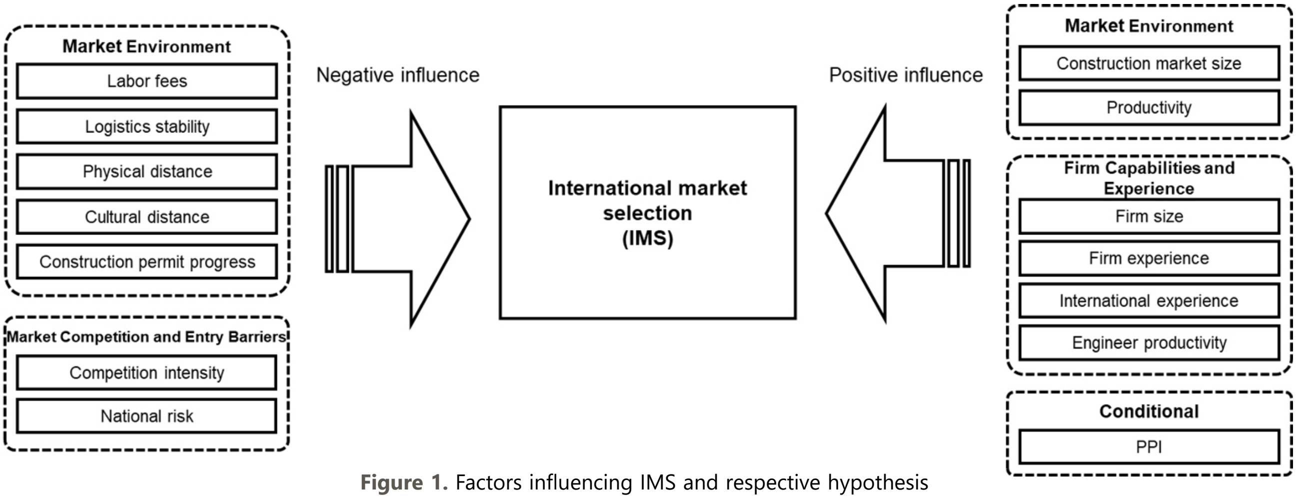


Figure 1. Factors influencing IMS and respective hypothesis

3. Methodology

3.1. Research design

This study, as outlined in Figure 2, aims to analyze the factors influencing International Market Selection (IMS) in the construction sector. It proposes a construction-specific IMS model by comparing conventional methodologies with AI-based approaches, thereby addressing the industry's unique characteristics and decision-making needs. Previous research has focused primarily on macro-level determinants such as labor costs, competitive intensity, firm size, international experience, national risk, physical distance, and cultural distance. However, the construction industry is uniquely characterized by its project-based operations, varying legal and institutional frameworks across countries, and high vulnerability to supply chain disruptions. To address these limitations, this study incorporated four additional factors that reflect the distinct characteristics of the construction industry: construction permit procedures, public participation in infrastructure, logistics stability, and engineer productivity. Then, thirteen key factors were selected following a review by three experts specializing in overseas construction investment. Through approximately two rounds of expert meetings, the final framework was established. Then, relevant data associated with each factor were successfully collected.

When the framework was developed, a systematic procedure encompassing data collection, preprocessing, and analysis was executed to facilitate model implementation (Figure 2). After the data collection, the data were categorized according to the proposed framework's variables and preprocessed for optimal utilization. The resulting dataset was then bifurcated into training and test sets for the analytical phase. To evaluate the influence of each IMS factor, four models combining conventional statistical and AI-based approaches were employed. Logistic regression (LR) is a widely used method in IMS studies. It was used to quantitatively assess the impact of individual variables. Structural equation modeling (SEM) was adopted to analyze the complex interrelationships among variables, including latent constructs. Additionally, an ANFIS (which integrates machine learning with fuzzy logic) was used to capture nonlinear patterns and model the complexity of IMS decision-making more effectively. Finally, the fuzzy analytic hierarchy process (AHP) was applied to account for subjective assessments and uncertainties inherent in the IMS process. This provided an effective framework for prioritization under ambiguity. The hypotheses were accepted or rejected appropriately based on the results of the models and their recommendations on the direction of influence of the factors. Thus, this study emphasized the factors that influence the decision-making process in IMS.

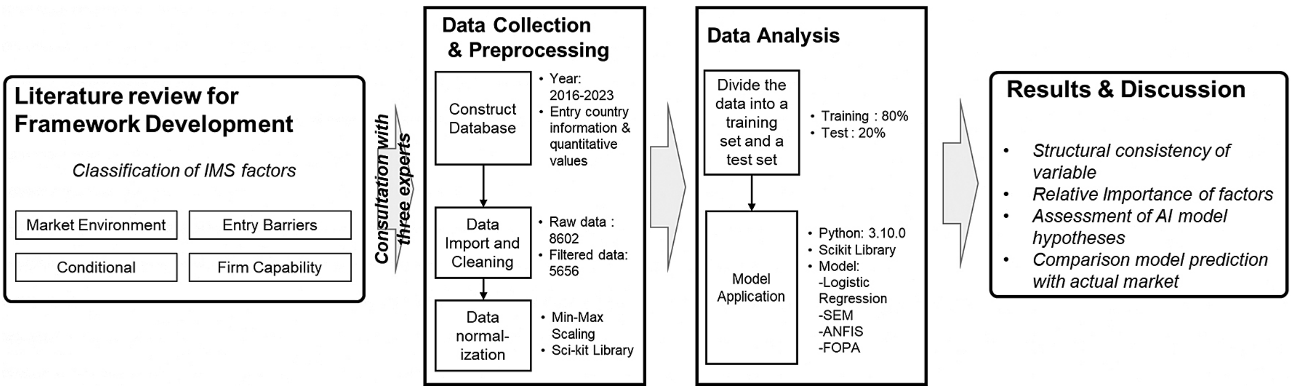


Figure 2. Research process

Based on the results, structural consistency of variable influence was examined by comparing the outputs across models, allowing for a deeper validation of the AI-based analysis process. Each model was also used to evaluate the relative importance of the selected IMS factors. By classifying variables into internal capabilities and external environmental conditions, the study incorporated a meta-level perspective that goes beyond individual variable analysis. Furthermore, the degree to which each proposed AI model supported the research hypotheses was assessed, enhancing the reliability of the theoretical framework. Lastly, by comparing model predictions with actual market entry data, the study secured external validity and practical applicability of the proposed IMS approach.

3.2. Data collection

Data were collected from 5,656 Indian construction firms participating in international projects. The selection of Indian firms as the primary sample was a strategic decision driven by more than mere data availability; it was intended to rigorously validate the advancement of the IMS model. As a representative emerging market contractor (EMC), the Indian construction sector is characterized by rapid market volatility and resource constraints, driving firms to actively seek international expansion beyond the domestic market. Consequently, this context provides an optimal empirical setting to compare the explanatory power of traditional statistical models against AI-based approaches (Viswanathan & Jha, 2019). Initially, a total of 8,602 data entries were collected. However, after aligning the data with the theoretical framework introduced in Figure 2 and filtering for completeness, 5,656 valid data points from the period between 2016 and 2023 were retained, resulting in a data retention rate of approximately 65.75%. To ensure the validity of the variables within the framework, discussions were conducted with two experts in the field of international construction business entry.

Table 2 summarizes the size of the dataset, key influencing variables, and representative input values used in the model analysis. This refined dataset enabled the identification of key values for each factor, as well as detailed insights into the countries targeted by the firms for overseas expansion. A subset of target countries was selected based on specific criteria – extreme values in cultural distance (CD), political and policy instability (PPI), and firm size (FS) – to reflect diverse market contexts. The outputs were expressed as coefficients indicating the direction and magnitude of influence. To facilitate model development, the dataset was randomly partitioned into training (80%) and testing (20%) sets. This partitioning allowed for the application and comparative evaluation of multiple algorithms, ensuring that the developed models were validated against unseen data in accordance with standard machine learning practices.

3.3. Data analysis

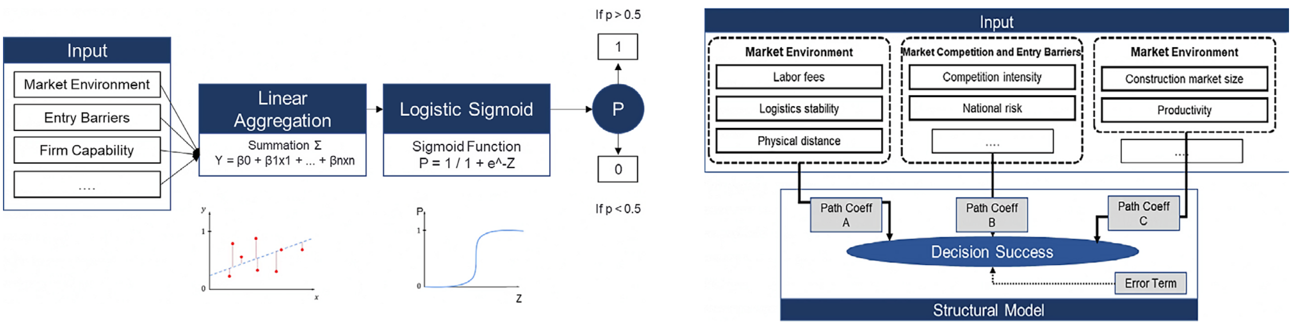
All analyses in this study were performed using an in-house high-performance workstation. The hardware configuration was as follows: CPU: AMD Ryzen 9950X @ 4.3 GHz, RAM: 64 GB, GPU: NVIDIA GeForce RTX 5080 (24 GB). The analytical models employed in this study were implemented using Python 3.10.0. Model architectures and methodologies were adapted from previous research (Chen et al., 2017; Li et al., 2020; Viswanathan & Jha, 2019; Zhou et al., 2024). Before analysis, the dataset was normalized using the min-max scaling function provided by the scikit-learn library to ensure consistency in variable ranges.

Figure 3 shows the model architecture and process flow of algorithms applied in this research. Four distinct models: logistic regression (LR, Figure 3a), structural equation modeling (SEM, Figure 3b), ANFIS (Figure 3c), and FOPA (Figure 3d) were applied to evaluate the influence of each variable on IMS decisions. A confusion matrix was employed to facilitate a comprehensive evaluation of the predictive performance of the models. As noted by Sonmez and Sözgen (2017), the confusion matrix provides granular insights into classification outcomes, enabling a detailed assessment of misclassification patterns. Key metrics including accuracy, precision, and recall were adopted to capture different facets of model performance. The F1-score was further integrated to provide a balanced evaluation by calculating the harmonic mean of precision and recall.

Table 2. Sample summary of influencing factors for international market selection

Total Dataset		8,602		Valid dataset		5,656		Data retention rate			65.75%		
Train and Test ratio (%)						80:20							
	Influencing factors												
Country	LC	LP	PD	CD	MP	CI	FS	FE	IE	LS	PP	PPI	NR
Myanmar	0.03491	0.35844	1766	0.06163	3.9	32.2	519	38	2	2.3	7.54	638	3.7
Argentina	0.50247	1.17345	15926	2.0504	39.5	24.0	282	82	13	2.8	5.64	759	3.0
China	0.14207	1.84178	2984	0.83996	3861.4	44.0	193	38	4	3.7	7.73	10366	6.2
Philippines	0.03297	0.31229	4625	0.5434	47.3	46.2	27,179	79	60	3.0	7.0	1740	2.3
Indonesia	0.04948	0.02857	4485	0.55235	356.8	66.8	1632	56	9	6.0	8.66	2377	2.3
Thailand	0.10753	0.39374	2383	1.13981	39.7	43.4	7796	33	1	3.5	7.73	1475	2.1
Vietnam	0.02623	0.58715	3190	0.52058	32.3	56.4	1096	79	19	3.3	7.93	1477	1.8

a) Logistic regression **b)** Structural equation



c) Adaptive neuro-fuzzy inference system **d)** Fuzzy ordinal priority approach

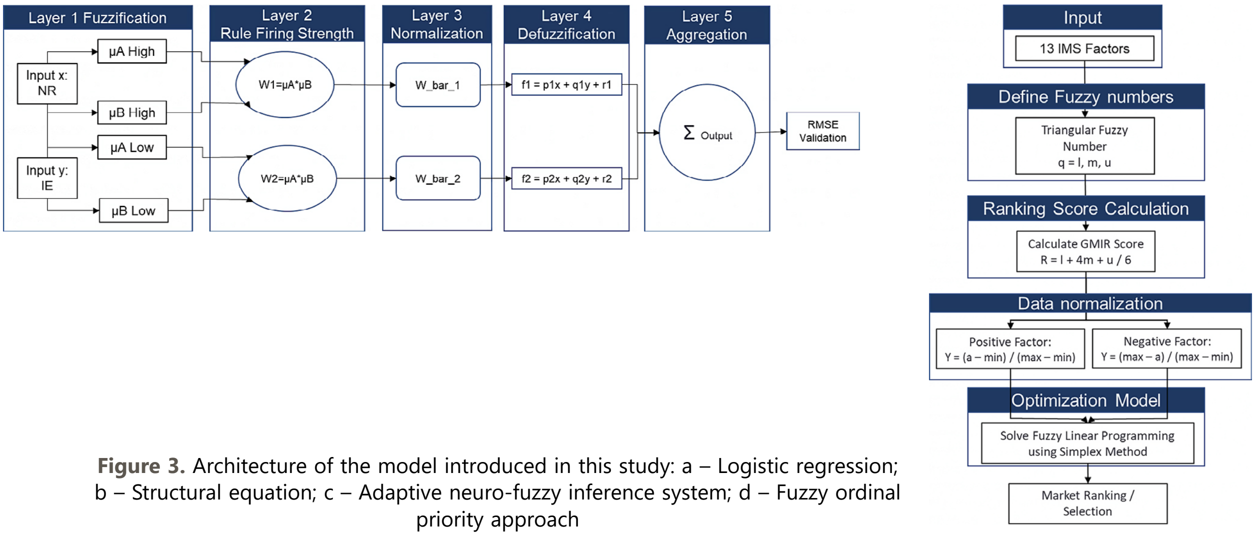


Figure 3. Architecture of the model introduced in this study: a – Logistic regression; b – Structural equation; c – Adaptive neuro-fuzzy inference system; d – Fuzzy ordinal priority approach

The AUC-ROC value was measured to validate the diagnostic capability of the models; this metric reflects the discriminatory power of a model, with values approaching 1 signifying superior performance (Lee et al., 2022).

In addition to estimating the individual effects of IMS factors, the study performed cross-model comparisons to evaluate the structural consistency of variable influences. Each variable was also tested against its corresponding hypothesis across the four models, allowing for an assessment of theoretical alignment. To verify external validity, model predictions were compared with actual market entry data of Indian firms. A regional sensitivity analysis was conducted to account for context-dependent variability, highlighting how market conditions such as distance and regulatory stability affect predictive accuracy. Furthermore, the limitations of purely quantitative models were acknowledged, suggesting the need for complementary qualitative evaluations to support strategic decision-making.

4. Results

4.1. Identification of the factors and influences of impact variables among models

To optimize the performance of the models utilized in this study, we configured the parameters for each model as presented in Table 3. Based on these parameter settings, the training times were recorded as follows: 0.003 s for LR, 0.001 s for ANFIS, 0.002 s for PLS-SEM, and 0.676 s for FOPA.

Table 4 presents several factors that influence a particular outcome. Each factor is represented by a code, its corresponding coefficient, and its overall influence direction (positive or negative) across four models: LR, ANFIS, SEM, and FOPA. A positive coefficient indicates that as the factor increases, it contributes positively to IMS decisions, whereas a negative coefficient suggests that the factor suppresses or reduces the likelihood of selection. Factors such as IE, FS, and EP show consistent positive influences, implying that firm-level capabilities tend to support market selection. In contrast, NR, CD, PD, and PP exhibit consistently negative coefficients, reflecting challenges related to institutional uncertainty, cultural mismatch, geographical distance, and administrative inefficiencies.

A graphical representation of the model analysis results is shown in Figure 4. Notably, NR has the largest negative coefficient across models, indicating that higher national risk strongly reduces the likelihood of market selection. The logistic regression model results reveal the influence of these factors on the decision-making process for IMS and their respective coefficients. As shown in Figure 4a, the SEM modeling results show that NR, CD, LS, and LF have adverse impacts, with NR being the most prominent. In contrast, IE, CI, and EP contribute positively.

Table 3. Hyperparameter settings of each model

Model	Parameter	Value	Description	Search Range
Logistic Regression	C	0.1	Regularization strength	[0.00001~100.0]
	penalty	L2	Ridge regularization	[L1, L2]
	solver	liblinear	Optimization algorithm	[liblinear, lbfgs, saga]
	max_iter	10000	Maximum iterations	Fixed
ANFIS	alpha	0.1	Ridge parameter	[0.000001~10.0]
	implementation	Ridge	Fuzzy approximation	Ridge Regression
PLS-SEM	n_components	7	Latent variables	[2, 3, 4, 5, 6, 7, 8, 10, 12]
	max_iter	1000	NIPALS iterations	Fixed
FOPA	n_estimators	150	Boosting stages	[50, 100, 150, 200]
	max_depth	4	Tree depth	[2, 3, 4, 5, 6]
	learning_rate	0.005	Step size	[0.001~0.1]

Table 4. Results for the model, including coefficient and respective direction of influence

Code	Factor	LR		ANFIS		SEM		FOPA	Hypothesis	Supported
		Coefficient	Influence	Coefficient	Influence	Coefficient	Influence	Influence		
LF	Labor fees	–0.10602	Negative	–2.0542	Negative	–0.07774	Negative	Negative	Negative	4/4
PR	Productivity	–0.09485	Negative	–1.6200	Negative	–0.08815	Negative	Positive	Positive	1/4
PD	Physical distance	–0.00025	Negative	–4.2068	Negative	–0.00025	Negative	Negative	Negative	4/4
CD	Cultural distance	–0.16075	Negative	–3.0442	Negative	–0.19298	Negative	Negative	Negative	4/4
MS	Construction market size	0.00051	Positive	0.5936	Positive	0.00022	Positive	Positive	Positive	4/4
CI	Competition intensity	0.03035	Positive	2.0644	Positive	0.02968	Positive	Negative	Negative	1/4
FS	Firm size	0.00002	Positive	0.4832	Positive	0.00002	Positive	Positive	Positive	4/4
FE	Firm experience	–0.00369	Negative	–0.5421	Negative	–0.00360	Negative	Positive	Positive	1/4
IE	International experience	0.08466	Positive	9.6695	Positive	0.08337	Positive	Positive	Positive	4/4
NR	National risk	–0.44305	Negative	–1.7039	Negative	–0.47543	Negative	Negative	Negative	4/4
EP	Engineer productivity	0.04588	Positive	1.1422	Positive	0.05720	Positive	Positive	Positive	4/4
LS	Logistics stability	–0.19370	Negative	–0.1756	Negative	–0.19760	Negative	Positive	Negative	3/4
PP	Construction permit progress	–0.01331	Negative	–0.9259	Negative	–0.01268	Negative	Negative	Negative	4/4
PPI	PPI	–0.00032	Negative	–3.1225	Negative	–0.10283	Negative	Negative	Positive	0/4
			10/14		10/14		10/14	12/14		

Although statistically significant, PD and FS have negligible effects due to their small coefficients. The ANFIS model yielded a mix of results. Significant adverse influences were observed for LF, PD, and PPI, while IE and CI were strong positive drivers. Other variables such as MS and EP showed moderate positive impacts. The FOPA model, being binary in nature, shows that PR, MS, FS, FE, IE and EP exert positive influence, while LF, PD, CD, CI, NR, PP, and PPI act as obstructions.

Figures 4a, 4b, 4c, and 4d correspond to LR, SEM, ANFIS, and FOPA, respectively. While LR and SEM produce similar coefficient patterns, the fuzzy-based models (ANFIS and FOPA) diverge slightly. Nonetheless, international experience (IE) consistently emerges as the most influential positive factor.

A comparative analysis across the models reveals that firm-level capabilities such as productivity, experience, and engineering strength tend to enhance IMS, while external challenges like national risk, distance, and permit issues deter entry. This integrated model approach thus offers a comprehensive and balanced perspective on international market selection in the construction industry.

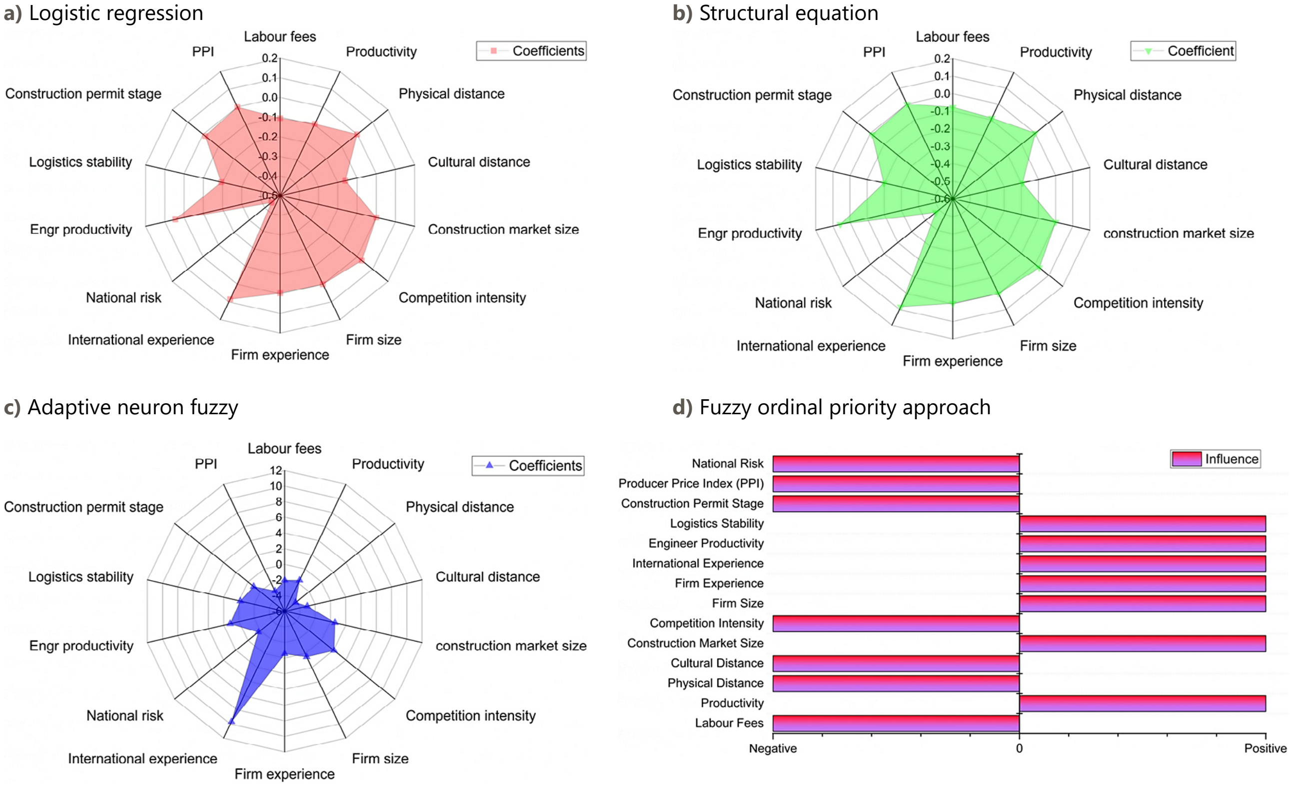


Figure 4. Factors and their influence according to the results of the model: a – Logistic regression; b – Structural equation; c – Adaptive neuron fuzzy; d – Fuzzy ordinal priority approach

Table 5 summarizes the evaluation metrics for each model performance. In terms of accuracy, ANFIS and PLS-SEM achieved 94.523%, outperforming LR (93.993%) and FOPA (94.435%). Notably, ANFIS and PLS-SEM showed higher class-wise detection performance, with a precision of 63.636%, recall of 20.588%, and F1-score of 0.311, than LR (precision 50.0%, recall 5.9%, F1 = 0.105) and FOPA (precision 100.0%, recall 7.353%, F1= 0.137). Regarding discriminative ability, ANFIS and PLS-SEM recorded an AUC-ROC of 0.874, which was higher than that of LR (0.856) but slightly lower than that of FOPA (0.901). Considering the overall balance between accuracy and class-wise performance, ANFIS was selected as the final model for subsequent analysis.

4.2. Comparative model findings

Table 4 shows a clear division between the factors that consistently support the hypotheses and those with mixed results. EP and PP are universally in agreement, whereas LF, CD, and CI show significant variance between models. The diversity of the model outcomes indicates that certain factors have a relatively straightforward influence on IMS. Others are highly context-dependent and require a more refined understanding of the specific conditions in each market.

The factors were assessed based on whether these are supported by a hypothesis that indicates their relationship across the four criteria. For instance, LF exhibits negative effects in ANFIS, SEM, and FOPA, while showing a positive effect in LR. Accordingly, it supports three out of the four hypotheses. PR supports two of the four hypotheses, with predominantly positive correlations. Meanwhile, PP consistently shows negative effects across all four models, fully aligning with the hypothesized direction. Similarly, EP, FS, IE, CD, PD, PP, and NR demonstrate consistent effects and support all four hypotheses. MS, LS, and LF show relatively strong consistency, supporting three out of the four hypotheses. PR supports two out of the four hypotheses, showing moderate alignment. In contrast, CI and FE support only one out of the four hypotheses, indicating considerable variability in their influence. These results suggest that while certain factors such as EP, FS, IE, CD, PD,

Table 5. Evaluation metrics of model performance

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	93.993	50.000	5.9	0.105	0.856
ANFIS	94.523	63.636	20.588	0.311	0.874
PLS-SEM	94.523	63.636	20.588	0.311	0.874
FOPA	94.435	100.000	7.353	0.137	0.901

PP, and NR show clear and consistent effects across models, others such as CI and FE exhibit more variable outcomes depending on the analytical framework.

As shown in Figure 2 and Table 4, several variables demonstrated consistent influence across the models, while others varied depending on the analytical framework. EP and CD maintained the same direction in all four models, indicating a stable and predictable role in international market selection. FS and IE also supported all four hypotheses, showing consistently positive effects. LF and MS were positively aligned with the expected outcomes in three of the four models, suggesting these factors are generally robust in supporting IMS decisions. On the other hand, CI and FE showed mixed results, with only partial alignment depending on the model used. These observations imply that firm-level capability factors tend to exhibit greater consistency in their impact, whereas external and contextual variables may behave differently across varying market conditions and model structures.

4.3. Comparison of IMS results by comparing ANFIS models with actual data values

While the FOPA algorithm exhibited higher numerical classification accuracy, this is likely due to the simplification of all factors influence into a binary form. In contrast, the ANFIS model, which showed a higher degree of alignment with the hypotheses, combines the learning capabilities of artificial neural networks (ANNs) with the reasoning capability of fuzzy logic. The hybrid approach allows for real-time updates of rules and predictions by incorporating new data. This makes it particularly suitable for application in international markets, where country-specific conditions transition rapidly.

The model demonstrated a high level of predictive consistency for internal firm capability factors such as productivity (PR), engineer productivity (EP), and international experience (IE). In contrast, external factors like cultural distance (CD) and physical distance (PD) showed more variable patterns across models, reflecting context-dependent influences. Labor fees (LF), while consistently showing negative effects, also revealed region-specific sensitivities that may affect predictive alignment in certain cases.

Table 6 presents representative results comparing ANFIS model outputs with actual data, highlighting cases with both high and low prediction accuracy. This comparison demonstrates the model's effectiveness in differentiating prediction performance across countries. Countries with lower alignment between algorithmic predictions and actual investment outcomes include Latin American nations such as Brazil and Mexico. Meanwhile, countries with higher alignment include Asian countries such as Afghanistan, Qatar, Thailand, and Myanmar. This observation indicates that a larger physical distance poses significant challenges to firms' entry into foreign markets. Furthermore, physical remoteness generally correlates with higher cultural distance. This adds another layer of complexity. These characteristics indicate that market entry in these countries is inherently difficult to predict.

Although a few of these countries have large construction markets, their weak enterprise foundations and limited international experience reduce trust in local partners and increase the risks associated with project execution. Consequently, in environments in which operational execution is challenging, the predictive accuracy of the model tends to decrease. Additionally, the generally low levels of productivity and technical capabilities in these regions imply that the complexity of construction execution and

Table 6. Comparison of ANFIS model value with actual data values

Classification	ANFIS Result	Name	LR	PR	PD	CD	MS	CI	FS	FE	IE	NR	EP	LS	PP	PPI
Country where the predicted result value is close to the actual data value	–953.911	Afghanistan	0.00368	0.82137	1,851	0.06127	1.7	8.4	14,289	82	13	4.6	0.62	1.9	34.5	52
	–934.977	Qatar	0.00076	0.52859	2,887	0.01279	42.2	56.4	22,526	46	22	1.5	0.04	3.5	84.2	0
	–854.34	Thailand	0.10753	0.39374	2,383	1.13981	39.7	43.4	27,179	79	60	2.1	0.62	3.5	77.3	1,475
	–833.063	Myanmar	0.03491	0.35844	1,766	0.06163	3.9	32	17,403	66	16	3.7	0.69	2.3	75.4	638
	–804.868	Saudi Arabia	0.50621	0.42316	3,498	0.35344	111.0	87.4	27,179	79	60	2	0.62	3.4	78.3	0
	–771.443	Bhutan	0.03491	0.35844	1,395	0.01539	0.3	0	11,234	49	14	1.6	0.69	2.5	68.9	140
	–736.297	United Arab Emirates	0.34716	1.40737	2,605	0.03603	80.5	52	20,734	78	10	1.6	0.62	4.0	89.8	0
	–704.749	Singapore	2.12359	1.68484	3,443	1.02456	30.4	49.4	27,179	79	60	0.7	0.98	4.3	87.9	0
	–652.729	Kazakhstan	0.10224	0.31229	3,235	0.09277	17.4	42	27,179	79	60	2.2	0.62	2.7	76.5	258
Country where the predicted result value is far from the actual data value	–102916	Brazil	0.19044	0.32047	14,775	1.08151	146.9	30.6	96	51	6	2.4	0.35	3.2	51.9	13,124
	–75802	Peru	1.88475	0.20278	16,950	1.84300	30.0	32.6	10	19	1	2.3	0.20	3.0	72.5	1,464
	–73361.444	Mexico	0.36742	0.59873	15,094	3.20969	146.2	49.2	10	19	1	2.7	0.04	2.9	68.8	3,215
	–72031.7	Colombia	0.84034	0.44346	15,971	2.93035	47.1	25.2	149	15	1	2.5	0.00	2.9	69.1	1,596
	–71461.7	Ecuador	1.11468	0.52859	16,774	1.26367	18.3	18.6	60	30	8	2.6	0.04	2.9	66.4	328
	–70133.1	Chile	3.47027	0.81114	16,691	2.49838	40.1	33.4	10	19	1	2	0.16	3.0	75.9	0

collaborative management is likely to be high. Therefore, although Latin American markets may appear attractive in terms of size, the ANFIS model's predictive reliability reduces. This indicates the need for complementary qualitative assessments beyond quantitative analysis, such as the evaluation of local regulatory systems and partnership structures.

In contrast, although South Asian countries identified as favorable for market entry have relatively small market sizes, these exhibit higher feasibility because of the lower entry barriers and institutional stability (e.g., consistent permission processes). Their geographical and cultural proximity to India further facilitates entry. Moreover, firms operating in these regions tend to exhibit superior experience and scale. This indicates the presence of a robust enterprise ecosystem capable of managing complex projects. Moreover, the higher average productivity and engineering productivity in these countries indicate that these are well equipped for efficient construction and technically intensive project execution.

In summary, the ANFIS model effectively captures market accessibility based on quantitative indicators such as construction productivity, technological capacity, and firm capabilities. These insights are consistent with the actual entry data, thereby validating the applicability of the model. Furthermore, the results emphasize that successful market-entry predictions are determined by the GDP, the market size, and a country's project execution capacity and responsiveness to operational challenges.

5. Discussion

This study examined the IMS process in the construction sector by extending previous research in international business while integrating construction-specific variables. Based on this objective, thirteen key factors were identified and employed in a series of hybrid machine learning models (LR, ANFIS, SEM, and FOPA) to explore and predict the international market entry decisions of firms.

Theoretically, this study addressed international market entry by incorporating novel construction-specific variables. Methodologically, it conducted a comparative analysis of different models. Furthermore, regarding corporate capability strategies, the study identified both positive and negative influencing factors, thereby proposing practical measures for risk management. Furthermore, the validation of construction-specific variables and AI-based methodologies justifies the need for a theoretical evolution in IMS research, moving beyond traditional manufacturing-centric models.

5.1. Theoretical implications

IMS is a critical and essential decision-making process for companies that formulate internationalization strategies. However, existing IMS research has focused primarily on manufacturing firms, thereby failing to reflect the unique characteristics of the construction industry. Although previous studies have utilized traditional variables such as permitting procedures and supply chain stability, the practical application of these increasingly available datasets has remained limited in scope (Dikmen & Birgonul, 2004; Musso & Francioni, 2012). Furthermore, these studies did not conduct in-depth contextual analyses of risk factors, such as national risk (NR), political instability, and economic volatility, and were largely confined to specific regional contexts.

Given the substantial differences between the construction and manufacturing sectors, there is a growing need for an IMS model specifically tailored to global construction firms. To address this gap, this study examined the IMS process in the construction sector by extending prior research in international business while integrating construction-specific variables. In line with this objective, thirteen key factors, many of which are rooted in conventional IMS frameworks, were identified. These variables were subsequently employed in a series of hybrid machine learning models to explore and predict firms' international market entry decisions more effectively. Consequently, consistent with previous studies, this study reaffirmed that entry experience is a critical driver; furthermore, it identified that firm size and engineer productivity exert a significant influence on market entry (Utama et al., 2019). Moreover, while some studies suggest that geographical and cultural distances do not act as barriers to the international market selection of Indian firms, the practical findings of this research indicate that physical and cultural proximity – along with the complexity of construction permitting procedures in the host country – serve as significant deterrents (Viswanathan & Jha, 2019).

The different outcomes across the four models (LR, ANFIS, SEM, and FOPA) highlight the complexity of decision-making in international construction markets. Firms need to account for multiple factors and acknowledge that certain influences may interact differently depending on market conditions, firm characteristics, and the specific characteristics of the construction industry. In particular, ANFIS demonstrates a strong capability to capture nonlinearity and complex interactions among variables. This makes it particularly effective for decision-making in the intricate environment of international construction. Furthermore, its relatively high consistency with the proposed hypotheses emphasizes its practical applicability and interpretability. This positions it as a robust analytical tool for both research and practice (Utama et al., 2019).

5.2. Practical implications

This study provides actionable insights for strategic decision-making by clearly delineating the positive and negative influences of specific factors on the IMS process presented in Figure 5. A critical insight from this study is the clear delineation of the positive and negative influences of specific factors on the IMS process. Factors such as LF, FS, CI, and IE were consistently observed to have positive impacts across multiple models. These factors highlight the

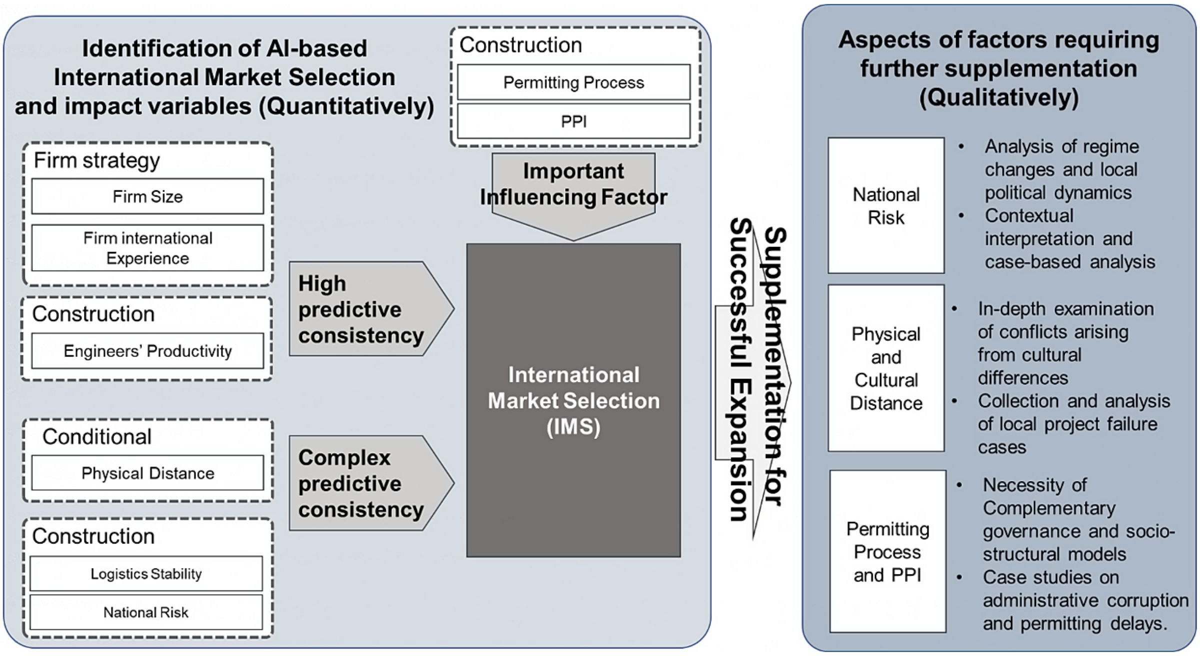


Figure 5. Schematic and further directional presentation of study results

critical role of firm characteristics and the competitive environment in shaping market entry decisions. Larger firms with more resources and experience in international markets are better equipped to mitigate risks and capitalize on opportunities (Lee et al., 2023).

Conversely, factors such as NR, PD, CD, and LS pose significant challenges for successful market entry. NR was highlighted as one of the most influential negative factors. This aligns with previous research emphasizing the vulnerability of the construction industry to political and economic instability (Musso & Francioni, 2012). The high PD and CDs between India and many potential foreign markets further exacerbate the challenges encountered by firms, particularly when operating in culturally or physically distant countries. These distances result in increased costs of transportation, communication, and project management, with the risk of potential misalignments in project execution owing to cultural misinterpretations.

A significant contribution of this study is the inclusion of construction-specific factors such as LS, PP, and PPI. These have not been evaluated thoroughly in previous IMS models for construction projects. The observations reveal that these factors have a substantial impact on the market selection process, with both positive and adverse effects depending on the context.

LS presents the risks in international markets because of the complexity of global logistics and procurement. In construction, the timely delivery of materials is essential for the success of projects. Therefore, instability in supply chains can cause delays, cost overruns, and project cancellations. The negative influence of this factor on certain models emphasizes the need for construction firms to carefully assess the logistics infrastructure of potential markets before making entry decisions. Similarly, PP emerged as a critical factor with inefficiencies in the permitting process and was identified as having a negative influence in all the models. This observation is particularly relevant for developing countries, where delays, corruption, and inconsistent regulations can severely affect project timelines (Robertson & Wood, 2001). The complexity of obtaining construction permits increases costs and introduces uncertainty into project planning. This makes markets with slow or unpredictable permitting processes less attractive for international construction firms.

PPI showed mixed results. Although PPI can provide a supportive environment for public–private partnerships and infrastructure development, excessive participation can also result in complications such as increased scrutiny, extended timelines, and higher project costs. In contexts wherein public engagement is managed effectively, PPI can yield better project outcomes through enhanced stakeholder collaboration. However, in less-structured environments, this can become a barrier to efficiency, as reflected in the observations of this study. PPI was observed to have both positive and negative influences across the models.

For Indian construction firms aiming to expand internationally, this study's observations provide effective insights into the strategic considerations required for successful market entry. The consistent positive influence of IE across the models emphasizes the importance of accumulating experience in foreign markets as a key determinant of success. Firms that already operate in multiple countries or regions are better capable of navigating the complexities of international construction projects, including managing diverse workforces, adapting to different regulatory environments, and mitigating risks related to distance and logistics (Dikmen & Birgonul, 2004).

FS has also emerged as a critical factor, with larger firms generally performing better in international markets. This indicates that smaller firms may need to form strategic alliances or joint ventures with larger firms to overcome the challenges posed by resource constraints. Furthermore, CI was observed to positively influence the construction industry. This implies that construction firms should consider entering competitive markets.

However, firms should remain cautious regarding markets with high NR because political and economic instability can significantly derail projects. The strong negative influence of NR across the models indicates that firms should prioritize markets with stable governance and predictable economic environments (Kwon et al., 2023). Entering markets with significant cultural differences or logistical challenges may require firms to invest in localized expertise, logistics improvements, and cross-cultural management training to mitigate these risks.

6. Conclusions

To summarize, this study emphasizes the importance of macroeconomic and construction-specific factors in the IMS process for Indian construction firms. Although FS, CI, and IE positively influence market-entry decisions, challenges related to NR, PD, CD, and LS should be managed meticulously. The inclusion of construction-specific variables such as LS and PP emphasizes the need for a nuanced approach to IMS in the construction industry. Leveraging these insights, construction firms can make more informed decisions regarding which international markets these can enter and how to successfully navigate the complexities of global construction projects. This research further underscores the efficacy of AI methodologies in processing industry-specific data. The ANFIS model, characterized by its 94.523% accuracy and superior discriminatory power (via AUC-ROC), provides quantitative evidence that the proposed framework accurately delineates the intricate interdependencies and volatile constraints inherent in the construction sector. Consequently, the study confirmed that this AI-integrated approach serves as a highly reliable instrument for navigating complex decision-making processes in global market expansion.

Based on the analysis presented in this paper, this study examined the impact of various factors on international market selection for construction firms using data from Indian companies. The study identified a range of positive and negative influences that affect the decision-making process when entering international construction markets. A hypothesis was made regarding the direction of the factors in conducting IMS. It was verified using models such as LR, SEM, ANFIS, and FOPA. The study verified that factors such as LF, CI, FS, and IE have a generally positive influence, whereas factors such as NR, PD, CD, and LS have the converse effect. The addition of construction-related factors such as LF, EP, PP, and PPI has further enriched our understanding of the complexities involved in international market entry. This study contributes to the existing body of knowledge by extending previous models to include new construction-specific variables and testing their validity across multiple analytical frameworks.

To conclude, these observations emphasize the importance of meticulously considering both macroeconomic and construction-specific factors when making decisions regarding IMS. In the context of construction projects, the distinct impacts of these variables highlight the need for a customized approach to solving industry challenges. The study also emphasizes the critical role of IE in ensuring successful market entry and long-term competitiveness.

Several theoretical contributions have been made in the field of IMS in the construction industry. Incorporating construction-specific factors and utilizing a multi-model approach broadens the scope of conventional IMS research, which generally focuses on macroeconomic factors and industry-level variables. The use of the ANFIS and FOPA models, in addition to more conventional methods such as LR and SEM, demonstrates the effectiveness of employing hybrid models to capture the complexity and uncertainty inherent in international market selection.

Nevertheless, this study had limitations regarding generalizability, as the analysis was centered on the specific context of India. The market entry patterns of Indian firms may not be directly applicable to other nations, particularly owing to potential institutional and managerial biases inherent to the Indian business environment. Consequently, applying these findings to other advanced economies may result in cross-cultural management bias. Future research should expand upon this study by incorporating diverse cultural contexts, which will necessitate re-training the models to reflect country-specific characteristics. Such efforts are required to extend the analysis to multi-country samples and ensure broader applicability.

Furthermore, a multi-faceted analysis of IMS determinants should be conducted by incorporating a wider range of variables. Future research should evaluate additional factors specific to the construction industry, such as BIM and sustainability initiatives, to examine the influence of these innovations on international expansion. Although this study leveraged established models from the existing literature, subsequent studies can build upon this foundation by integrating more diverse, context-specific variables. Thus, it could provide a foundation for developing a method that employs state-of-the-art techniques such as deep learning. Furthermore, long-term observational studies that monitor the performance of firms in international markets provide deeper insights into the effects of initial market-entry decisions on long-term success.

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Author contributions

Kyung-Tae Lee: Conceptualization, Methodology, Investigation, Funding acquisition, Writing – Original Draft; Seung-Hye Shin: Methodology, Software, Validation, Investigation, Visualization, Writing – Original Draft; Jin-Bin Im: Software, Validation, Formal analysis, Data Curation; Hyoungmin Choi: Conceptualization, Resources, Data Curation; Ju-Hyung Kim: Project Administration, Validation, Supervision, Writing – Review & Editing.

Disclosure statement

Authors are required to include a statement at the end of their article to declare whether or not they have any competing financial, professional, or personal interests from other parties.

Data availability statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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