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Modeling the Causal Relationships of Country Risk Factors Using Expert Experience and Intuition-based Sensing Data

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International construction projects inherently involve risks that fundamentally differ from those encountered in domestic projects due to variations in legal, political, and economic environments. Given the confidentiality and data limitations of such projects, this study introduces an innovative approach by conceptualizing expert judgment as sensor-like data to compensate for the absence of direct measurements. Specifically, Expert-Driven Experience and Intuition-Based Sensing Data are treated as qualitative proxies for sensor input, enabling the extraction of structured knowledge from tacit insights. These data are integrated with Partial Least Squares Structural Equation Modeling to quantitatively analyze the organic interactions and causal relationships among country-specific risk factors and their impact on cost overruns. The proposed framework demonstrates enhanced reliability and robustness, even in data-constrained contexts. The empirical analysis reveals that 'Environmental' risk exerts the most significant direct effect on cost overruns (standardized path coefficient = 0.360), whereas 'Legal' risk has the smallest indirect impact (0.067). The results emphasize the importance of economic and environmental risks, offering a foundation for developing targeted risk management strategies to ensure the financial stability of construction projects.

1. Introduction

International construction projects inherently involve risks that are fundamentally different from those encountered in domestic projects executed by contractors. These risks arise owing to differences in the legal and political environments across countries, among which country risk is widely recognized as a critical determinant in international construction projects. In the context of construction, risk is defined as any factor that poses potential threats and losses, negatively affecting the success of a project.(1,2) Country risk is generally referred to as the "responsibility

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of foreigners" and is described as the risk that creates significant uncertainty for foreign firms operating in a particular country.[3,4]

Country risk encompasses factors that directly affect the operation and performance of a project, including national laws and regulations, policy changes, economic volatility, cultural differences, and environmental regulations. In the case of international construction projects, it is crucial to systematically analyze the interactions between various country risk factors, rather than evaluating individual risks independently. Thus, a quantitative analysis of the organic interactions and causal relationships between country risk factors is essential.

Given the inherent data scarcity and confidentiality constraints in international projects, direct measurement of many country risk variables is often infeasible. In this context, expert judgment can be conceptualized as sensor-like qualitative data, serving as proxy "sensing inputs" that capture tacit insights otherwise unobtainable from conventional datasets.

To conduct a quantitative analysis of these causal relationships between country risk elements, a sufficiently large sample size is required; however, existing studies have faced limitations in performing such analyses owing to difficulties in sample collection. In particular, the inherent confidentiality of international construction projects has further exacerbated the challenges in data collection.[5,6] Therefore, there is a need for methods that enable the collection of a sufficient sample size for such analyses.

Building on the notion of experts as "human sensors", this study treats Expert-Driven Experience and Intuition-Based Sensing Data as qualitative proxies analogous to sensor-derived inputs, enabling structured quantification of subjective assessments. Such sensor-inspired data provisioning allows us to integrate otherwise unavailable insights into an analytical framework.

In such cases, utilizing Expert-driven Experience and Intuition-based Sensing Data can serve as an effective alternative. In situations where direct data collection is challenging, quantitative data based on experts' experience and intuition can be used to ensure the reliability and robustness of the analytical models. Here, experts can be defined as sensors providing subjective data.[7,8]

In this study, we aim to develop an analytical framework that systematically analyzes the interactions and causal relationships between country risk factors, leveraging Expert-driven Experience and Intuition-based Sensing Data, and we quantitatively assessed their impact on cost overruns in international construction projects. To achieve this, we employed Partial Least Squares-Structural Equation Modeling (PLS-SEM). PLS-SEM is a statistical technique focused on predictive and exploratory analysis, known for its strong performance in modeling relationships between latent variables despite data non-normality and small sample sizes. PLS-SEM is increasingly attracting attention as a methodology capable of effectively identifying complex relationships between variables, even with smaller sample sizes, compared with the traditional Covariance-based Structural Equation Modeling (CB-SEM).

By integrating sensor-inspired expert inputs into PLS-SEM, the proposed framework bridges the gap between qualitative insights and quantitative modeling, offering a technology-aligned approach to risk interdependency analysis under data-constrained conditions. The structure of this paper is as follows. First, we review the concept and classification of country risk, including existing risk analysis methodologies. Second, we present the research methodologies employed in country risk analysis. Third, we explain the key findings derived from the analysis results. Fourth, we discuss the interpretation and implications of the findings. Finally, we outline the limitations of the study and suggest directions for future research, with the expectation that it will contribute to the development of appropriate country risk management strategies for international construction projects.

2. Theoretical Consideration

2.1 Country risk

A literature review identified that these country risks can be broadly categorized into six main types. The country risks identified in previous studies are classified as "Political risk", "Economic risk", "Cultural risk", "Environment risk", "Market risk", and "Legal risk". "Political risk" refers to the risk that a foreign company encounters in another country owing to political issues originating within that country that can affect the business. "Economic risk" is the risk impacting the business costs owing to fluctuations in wages, material costs, or exchange rates in the host country. "Cultural risk" involves the impact on the business owing to the religious or cultural differences in the host country. "Environment risk" refers to the impact on the business owing to the climate or ground conditions in the host country. "Market risk" is the risk affecting the business owing to challenges in securing local labor, materials, or equipment, as well as the local project experience of the workers. "Legal risk" refers to the impact on the business owing to the different legal systems or administrative procedures in the host country.

Previous studies have identified and analyzed country risks. For example, Wang *et al.* focused on political risk factors. They identified and categorized these into six areas including "change in law", "delay in approval", and "force majeure".(9) Baloi and Price further refined the classification of country risks into seven categories, such as "construction practices in the host country", "level of competition with local construction companies", and "economic conditions of the host country".(10) Dikmen *et al.* proposed a classification system for the major country risk factors in international construction projects. It comprises nine categories including "cultural/ religious differences" and "political instability".(11) Bu-Qammaz *et al.* differentiated country risks into "country risk" related to the host country and "intercountry risk" concerning the differences between the host and home countries.(12) Thereby, they presented a classification system for these risk factors. Other studies that have identified and analyzed country risks are summarized in Table 1.

2.2 Analysis of risk factor relationships

Analyses considering the relationships among risk factors have been performed for a long time. Presently, more advanced analyses that combine the advantages and mitigate the disadvantages are being performed.

Analyzing risks in construction projects is a crucial process for developing and managing responses to the uncertain factors that affect project costs and durations, thereby ensuring

Table 1
Literature review on risk identification and analysis.

Analysis method	Research method	Reference
Risk breakdown structure (RBS)	Literature review, case study	Ref. 13
	Survey	Ref. 14
	Survey	Ref. 15
	Case study	Ref. 16
	Literature review, interviews	Ref. 17
	Literature review	Ref. 18
SWOT analysis	Case study	Ref. 19
	Questionnaire, case study	Ref. 20
Risk impact analysis	Literature review, case study	Ref. 21
	Survey, case study	Ref. 22
	Literature review, case study	Ref. 23

project success. Conventional methods for risk analysis include risk probability-impact (PI) evaluation, risk matrices, and extensive expert interviews. However, risk analysis has evolved through continuous research, leading to the proposal of various new methods. Recently, the importance of analyzing the relationships among risk factors has been emphasized, and related analyses are now being conducted. Previous studies focusing on these relationships are summarized in Table 2.

Previous studies have explored various methods for analyzing the relationships among risk factors, including Bayesian network analysis, regression analysis, analytic hierarchy process (AHP) analysis, and CB-SEM.(23–28) However, each of these methods has its limitations. Regression analysis can consider only the relationships between individual risk factors and the dependent variable. This hinders the estimation of the organic relationships among risk factors. AHP analysis allows for an analysis with a small number of samples. It can prioritize the key risk factors through hierarchical analysis and weight application. However, similar to regression analysis, it cannot estimate the organic relationships among risk factors. Bayesian network and CB-SEM can estimate these relationships. However, these require a large number of samples. For example, CB-SEM typically requires a minimum of 150 samples and is generally used to validate existing theories. This involves stringent assumptions and reduces the accessibility for analysis.

Owing to these limitations, PLS-SEM has attracted attention recently. It is an analytical method that performs path analysis based on exploratory factor analysis and is generally used for theory development and prediction. PLS-SEM overcomes the limitations of CB-SEM and has emerged as a viable alternative. It uses nonparametric bootstrapping for significance testing of research models. This enables it to circumvent distributional assumptions. Additionally, PLS-SEM is more flexible than CB-SEM with regard to the determination of the minimum sample size. This is because it can be utilized effectively with sample sizes smaller than 100 while maintaining a high level of statistical validation capability.(30) Therefore, PLS-SEM is more advantageous than CB-SEM when the data does not satisfy the fundamental assumptions of CB-SEM, and the focus is more on estimation rather than validation of existing theories.

Table 2
Literature review on analysis of risk factor relationship.

Analysis Method	Research method	Reference
Structural equation modeling (SEM)	Literature review, survey	Ref. 24
	Case study, survey	Ref. 25
AHP	Case study, survey	Ref. 26
Regression analysis	Case study	Ref. 27
	Literature review, survey	Ref. 28
	Survey, expert interviews	Ref. 29

3. Research Method

3.1 Risk PI evaluation

The PI evaluation technique applies the concept of distance to assess the level of risk.(31) The distance concept refers to defining the axes of a coordinate plane as the probability and impact of the risk, and calculating the distance from the origin to the point representing the risk. The calculation method for the *PI* evaluation of international construction country risk factors is given by Eq. (1).

$$PI = \sqrt{P^2 + I^2} \tag{1}$$

Here, *PI* represents the distance from the origin to the specific risk, whereas *P* and *I* denote the probability of occurrence of the risk factor in construction and its impact on the construction costs, respectively.

3.2 PLS-SEM

PLS-SEM is a nonparametric method that estimates relationships by minimizing the prediction error among latent variables by repeatedly performing ordinary least squares regression analysis and exploratory factor analysis with principal component factor rotation. The structural equation model combines a measurement model (which represents the causal relationships between observed and latent variables) and a structural model (which represents the causal relationships among latent variables). In this context, measurement variables are directly observed variables used to measure latent variables. Latent variables are variables that are not observed directly and are measured indirectly through measurement variables.

3.2.1 Measurement model

The evaluation of the measurement model pertains to assessing the relationship between latent variables and observed variables. To evaluate the measurement model, we adopted widely accepted thresholds for internal consistency reliability, convergent validity, and discriminant validity, as recommended in the PLS-SEM literature.

Internal consistency reliability assesses whether the various observed variables that compose a latent variable are consistent. The common metrics for evaluating the internal consistency reliability include Cronbach's alpha, Dijkstra–Henseler's rho, and composite reliability (*CR*). Among these, *CR* is considered the most suitable metric for PLS-SEM.[32] Typically, a *CR* value of 0.6 or above is considered reasonable. This threshold supports the reliability of the constructs by confirming that the observed variables consistently represent the intended latent concepts. The formula for calculating *CR* is given by Eq. (2). Here, L_i represents the standardized outer loading of measurement variable i for a specific latent variable, e_i is the measurement error of measurement variable i, $\mathrm{var}(e_i)$ is the variance of the measurement error, and M is the number of measurement variables.

$$CR\left(\rho_c\right)=\frac{\left(\sum_{i=1}^{M}L_i\right)^2}{\left(\sum_{i=1}^{M}L_i\right)^2+\sum_{i=1}^{M}\mathrm{var}\left(e_i\right)} \tag{2}$$

Convergent validity determines the degree to which the observed variables are related to their corresponding latent variable. It is evaluated through the average variance extracted (*AVE*). Following the criterion proposed by Fornell and Larcker,[33] an *AVE* value of 0.5 or higher indicates that a latent construct explains more than half of the variance in its associated indicators. The formula for *AVE* is given by Eq. (3). Here, λ represents the standardized loading, and ϵ denotes the measurement error of the variables.

$$AVE=\frac{\sum\lambda^2}{\left(\sum\lambda^2+\sum\mathrm{Var}(\epsilon)\right)} \tag{3}$$

Discriminant validity assesses whether the observed variables are not related to other latent variables. The discriminant validity can be evaluated using the Fornell–Larcker criterion, cross-loadings, and heterotrait–monotrait (HTMT) ratio. The HTMT ratio is the most suitable criterion for assessing discriminant validity in PLS-SEM. The acceptance criteria for HTMT can be broadly categorized into three types: HTMT, HTMT.90, and HTMT inference using bootstrapped confidence intervals. First, HTMT.85, as proposed by Clark and Watson[34] and Kline,[35] is the most conservative criterion. The discriminant validity is considered established if the HTMT ratio is less than 0.85.[32,33] Second, HTMT.90 (recommended by Gold *et al.*[36] and Teo *et al.*[37]) is a more general, intermediate criterion. The discriminant validity is considered established if the HTMT ratio is less than 0.90.[38,39] Finally, the HTMT inference using bootstrapped confidence intervals (proposed by Shaffer[40]) is the most liberal criterion. The discriminant validity is considered established if the confidence interval does not include one.[41] The HTMT ratio, used as the preferred criterion for assessing discriminant validity in PLS-SEM, is computed as shown in Eq. (4).

Here, Y_1 and Y_2 represent each latent variable, α is the average of the *H–H* correlations, and M_1 and M_2 are the averages of the *M–H* correlations for each latent variable.

$$HTMT\left(Y_1, Y_2\right) = \frac{\alpha}{\sqrt{M_1 M_2}} \tag{4}$$

3.2.2 Structural model

Structural model evaluation refers to the assessment of the relationships among latent variables. It involves several metrics including the statistical significance and fit of path coefficients, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2).

Multicollinearity refers to the presence of strong correlations among latent variables and is assessed using the internal variance inflation factor (*VIF*). An internal *VIF* below 5.0 indicates that multicollinearity is not a concern among the latent variables; however, an internal *VIF* of 5.0 or higher suggests problematic multicollinearity. In such cases, the issue can be addressed by removing the problematic latent variable or by combining it with other latent constructs to mitigate redundancy.[42]

To evaluate the significance and fit of path coefficients, standardized path coefficient estimates are used. Path coefficients range from −1 to +1. These indicate the strength and direction of relationships among latent variables. A value close to −1 or +1 indicates a strong negative or positive relationship, respectively. Meanwhile, a value close to zero implies a weak relationship. The significance and fit of path coefficients should be verified using bootstrapping methods. If the magnitude of the *t*-value exceeds the critical value (typically ±1.96 at a 5% significance level), the path coefficient is considered statistically significant.

R^2 serves as a measure of the explanatory capability of the structural model. It is calculated as the squared correlation between the actual and predicted values. In complex models such as PLS-SEM, a coefficient of determination ($R^2{}_{adj}$) that accounts for the number of latent variables and sample size is generally used. No absolute standard exists for the coefficient of determination. However, values above 0.26 are generally considered to indicate a high explanatory capability, those between 0.13 and 0.26 a moderate explanatory capability, and those between 0.02 and 0.13 a low explanatory capability.

Effect size (f^2) measures the extent to which latent variables contribute to the coefficient of determination. The formula for calculating the effect size is given by Eq. (5).

$$f^2 = \frac{R_i^2 - R_d^2}{1 - R_i^2} \tag{5}$$

Here, R_i^2 represents the coefficient of determination for a latent variable when it is included in the model, and R_d^2 represents that for the same variable after reestimation with the latent variable removed. In general, an effect size of 0.35 or higher indicates a large effect, 0.15–0.35 indicates a medium effect, and 0.02–0.13 indicates a small effect.[38]

Q^2 assesses whether the latent variables in the structural model have predictive relevance. It is determined using the cross-validated redundancy measure. A value higher than zero indicates that the model has predictive relevance, whereas that less than zero indicates an insufficient predictive relevance.(38)

3.3 Framework

In this study, a framework was developed to identify the latent relationships among risk factors with a small sample size and to determine the impact of these risk factors on cost overrun. The developed framework is illustrated in Fig. 1.

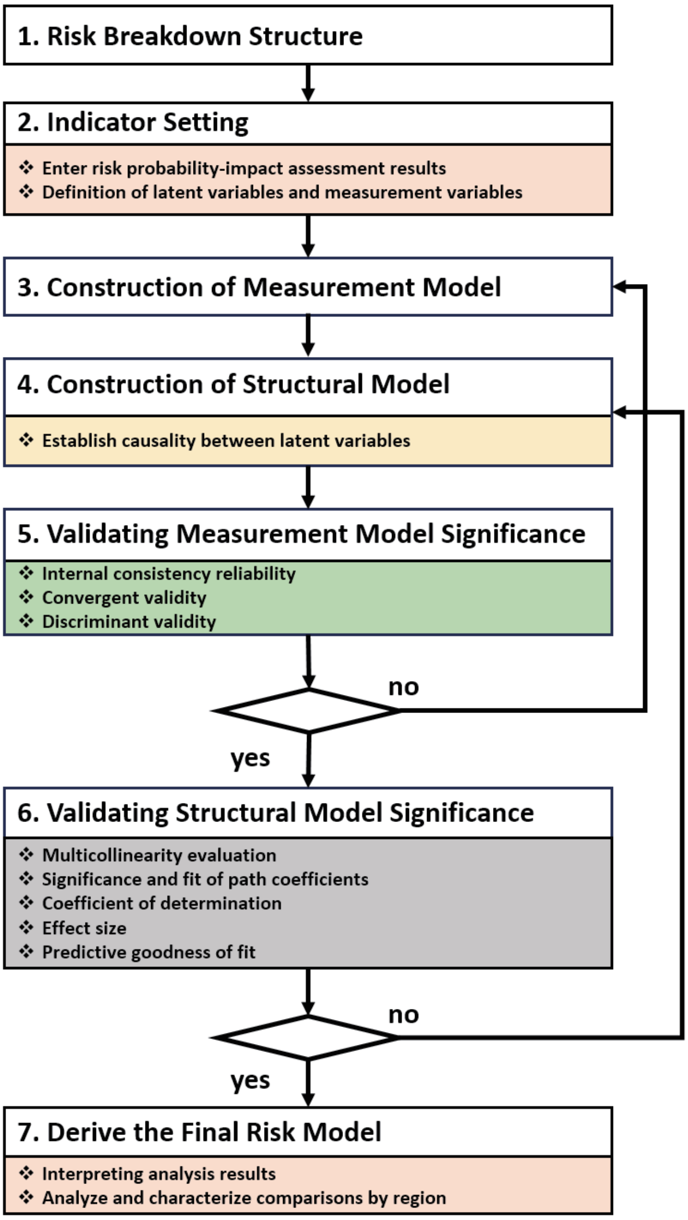

Fig. 1. (Color online) Risk analysis framework considering relationships among risk factors.

In Step 1, the risks to be analyzed are collected to construct a risk breakdown structure (RBS). In this study, we aimed to analyze country risks in international construction projects. Therefore, country risk factors were investigated through previous research, and the key country risk factors were selected to construct the RBS.

In Step 2, a basic evaluation of the risk factors is conducted. In this study, an expert survey was used to evaluate the country risk factors. This basic evaluation involves assessing the impact and occurrence probability of each country risk factor on cost overrun for international construction projects. The experts in this context are practitioners with experience in executing international construction projects.

In Step 3, the risk indices for the risk factors are calculated using the probability and impact information collected from the surveys. The risk indices are calculated by a PI evaluation, which is a method for comprehensively assessing the occurrence probability and impact of risks. The risk indices derived from this analysis help identify the apparent level of risk for each risk factor. Furthermore, it can be observed that the same risk factors exhibit different characteristics depending on spatial differences. In this study, the risk indices were calculated on the basis of country risk factors.

In Step 4, a PLS-SEM analysis is conducted using the calculated risk indices to reveal the latent relationships among the risk factors and determine their impact on cost overrun.

4. Results

4.1 RBS

In this study, the RBS of country risk factors proposed in a previous research was utilized.(43) First, a total of 29 risk factors were identified by integrating overlapping and semantically similar risk factors. Second, 21 key country risk factors primarily considered in international construction projects were derived through consultations with experts experienced in executing such projects. Country risks were categorized into six types: Political, Economic, Culture, Environment, Market, and Legal. The finalized RBS is presented in Table 3.

4.2 Risk PI evaluation

In this study, a PI evaluation of country risk factors was conducted using survey data. Through this evaluation, the risk levels of each factor were calculated, and their risk ranks were derived. The survey served as a "detection sensor" that collected data on risks by leveraging the expertise of professionals to identify and evaluate country risk factors.(44) The survey data consisted of 93 responses regarding country risk factors, as outlined by Na *et al.*(43)

The survey targeted Korean experts with experience in executing international construction projects. The evaluation criteria used in the survey for risk factors were categorized into probability and impact. Probability refers to the likelihood that country risk factors will occur during international construction projects. Impact refers to the extent to which these risk factors affect construction cost. The evaluations were conducted using a 7-point Likert scale, ranging from "Very Low" (1) to "Very High" (7).

Table 3
Identification of country risk factors in international construction projects.

Category	Item	Risk
Political	P1	Interference and regulation by state and central government
	P2	Business suspension and adverse results due to regime change, civil war, etc.
	P3	Corruption in target country, such as bribery, conspiracy, etc.
Economic	E1	Economic/financial downturn in target country
	E2	Fluctuation in wage or unit price of materials
	E3	Effects of fluctuations in international currencies and exchange rates
Culture	C1	Language barrier and cultural differences
	C2	Conflict due to religious and cultural differences
	C3	Conflict with relevant organizations, etc.
Environment	En1	Climate and weather effects
	En2	Force majeure effects
	En3	Ground/territorial effects
	En4	Environmental protection regulation in the target country
Market	M1	Status of technical personnel in target country
	M2	Different field conditions from design
	M3	Lack of infrastructure
	M4	Difficulty in securing local material/equipment
	M5	Project experience in target country
Legal	L1	Delay in licensing and construction paperwork process
	L2	Irrational claims and litigation
	L3	Unfair imposition of tax and application of tax rates

The PI evaluation of country risk factors revealed the top five factors most significantly affecting international construction costs: “En1 (economic/financial downturn in target country)”, “L1 (delay in licensing and construction paperwork process)”, “M4 (difficulty in securing local material/equipment)”, “E2 (fluctuation in wage or unit price of materials)”, and “En3 (ground/territorial effects)”. The PI evaluation results of the country risk factors are summarized in Table 4.

4.3 Results of PLS-SEM for country risk factors

4.3.1 Measurement model evaluation results

In this study, we constructed a measurement model based on the PI evaluation results of the previously identified risk factors and performed a significance assessment of the measurement model. From the significance verification, three risk factors were determined to be nonsignificant: “En1 (climate/weather-related impacts)”, “C1 (language barriers and cultural differences)”, and “C2 (religious and cultural differences)”. Therefore, these were excluded from the analysis. The risk factor “C3 (conflicts with relevant organizations)” was excluded from the significance evaluation because it individually represented a “Culture” risk. For the remaining measurement variables (which were not considered inadequate), the CR values exceeded the reasonable threshold of 0.6. This ensured internal consistency reliability. The results of the internal consistency reliability evaluation are shown in Table 5.

Table 4
Results of *PI* evaluation for country risk factors.

Rank	Risk factors	Results	Rank	Risk factors	Results	Rank	Risk factors	Results
1	En 1	5.408	8	E 3	4.317	15	En 4	3.654
2	L 1	4.715	9	M 2	4.293	16	C 1	3.570
3	M 4	4.644	10	P 1	4.127	17	L 3	3.258
4	E 2	4.565	11	L 2	4.076	18	C 3	3.176
5	En 3	4.461	12	M 3	4.025	19	C 2	3.120
6	M 1	4.426	13	En 2	3.752	20	P 2	2.976
7	M 5	4.418	14	E 1	3.726	21	P 3	2.972

Table 5
Internal consistency reliability evaluation of the measurement model.

Category	*CR* values
Economic	0.883
Environment	0.871
Legal	0.853
Market	0.886
Political	0.826

Next, in the evaluation of convergent validity, the measurement variables achieved an AVE exceeding the reasonable threshold of 0.5. This validated the relationship between the latent and measurement variables. The results of the AVE evaluation are presented in Table 6.

Finally, in the evaluation of the discriminant validity, the *HTMT* ratios of the measurement variables were below 0.85. This verified that the individual measurement variables did not relate to the other latent variables, thereby ensuring discriminant validity. The results of the HTMT evaluation are shown in Table 7. Note that the "Political" category (composed of one measurement variable) was excluded from the HTMT evaluation criteria.

The thresholds applied for evaluating the measurement model were selected in accordance with established guidelines for PLS-SEM to ensure the reliability and validity of the constructs. The CR values for all latent variables exceeded the threshold of 0.6, indicating satisfactory internal consistency reliability across the measurement model. Similarly, the AVE values surpassed the 0.5 benchmark, thereby confirming convergent validity and demonstrating that each latent construct adequately captures the variance of its associated indicators (Fornell and Larcker[33]). Furthermore, the HTMT ratios for all constructs were below the conservative threshold of 0.85, as recommended by Clark and Watson[34] and Kline,[35] thereby verifying discriminant validity and confirming the empirical distinctiveness of the latent constructs.

Collectively, these results substantiate the robustness of the measurement model, despite the challenges associated with the relatively small sample size, which is a common limitation in empirical studies involving international construction projects.

Table 6
AVE evaluation results of the measurement model.

Category	*AVE*
Culture	1.000
Economic	0.716
Environment	0.693
Legal	0.665
Market	0.609

Table 7
HTMT evaluation results of the measurement model.

	Cost Overrun	C	E	En	L	M	P
Cost Overrun							
C	0.280						
E	0.289	0.262					
En	0.406	0.625	0.660				
L	0.343	0.379	0.562	0.566			
M	0.353	0.395	0.766	0.808	0.741		
P	0.165	0.257	0.608	0.393	0.688	0.581	

4.3.2 Assessment of structural model

In this study, the structural model was evaluated to identify the impact relationships among latent variables. The results are shown in Fig. 2.

First, the significance and fit of the path coefficients were assessed. All the latent variables had path coefficients that did not include zero within their confidence intervals. The *t*-values and p-values satisfied the acceptance criteria, being above 1.96 and below 0.05, respectively. In terms of the relationship between the country risk factors and cost overrun, "Environment" risk was verified to have a direct impact on cost overrun. Meanwhile, "Culture", "Economic", and "Legal" risks were observed to have indirect effects. Among the relationships among country risk factors, "Culture" risk was observed to directly affect "Environment" risk. "Economic" risk directly impacts "Environment", "Market", and "Political" risks. Meanwhile, "Legal" risk has a direct effect on "Culture" risk and an indirect effect on "Environment" risk. The results of the path coefficients and their significance and fit evaluations for the structural model are shown in Table 8.

The evaluation results of the structural model verified that all the latent variables had explanatory capability. Moreover, the effect sizes for explanatory capability were also achieved. Additionally, by verifying that all the items had values higher than zero, the predictive relevance of the model was established. The results related to the explanatory capability, effect size, and predictive relevance of the country risk factors are shown in Table 9.

5. Discussion

In this study, PLS-SEM was used to analyze the direct and indirect relationships of key country risk factors encountered in international projects and to assess the impact of these factors on cost overrun. The analysis yielded the following key findings:

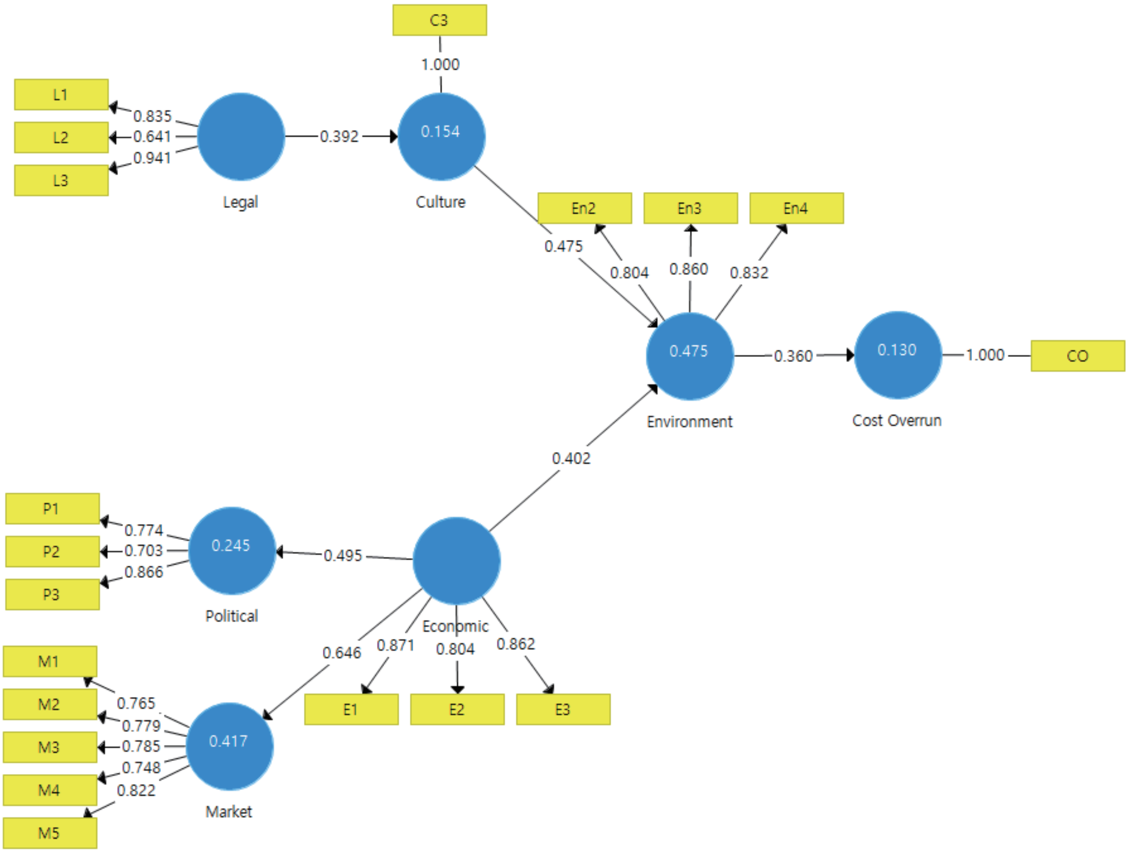

Fig. 2. (Color online) Final structural equation model of country risk factors.

Table 8
Significance and fit evaluation of path coefficients.

Latent variables	Path coefficients (β)	Confidence intervals 2.5%	Confidence intervals 97.5%	*t*-value	*p*-value	Relationship
Environment → Cost Overrun	0.360	0.147	0.535	3.646	0.000	direct
Culture → Cost Overrun	0.171	0.058	0.298	2.778	0.005	indirect
Economic → Cost Overrun	0.145	0.045	0.248	2.786	0.005	indirect
Legal → Cost Overrun	0.067	0.022	0.133	2.332	0.020	indirect
Culture → Environment	0.475	0.303	0.633	5.724	0.000	direct
Economic → Environment	0.402	0.222	0.554	4.787	0.000	direct
Economic → Market	0.646	0.539	0.760	11.269	0.000	direct
Economic → Political	0.495	0.339	0.660	6.033	0.000	direct
Legal → Culture	0.392	0.259	0.542	5.410	0.000	direct
Legal → Environment	0.186	0.103	0.297	3.730	0.000	indirect

Environmental risk exhibited the strongest direct effect on cost overrun ($\beta = 0.360$, $p < 0.001$), underscoring the importance of early environmental risk assessments, contingency planning for weather-related disruptions, and strict adherence to environmental regulations in the host country.

Table 9
Evaluation results of the structural model.

Method	Criteria			Results		
Coefficients (R^2)	High explanatory capability $R^2 > 0.26$	Mid explanatory capability $0.13 < R^2 < 0.26$	Low explanatory capability $R^2 < 0.13$	Environmental	0.463	High
				Market	0.411	High
				Political	0.236	Mid
				Culture	0.144	Mid
				Cost Overrun	0.120	Low
Effect size (f^2)	High effect size $f^2 > 0.35$	Mid effect size $0.15 < f^2 < 0.35$	Low effect size $f^2 < 0.15$	Economic → Market	0.716	High
				Culture → Environment	0.406	High
				Economic → Political	0.324	Mid
				Economic → Environment	0.292	Mid
				Legal → Culture	0.182	Mid
				Environment → Cost Overrun	0.149	Low
Predictive relevance (Q^2)	$Q^2 > 0$			Cost Overrun	0.119	Predictive relevance established
				Culture	0.140	
				Environment	0.315	
				Market	0.236	
				Political	0.128	

Cultural risk had an indirect impact on cost overrun ($\beta = 0.171$) through its strong association with environmental risk ($\beta = 0.475$), indicating that cultural misalignment may intensify environmental challenges. This suggests the need for effective stakeholder communication strategies, local workforce integration, and culturally tailored project governance.

Economic risk showed statistically significant indirect effects on cost overrun ($\beta = 0.145$) while also affecting market ($\beta = 0.646$), political ($\beta = 0.495$), and environmental risks ($\beta = 0.402$). This highlights the critical role of macroeconomic conditions in shaping multiple project risks. Consequently, international firms should adopt financial risk mitigation strategies such as hedging, flexible contracting, and cost indexing mechanisms.

Although legal risk had the smallest effect on cost overrun ($\beta = 0.067$), it significantly affected cultural risk ($\beta = 0.392$), which in turn affected environmental risk. This finding points to the indirect but impactful role of legal risk in shaping project uncertainty. Early-stage legal due diligence, engagement with local regulatory bodies, and clear contract structuring are essential to minimize legal risk.

These findings highlight that effective risk management in international construction projects requires a holistic approach that accounts for both direct and mediated relationships among multiple risk categories. Prioritizing interconnected risks rather than treating them in isolation can enhance project resilience and cost control.

6. Conclusion

In this study, we aimed to develop an analytical framework that systematically analyzes the interactions and causal relationships between country risk factors, leveraging expert-driven experience and intuition-based sensing data, and we quantitatively assessed their impact on cost overruns in international construction projects. By conceptualizing expert judgment as sensor-like qualitative inputs and integrating these sensor-inspired data into PLS-SEM, the framework bridges tacit insights and quantitative modeling under data-constrained conditions. The findings provide significant insights into risk prioritization and mitigation strategies, contributing to the development of appropriate country risk management strategies for international construction projects.

The theoretical considerations in this study reviewed and categorized country risk factors into six dimensions: political, economic, cultural, environmental, market, and legal risks. The literature review reinforced the necessity of moving beyond traditional risk analysis methodologies by emphasizing the importance of quantifying the organic causal relationships among risk factors. Previous studies have primarily utilized regression models or CB-SEM, which require large datasets. However, we demonstrated that PLS-SEM effectively addresses these limitations by facilitating analysis with small sample sizes while capturing complex interactions among risk factors.

The research methodology employed a structured framework in which expert-driven inputs were integrated for PLS-SEM analysis to quantitatively assess the causal relationships among country-specific risk factors. Expert-driven inputs were treated as proxy sensing data, enhancing data accuracy and robustness when direct measurements are infeasible. The PI evaluation quantified risk factors on the basis of expert perceptions, serving as a foundation for constructing the structural equation model. The integration of sensors in data collection methodologies allowed for the enhancement of data accuracy and reliability, ensuring robust model estimation. The PLS-SEM framework validated the relationships among risk factors and provided empirical evidence supporting the hypothesized risk dependencies.

The results of this study confirmed that economic and environmental risks exert the most significant impact on cost overruns in international construction projects. The analysis revealed that economic risk factors, such as currency fluctuations and market instability, not only affect cost overruns but also propagate their effects through other risk categories, including market and political risks. Similarly, environmental risks demonstrated a direct impact on cost fluctuations, further emphasizing the necessity of country risk factors into project planning.

In the discussion section, we interpreted the findings within the broader context of construction risk management, reinforcing the practical implications for industry stakeholders. We underscored the importance of developing comprehensive risk mitigation strategies that account for the interdependencies among country risk factors rather than treating them as isolated variables. By leveraging PLS-SEM as an analytical tool, construction firms can optimize their risk management frameworks and enhance decision-making processes in international markets.

In conclusion, this study contributes to the field of construction risk management by proposing an innovative analytical framework that systematically evaluates the organic causal relationships among country-specific risk factors. The application of expert-driven experience and intuition-based sensing data and PLS-SEM demonstrated its effectiveness in overcoming the limitations of traditional methods, offering a viable alternative for analyzing complex risk structures with limited datasets. The key findings and implications derived from the analysis are as follows:

First, the organic causal relationships among country risk factors were identified, and their impact on cost overrun in international construction projects was quantified and verified. The analysis confirmed that the risk factor with the most direct and indirect relationships among country risks is "Economic" risk. Additionally, "Environment" risk was identified as the country risk factor with the greatest impact on cost overrun. These findings indicate that construction companies need to develop comprehensive response strategies that consider the interrelationships among risk factors, rather than addressing individual risk factors in isolation, when executing international construction projects.

Second, the validity of PLS-SEM was verified. By effectively analyzing complex organic causal relationships with a small sample size, PLS-SEM was shown to overcome the limitations of CB-SEM, such as its high sample size requirement and strict distributional assumptions.

This study is significant in that it proposed a framework capable of identifying the organic causal relationships among risk factors and quantifying their impact on cost overrun, even with a small sample size. However, the study has certain limitations that require further research to address, as follows:

First, the data used for the analysis relied on surveys of Korean experts, which may be affected by the subjective judgments of the respondents. To enhance the reliability of the analysis, it is necessary to expand objective analytical data, including quantitative indicators derived from this study's findings. Future work could explore integration of actual sensing technologies or secondary datasets (e.g., real-time economic indicators, environmental monitoring via IoT) to complement expert-derived inputs and strengthen empirical robustness.

Second, the validity of PLS-SEM should be further verified through comparative studies with existing methodologies such as Bayesian Network analysis and CB-SEM. Moreover, comparative evaluations could assess how the sensor-inspired expert inputs perform relative to purely objective sensor or big-data-driven approaches when such datasets are available.

Future research should secure sufficient sample sizes and, where appropriate, narrow the scope to specific countries or project types while validating the applicability of PLS-SEM through comparative evaluations with CB-SEM and Bayesian Network analysis. To enhance generalizability and practical relevance, datasets should be expanded to encompass diverse project contexts across regions and industry sectors, and longitudinal studies should be undertaken to observe how regional, institutional, and temporal conditions affect risk interactions over time. By embedding sensor-inspired expert inputs into this quantitative modeling paradigm, such efforts will pave the way for technology-supported risk analysis in international construction—enabling practitioners to make informed decisions under confidentiality and data constraints—and contribute to a more robust, adaptive, and data-driven framework for managing global construction risks.

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