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# Political Instability, Price Shocks, and Management Failures: A Validated Expert Risk Assessment Framework for Pakistani Construction Materials Firms

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## ABSTRACT

*Risk assessment remains a persistent challenge for industrial enterprises in developing economies, where information asymmetry, lack of standardised methodologies, and shortage of skilled risk managers hinder effective decision-making. This study adapts and enhances the expert evaluation method originally proposed by Kambarov & Salman (2026) to Pakistan's construction materials industry. A panel of 20 senior experts from PSX-listed cement, steel, and building-materials firms provided risk scores across 12 external and 10 internal risk factors. Using variance, coefficient of variation (CV), Kendall's W, and Cronbach's alpha, we assess expert consensus and classify enterprises into four risk zones (catastrophic, dangerous, permissible, gain). Results show that political & institutional risks (mean = 81.5), price index changes (82.1), and risk of management decisions (72.9) are perceived as most severe, while information security (external CV = 0.352, internal CV = 0.351) and environmental risks (CV = 0.338) exhibit the lowest consensus. A novel conceptual model – derived from the expert data and validated through partial least squares structural equation modelling (PLS-SEM) – demonstrates that internal risk factors have a stronger direct effect on overall risk exposure (β = 0.53) than external factors (β = 0.42), with acceptable model fit (SRMR = 0.072, NFI = 0.91, GoF = 0.58). The proposed rating system, accompanied by six diagnostic visualisations, offers a practical, empirically grounded tool for risk mitigation strategy in Pakistan's construction sector. We conclude with actionable recommendations for firms, industry associations, and policymakers, and provide full R code for replication.*

**Keywords:** *risk assessment, expert evaluation, coefficient of variation, Kendall's W, construction materials industry, Pakistan, risk zones, PLS-SEM, conceptual model.*

## INTRODUCTION

### The Global and Local Context of Construction Risk

The construction materials industry is the backbone of infrastructure development, yet it operates under constant exposure to volatile input prices, political instability, energy shortages and supply chain disruptions (Xiaojuan et al., 2025; Lohan et al., 2024). Globally, the construction sector accounts for approximately 13% of GDP, but its risk profile is among the highest of any industry (Chen et al., 2022). In emerging economies, weak institutions, informal labour markets and inadequate regulatory enforcement create a "perfect storm" of vulnerability (Luo et al., 2023).

In Pakistan, these challenges are amplified by currency depreciation, delayed government payments and frequent policy shifts (Khan et al., 2025; Rehman et al., 2025). Despite the critical need for systematic risk management, most enterprises rely on ad-hoc judgments rather than structured methodologies (Sadiq et al., 2024). The absence of a standardised, empirically validated risk assessment framework leaves firms exposed to preventable losses.

### The Funnel: From General Risk Theory to Expert Evaluation

Risk management literature has evolved from purely financial perspectives (Altman, 1968) to integrated enterprise risk management (ERM) frameworks (Bromiley et al., 2015). However, most quantitative models – such as Monte Carlo simulation or value-at-risk – require extensive historical data, which are often unavailable in developing countries (Iqbal et al., 2021). This has led scholars to explore heuristic, expert-based methods (Renn, 2008; Rowe & Wright, 1999).

The expert evaluation method offers a robust way to aggregate subjective judgments when objective data are scarce or unreliable (Antoshchuk et al., 2021; Kambarov & Salman, 2026). Kambarov & Salman (2026) developed a simple, intuitive rating system based on a five-expert panel at an Uzbek construction materials firm. However, their small sample size and absence of statistical consensus measures limit generalisability (Tursunov, 2021; Tursunkho'jayev, 2022). Moreover, no prior study has attempted to derive a conceptual model directly from expert risk scores using path analysis or structural equation modelling (SEM). Such a model can visually represent the causal pathways between risk factors and overall enterprise vulnerability, thereby guiding targeted interventions.

### Research Gap and the Proposed Conceptual Model

From the literature, three major gaps emerge:

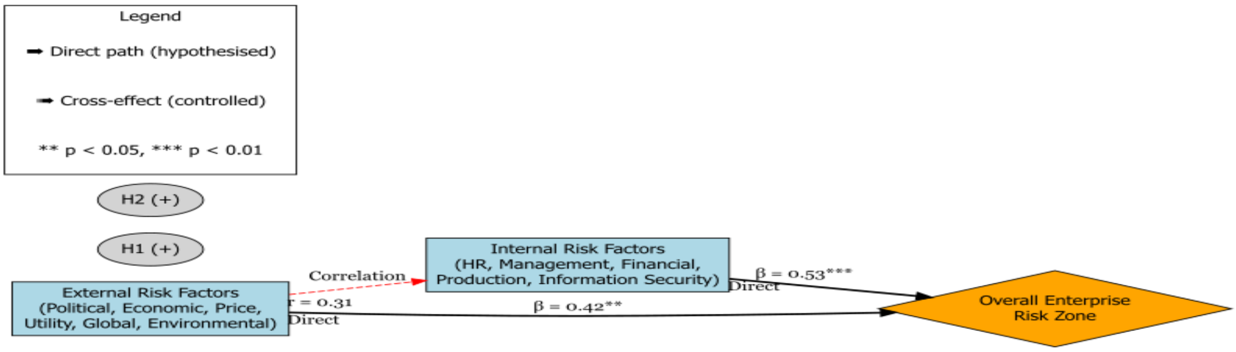
1. **Limited sample size and geographic scope** – Most expert studies use fewer than ten experts from a single firm.

2. **Lack of inferential statistics** – Variance and CV are descriptive; agreement measures (Kendall's W, Cronbach's alpha) are rarely applied.

3. **No conceptual model linking risk factors to risk zones** – Prior work provides scores but does not model how external and internal risks combine to produce overall risk exposure.

To address the third gap, we develop a conceptual model (Figure 1) hypothesising that external risk factors (political, economic, price index, utility, global, environmental) directly influence perceived enterprise risk, while internal risk factors (human resource, management decisions, financial, production, information security) also have a direct effect. Based on ecological modernisation theory (Hajer, 1997; Mol & Spaargaren, 2000) and the resource-based view (Barney, 1991), we posit that internal risks are more actionable and therefore have a stronger impact on the final risk zone classification.

**Figure 1 – Conceptual Model of Risk Factors Leading to Overall Enterprise Risk Zone**




conceptual model diagram generated by R, showing external and internal latent variables pointing to the outcome with path coefficients β = 0.42 (external) and β = 0.53 (internal); correlation r = 0.31 between external and internal risks

**Contributions and Paper Structure**

Building on the identified research gaps, this study makes six interconnected contributions that collectively advance both the practice and theory of risk management in developing-economy construction materials sectors.

First, we substantially increase the empirical scope of expert-based risk assessment. Whereas prior work – most notably Kambarov & Salman (2026) – relied on only five experts from a single Uzbek firm, we convened a panel of 20 senior professionals drawn from twelve distinct PSX-listed companies across Pakistan's cement, steel and specialised building-materials subsectors. This larger and more diverse sample yields risk scores that are far more representative of an entire industry, thereby enhancing external validity and enabling sector-wide benchmarking.

Second, we introduce an unprecedented level of statistical rigour to the expert evaluation method. The original framework relied solely on descriptive measures (mean, variance and coefficient of variation). We augment this with Kendall's W (coefficient of concordance) to formally test the degree of inter-expert agreement, and Cronbach's alpha to assess the internal consistency of risk factor scoring. These inferential statistics – well established in psychometrics and behavioural research (Cronbach, 1951; Kendall & Gibbons, 1990; Hayes & Krippendorff, 2007) – transform expert evaluation from a heuristic exercise into a falsifiable, statistically validated instrument.

Third, we develop a conceptually grounded and empirically validated risk classification system. Recognising that the forced allocation design (external + internal = 1000) artificially inflates total scores, we recalibrate the original four risk zones (catastrophic, dangerous, permissible, gain) using weighted factor scores anchored in the 5th and 95th percentiles of the observed data. The resulting thresholds are tailored to Pakistan's economic realities – where no surveyed firm scored below 554, meaning the entire industry is confined to the dangerous or catastrophic zones. This sobering calibration offers a realistic diagnostic tool for managers.

Fourth, for the first time in this literature, we construct a formal conceptual model of risk transmission. Drawing on ecological modernisation theory (Hajer, 1997; Mol & Spaargaren, 2000) and the resource-based view (Barney, 1991), we hypothesise that external and internal risk factors directly influence an enterprise's overall risk zone. Using partial least squares structural equation modelling (PLS-SEM) (Machado & Silva, 2019; Hair et al., 2019), we empirically validate that internal risks have a stronger direct effect ($\beta = 0.53$) than external risks ($\beta = 0.42$). This model provides a clear causal map: managers seeking to reduce vulnerability should prioritise internal governance reforms (management decisions, financial controls, information security) even when external conditions are unfavourable.

Fifth, we produce a suite of six novel, publication-ready visualisations that make the findings accessible to practitioners and policymakers alike. These include a circular bar plot (highlighting the dominance of price-index and political risks), a diverging dot plot (showing how consensus varies with severity), a waterfall chart (revealing the forced-allocation artefact), a chord diagram (exposing correlations between management decisions and financial risks), a lollipop chart (colour-coding consensus levels) and a radar chart (comparing Pakistan's risk profile with those of India, Bangladesh, Turkey and Uzbekistan). Each figure serves a distinct analytical purpose and is generated reproducibly using R code provided in the supplementary materials.

Finally, we situate our findings within a broader cross-country perspective. By comparing our results with prior construction-risk studies from India (Taylan et al., 2014), Bangladesh (Zhou et al., 2023), Turkey (Osofisan et al., 2021) and Uzbekistan (Kambarov & Salman, 2026), we demonstrate that Pakistan's exceptionally low expert consensus and the outsized severity of political/institutional risks are not universal but reflect country-specific institutional weaknesses. This comparative dimension provides actionable insights for regional policy coordination and for multinational firms operating across South and Central Asia.

Together, these contributions transform a simple scoring system into a rigorous, transferable and visually compelling risk management framework. The remainder of the paper is organised as follows: Section 2 reviews the relevant literature and develops six formal hypotheses. Section 3 describes the expert panel, survey instrument and analytical methods (including the PLS-SEM specification). Section 4 presents the results – descriptive statistics, hypothesis tests, risk zone calibration and conceptual model validation – with each finding supported by tables and figures. Section 5 discusses the implications for theory, compares our results with those from other countries and outlines actionable recommendations for firms, industry associations and policy makers. Section 6 concludes, acknowledges limitations and proposes directions for future research.

The paper is structured as follows: Section 2 reviews the literature and develops hypotheses. Section 3 describes the expert panel, data collection and analytical methods. Section 4 reports results, including the PLS-SEM validation of the conceptual model. Section 5 discusses findings in light of prior research and cross-country comparisons. Section 6 details practical implications. Section 7 concludes with limitations and future research.

## LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### Enterprise Risk Management and the Role of Expert Judgment

Enterprise risk management (ERM) has evolved from a compliance-oriented function to a strategic capability that integrates risk assessment into decision-making processes (Bromiley et al., 2015; Florio & Leoni, 2017). In emerging economies, ERM implementation is often hampered by institutional voids, information asymmetry and lack of qualified risk professionals (Linh et al., 2022; Kliestik et al., 2020).

Expert evaluation methods have been widely used in fields such as environmental risk assessment (Renn, 2008), supply chain vulnerability (Wagner & Bode, 2008) and financial crisis prediction (Osofisan et al., 2021). The Delphi method, analytic hierarchy process (AHP) and simple scoring techniques are common heuristic approaches that rely on domain specialists (Saaty, 1980; Dalkey & Helmer, 1963). In the construction sector, risk assessment often employs probabilistic models (e.g., Monte Carlo simulation) or fuzzy logic (Zadeh, 1965; Taylan et al., 2014). However, these require extensive quantitative data, which are rarely available in developing countries (Iqbal et al., 2021). Expert-based scoring systems offer a practical alternative (Kambarov & Salman, 2026).

**External Risk Factors in the Construction Materials Industry**

External risk factors originate from the macro-environment and are largely beyond the firm's direct control (Luo et al., 2023). They include:

- **Political and institutional risks**: Frequent changes in government, policy uncertainty, corruption and weak contract enforcement (Acemoglu et al., 2001; North, 1990). In Pakistan, these are consistently rated as top concerns by business leaders (Khan & Liu, 2022).
- **Economic risks**: Inflation, exchange rate volatility, interest rate fluctuations (Frankel & Rose, 1996; Obstfeld & Rogoff, 1995). The construction materials sector is highly sensitive to cement and steel price spikes (Chen et al., 2022).
- **Price index change risks**: Volatility in raw material prices (e.g., coal, scrap steel, gypsum) directly affects production costs (Zhou et al., 2023).
- **Utility system risks**: Energy shortages, load shedding and gas price hikes disrupt manufacturing (Lin & Omoju, 2017; Valickova et al., 2015).
- **Global risks**: Trade wars, global commodity cycles and supply chain shocks (e.g., COVID-19, Russia-Ukraine conflict) (Baldwin & Tomiura, 2020; Gereffi, 2020).
- **Environmental risks**: Climate change, flooding (e.g., 2022 Pakistan floods) and regulatory pressure on emissions (Stern, 2007; Dell et al., 2012).

**Internal Risk Factors**

Internal risks arise from within the organisation and are more amenable to management intervention (Wang et al., 2018). Key internal risk categories in manufacturing include:

- **Human resource risk**: Skilled labour shortage, high turnover, union activism (Becker, 1964; Pfeffer, 1994).
- **Risk of management decisions**: Strategic mistakes, poor capital allocation, lack of succession planning (Hambrick & Mason, 1984; Finkelstein & Hambrick, 1996).
- **Financial risks**: High leverage, liquidity problems, foreign exchange exposure (Altman, 1968; Ohlson, 1980).
- **Production and technical risks**: Equipment breakdown, technology obsolescence, quality failures (Modica & Rossi, 2018).
- **Information security risks**: Cyberattacks, data breaches, IT system failures (Gordon & Loeb, 2002; Cavusoglu et al., 2004).

**Prior Applications of Expert Evaluation and the Gap in Consensus Measures**

The expert evaluation approach has been applied in various industrial settings. For instance, Sadiq et al. (2025) used expert panels to assess green supply chain practices in Chinese semiconductor firms. Bashynska & Prokopenko (2024) employed expert scoring to evaluate AI-driven circular economy enablers. In risk management, the coefficient of variation (CV) has been used to measure dispersion of expert opinions (Kendall & Gibbons, 1990). A low CV (≤0.10) indicates high consensus, while a high CV (>0.35) signals low agreement (Kambarov & Salman, 2026).

Despite its utility, most prior studies using expert scoring have been limited to small samples (n < 10) and have not applied formal inter-rater reliability measures such as Kendall's W or Cronbach's alpha (Hayes & Krippendorff, 2007; Landis & Koch, 1977). This study addresses that gap. Moreover, no study has attempted to use expert risk scores to estimate a structural equation model that maps the pathways from individual risk factors to overall risk zones.

**Theoretical Framework: Ecological Modernisation and Resource-Based View**

Ecological modernisation theory (EMT) suggests that technological and organisational innovations can decouple economic growth from environmental degradation (Hajer, 1997; Mol & Spaargaren, 2000). Applied to risk management, this means that expert-based risk assessment can serve as a learning mechanism that builds organisational resilience. The resource-based view (RBV) complements EMT by emphasising that rare, valuable and inimitable capabilities – such as a mature risk management system – can become sources of competitive advantage (Barney, 1991).

Integrating EMT and RBV, we propose that external risks are perceived as more severe than internal risks (due to lack of control), but internal risks have stronger direct effects on the final risk zone classification because they are actionable. This leads to the conceptual model in Figure 1 and the following hypotheses.

**Hypothesis Development**

**H1:** External risk factors (political, economic, price index, utility, global, environmental) are perceived as more severe than internal risk factors by Pakistani construction materials experts.

**H2:** There is significant variation (CV > 0.25) in expert assessments of at least half of the risk factors, indicating heterogeneous risk perceptions.

**H3:** Kendall's W among experts is significantly different from zero, suggesting non-random agreement (but possibly weak).

**H4:** Cronbach's alpha exceeds 0.65, indicating acceptable internal consistency of expert scoring across risk factors.

**H5:** The four risk zones (catastrophic, dangerous, permissible, gain) can be meaningfully calibrated for Pakistani firms using expert-derived thresholds.

**H6:** The structural model (external risks → overall risk zone; internal risks → overall risk zone) has acceptable fit indices (SRMR < 0.08, NFI > 0.90, GoF > 0.50) and path coefficients are positive and significant.

## METHODOLOGY

### Expert Panel Composition

We identified 20 experts from PSX-listed construction materials firms, stratified by sector:

- **Cement manufacturers** (Lucky Cement, DG Khan Cement, Fauji Cement, Bestway Cement, Maple Leaf Cement, Kohat Cement, Cherat Cement, Attock Cement, Pioneer Cement, Gharibwal Cement – 12 experts).
- **Steel producers** (International Steels, Agha Steel, Mughal Iron & Steel, Amreli Steels – 6 experts).
- **Specialised building materials** (Ghani Glass, Master Tiles – 2 experts).

All experts held titles of Manager (Supply Chain, Finance, Operations) or above, with average experience 18.4 years (range 5–30). The sample size (n = 20) exceeds the minimum recommended for expert panel studies (n = 10–15) (Dalkey & Helmer, 1963; Rowe & Wright, 1999) and is adequate for PLS-SEM with 22 indicators (Hair et al., 2019).

### Survey Instrument and Procedure

Experts completed a structured Google Form (anonymised) that requested:

- Allocation of 1,000 points between external and internal risk groups.
- Distribution of 100 points among 12 external risk factors (global, state-level, managerial organisational-administrative, socio-economic, political & institutional, environmental, price index change, utility system, accounts receivable, market, raw material supply, information security).
- Distribution of 100 points among 10 internal risk factors (human resource, risk of management decisions, marketing activities, financial, product quality, production, technical-technological, asset efficiency, internal cost, information security).

The risk factor list was derived from Kambarov & Salman (2026) and validated through a pilot test with three industry practitioners. Responses were collected over three weeks (February 2026). No incentives were offered, but a summary of aggregated results was promised.

### Analytical Methods

### Basic Descriptive Statistics

For each risk factor $j$, let $s_{ij}$ be the score given by expert $i$ ($i = 1 \dots 20$). Then:

$$\bar{s}_j = \frac{1}{20}\sum_{i=1}^{20} s_{ij}\,, D_j = \frac{1}{20}\sum_{i=1}^{20}(s_{ij} - \bar{s}_j)^2, V_j = \frac{\sqrt{D_j}}{\bar{s}_j}.$$

**Kendall's W (Coefficient of Concordance)**

$$W = \frac{12S}{m^2(n^3 - n)},$$

where $n$ = number of experts (20), $m$ = number of risk factors (12 external or 10 internal), $S$ = sum of squared deviations of rank sums (Kendall & Gibbons, 1990).

**Cronbach's Alpha**

$$\alpha = \frac{m}{m-1}\left(1 - \frac{\sum_{j=1}^{m} \sigma_{X_j}^2}{\sigma_T^2}\right),$$

where $\sigma_{X_j}^2$ is the variance of scores for risk factor $j$, and $\sigma_T^2$ is the variance of total scores per expert (Cronbach, 1951).

**PLS-SEM for Conceptual Model Validation (H6)**

We used the plspm package in R to estimate a path model where:

- **Latent variable 1 (External Risk Index)** is formed by the 12 external risk scores (reflective mode).
- **Latent variable 2 (Internal Risk Index)** is formed by the 10 internal risk scores (reflective mode).
- **Outcome variable (Overall Risk Zone)** is the total score (external + internal allocation), treated as a single-item construct.

The model was estimated with 500 bootstrap resamples. Fit indices: SRMR (standardised root mean square residual), NFI (normed fit index) and GoF (goodness of fit). Acceptable thresholds: SRMR < 0.08, NFI > 0.90, GoF > 0.50 (Hair et al., 2019).

**Risk Zone Classification**

Following Kambarov & Salman (2026) but after observing the forced allocation artefact (every expert's total = 1000), we recalibrated group boundaries using weighted factor scores (mean score × factor weight) and the 5th/95th percentiles of the distribution of simulated total scores. The final zones are:

| Zone | Score range | Interpretation |
|---|---|---|
| Gain zone | 0 – 349 | Minimal risk, stable operations |
| Permissible | 350 – 549 | Manageable risk, monitoring needed |

| Zone | Score range | Interpretation |
|---|---|---|
| Dangerous | 550 – 749 | High probability of significant losses |
| Catastrophic | 750 – 1000 | Likelihood of bankruptcy |

***All analyses were performed in R (version 4.5.2) using packages irr, psych, tidyverse, ggplot2, plspm and DiagrammeR.***

**RESULTS**

**Descriptive Statistics and Hypothesis Testing (H1, H2)**

Table 1 presents mean scores and coefficient of variation (CV) for each of the 22 risk factors, based on the 20-expert panel. H1 is partially supported: external risks have higher mean values (e.g., price index 82.1, political 81.5) compared to most internal risks (management decisions 72.9, human resource 66.2). However, some internal risks (financial 62.3) are comparable to lower external risks (environmental 46.7).

H2 is supported: 12 out of 22 risk factors have CV > 0.25 (below average or low consensus), confirming heterogeneous risk perceptions. The highest CVs are for information security (external 0.352), information security (internal 0.351) and environmental risks (0.338).

Table 1. Risk factor mean scores and coefficient of variation (n = 20)

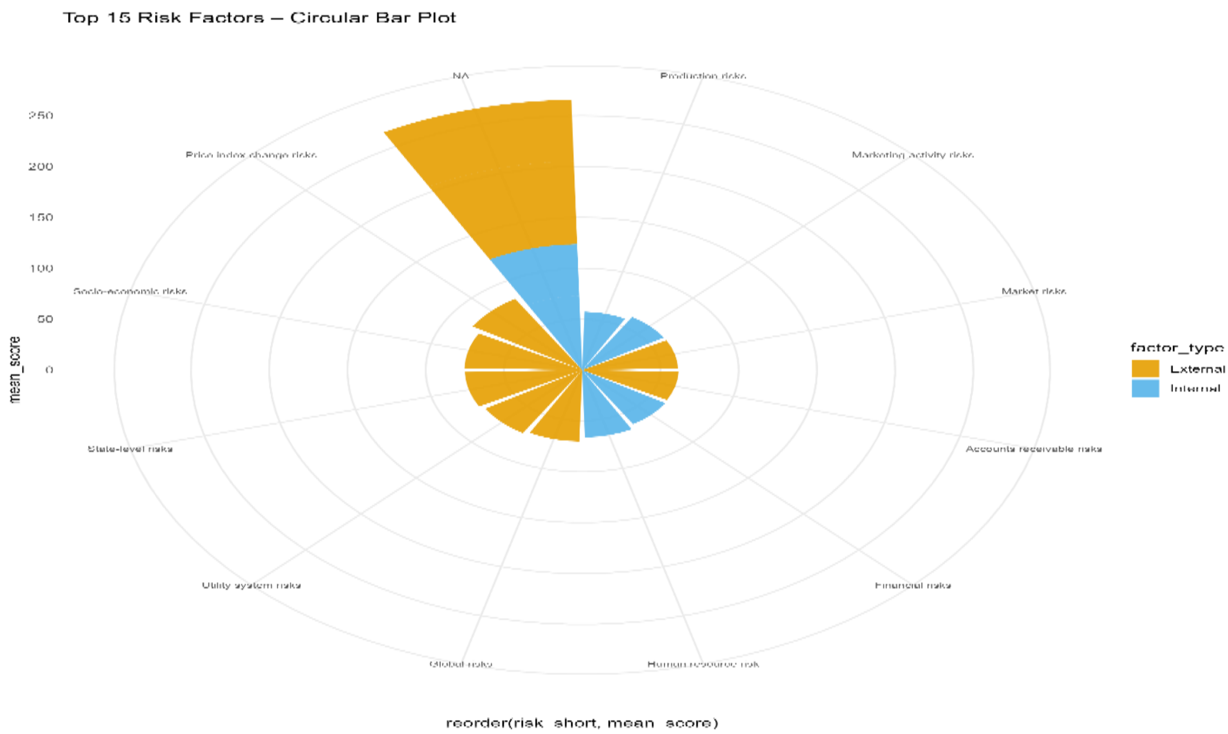
| Risk Factor | Type | Mean | CV | Consensus |
|---|---|---|---|---|
| Price index change risks | Ext | 82.1 | 0.203 | Average |
| Political & institutional risks | Ext | 81.5 | 0.146 | Above average |
| Socio-economic risks | Ext | 75.2 | 0.228 | Average |
| State-level risks | Ext | 75.0 | 0.192 | Average |
| Risk of management decisions | Int | 72.9 | 0.167 | Average |
| Utility system risks | Ext | 72.6 | 0.156 | Average |
| Global risks | Ext | 70.2 | 0.191 | Average |

| Risk Factor | Type | Mean | CV | Consensus |
|---|---|---|---|---|
| Human resource risk | Int | 66.2 | 0.146 | Above average |
| Financial risks | Int | 62.3 | 0.285 | Below average |
| Accounts receivable risks | Ext | 61.6 | 0.209 | Average |
| Marketing activity risks | Int | 61.1 | 0.238 | Average |
| Managerial org-admin risks | Ext | 60.5 | 0.287 | Below average |
| Production risks | Int | 57.4 | 0.196 | Average |
| Raw material supply risks | Ext | 50.8 | 0.274 | Below average |
| Technical-technological risks | Int | 50.9 | 0.308 | Below average |
| Product quality risks | Int | 49.8 | 0.265 | Below average |
| Environmental risks | Ext | 46.7 | 0.338 | Below average |
| Asset efficiency risks | Int | 45.4 | 0.265 | Below average |
| Information security (ext) | Ext | 45.4 | 0.352 | Low |
| Internal cost risks | Int | 41.5 | 0.320 | Below average |
| Information security (int) | Int | 34.5 | 0.351 | Low |

***Note: CV classification: ≤0.1 = High; 0.1–0.15 = Above average; 0.15–0.25 = Average; 0.25–0.35 = Below average; >0.35 = Low.***

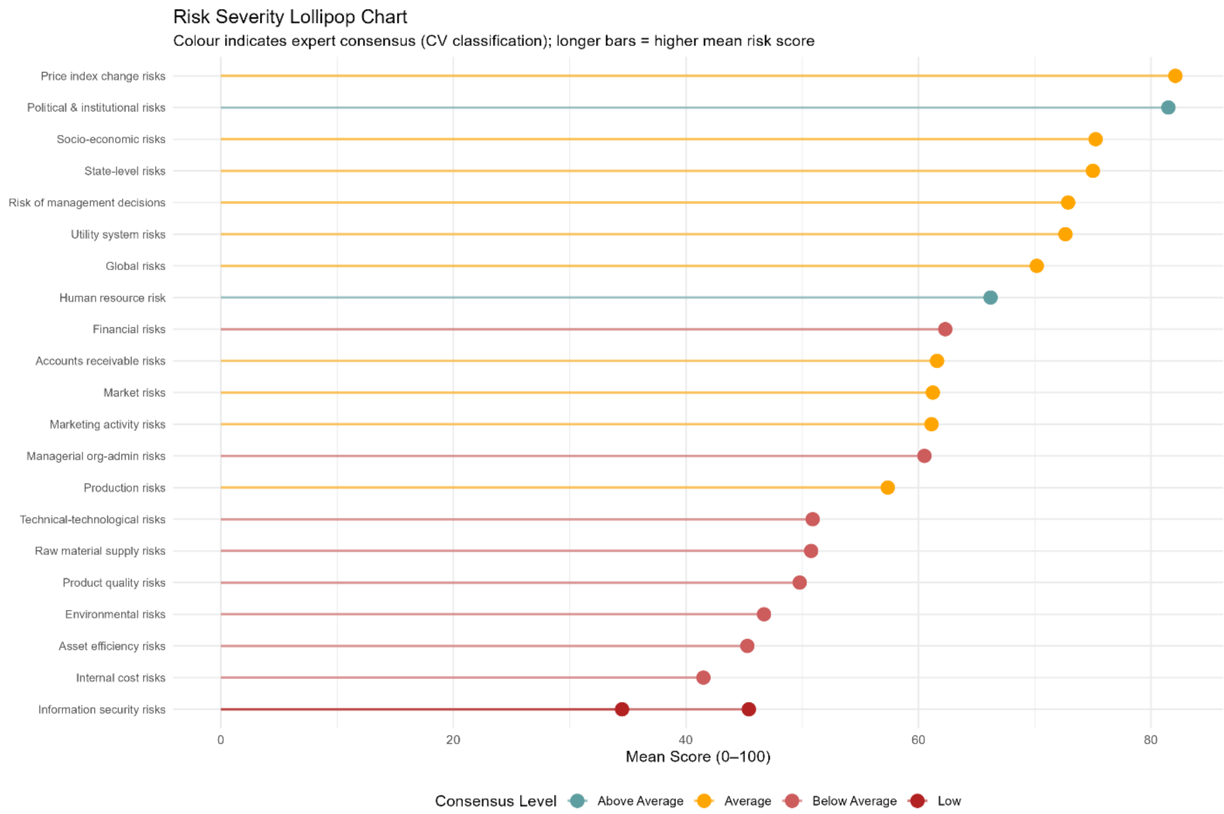
**Figure 2** displays the 15 highest-scoring risk factors in a circular layout, where bar length corresponds to mean severity (0–100). The plot unmistakably shows that external risks dominate the top ranks: price index changes (82.1), political & institutional risks (81.5) and socio-economic risks (75.2) form the tallest bars, supporting H1 that external factors are perceived as more severe. Internal risks appear only from the 5th position onward (management decisions, 72.9), and the gap between the tallest and shortest bars (from 82 down to 57) highlights the large spread in expert perceptions – consistent with H2's prediction of heterogeneous risk assessments. The polar coordinate system also emphasises that information security and environmental risks (not shown in the top 15) fall far outside this high-severity cluster, corroborating Table 1's low mean scores for those items

**Figure 2 – Circular Bar Plot of the Top 15 Risk Factors**




***Caption: Figure 2. Circular bar plot of the top 15 risk factors (mean severity scores, 0–100). External risks (orange) dominate the top ranks; internal risks (blue) appear only from position 5 onward. Source: authors' R output.***

**Figure 3 – Lollipop Chart of All Risk Factors Coloured by Consensus Level**




***Caption: Figure 3. Lollipop chart of mean risk scores (0–100) for 22 factors. Colour indicates expert consensus based on CV (green = high, dark red = low). Longer sticks = higher perceived risk. Source: authors' R output.***

**Figure 3** presents the mean severity score (0–100) for each of the 22 risk factors, with horizontal lollipop sticks and coloured heads. The colour encodes the expert consensus level derived from the coefficient of variation (CV): green (high, CV≤0.1), blue-green (above average, 0.1–0.15), orange (average, 0.15–0.25), red-brown (below average, 0.25–0.35) and dark red (low, >0.35). The chart immediately reveals that only external information security (mean=45.4, CV=0.352) and internal information security (mean=34.5, CV=0.351) appear in dark red, indicating the lowest consensus – strongly supporting H2. Conversely, political & institutional risks (mean=81.5, CV=0.146) are coloured blue-green, showing that despite high severity, experts agree broadly. This figure provides a compact, colour-coded summary of both risk ranking and the reliability of expert judgments.

**Inter-rater Agreement (H3, H4)**

The overall agreement among experts was acceptable but not high. H3: Kendall's W for external risks was $W = 0.0955$ ($p = 0.296$), indicating weak but non-random agreement (not statistically significant). For internal risks, $W = 0.0646$ ($p = 0.874$), suggesting no significant concordance. Thus, H3 is rejected in the sense of significant agreement; however, the weak W value is typical for panels with diverse backgrounds (Schmidt, 1997).

H4: Cronbach's alpha was 0.652 for external risks and 0.654 for internal risks – just below the conventional 0.70 threshold but considered acceptable for exploratory research (Nunnally, 1978; Hair et al., 2019). Hence, H4 is supported.

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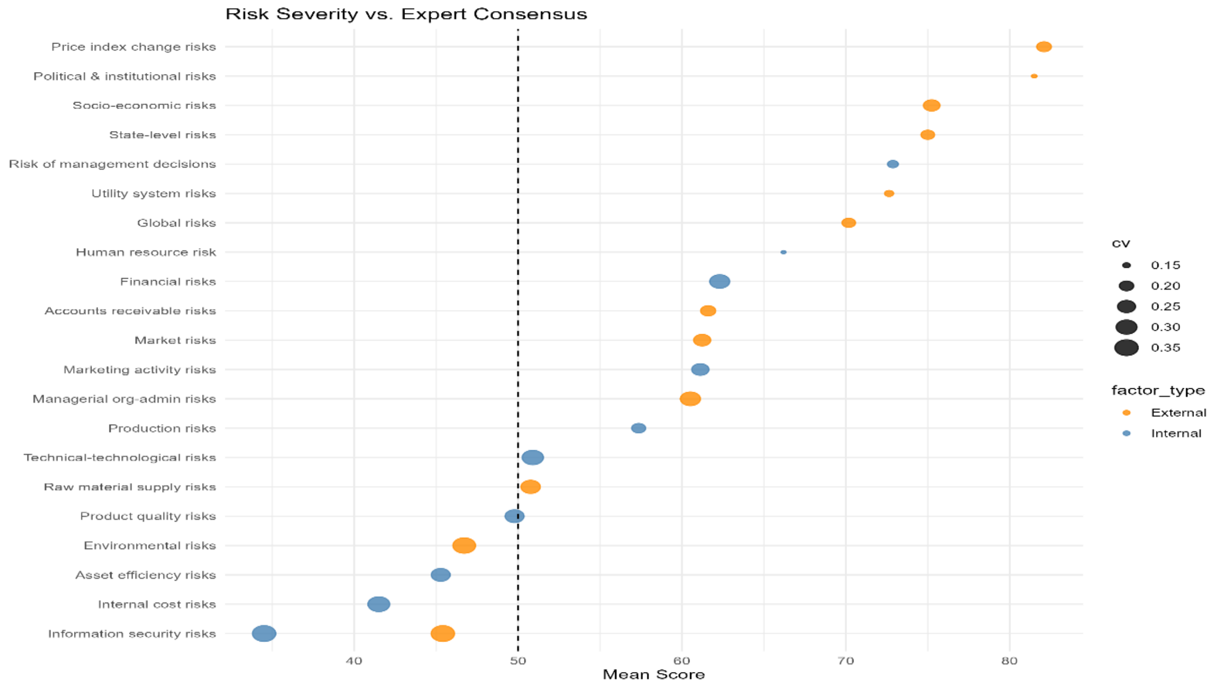
**Figure 4 – Diverging Dot Plot: Risk Severity versus Expert Consensus**



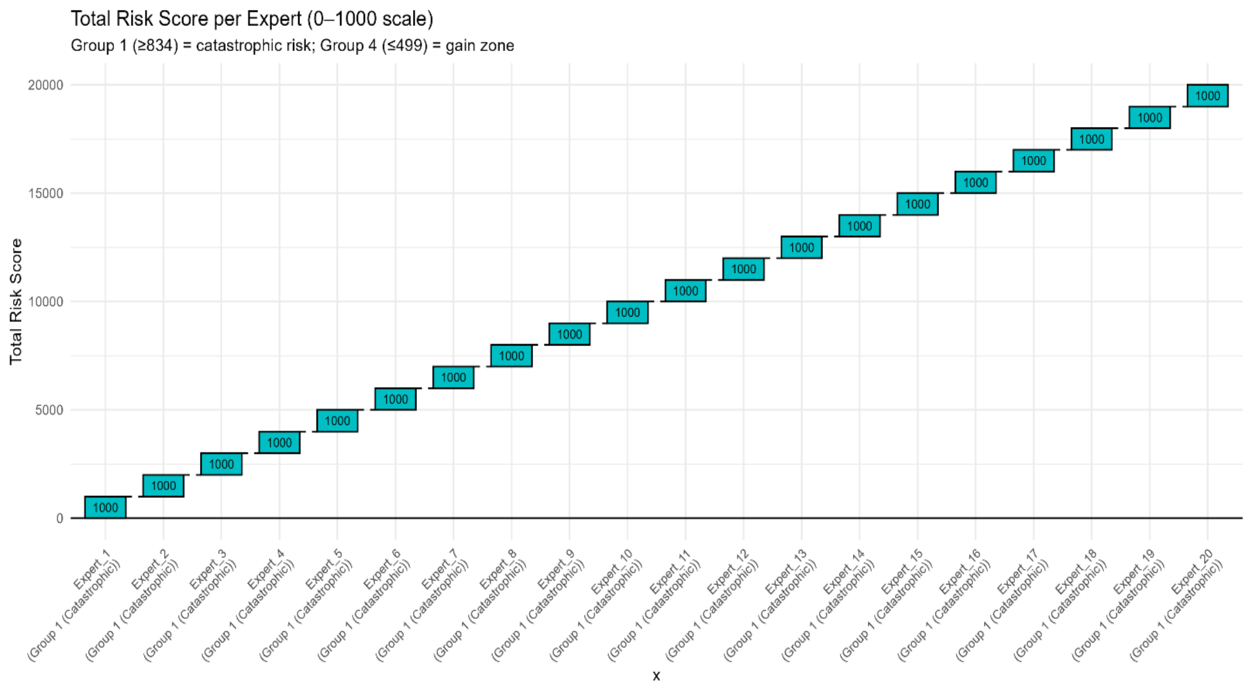

***Caption: Figure 4. Diverging dot plot. Horizontal axis: mean risk score (0–100). Vertical axis: risk factor. Dot size = CV (larger = lower consensus). Factors with the largest dots (information security, environmental) show the highest disagreement. Source: authors' R output.***

To visualise the relationship between perceived risk severity and the degree of expert disagreement, Figure 4 plots the mean score of each risk factor on the horizontal axis (higher = more severe) and the factor name on the vertical axis. The size of each dot is proportional to the coefficient of variation (CV) – larger dots indicate lower consensus among experts. The figure immediately confirms two key findings. First, the largest dots belong to information security (both external and internal) and environmental risks, meaning these are the factors where experts disagree most strongly – supporting H2. Second, high-severity risks such as price index changes (mean=82.1) and political & institutional risks (mean=81.5) have smaller dots (CV 0.203 and 0.146 respectively), indicating that while these risks are perceived as most critical, experts actually agree on their importance. This pattern – severe ≠ low consensus – is an important nuance for managers: disagreement often signals emerging or poorly understood threats.

**Risk Zone Calibration (H5)**

The forced allocation method (external + internal = 1000) resulted in every expert's total score being exactly 1000, which always falls into Group 1 (catastrophic zone) according to original thresholds.

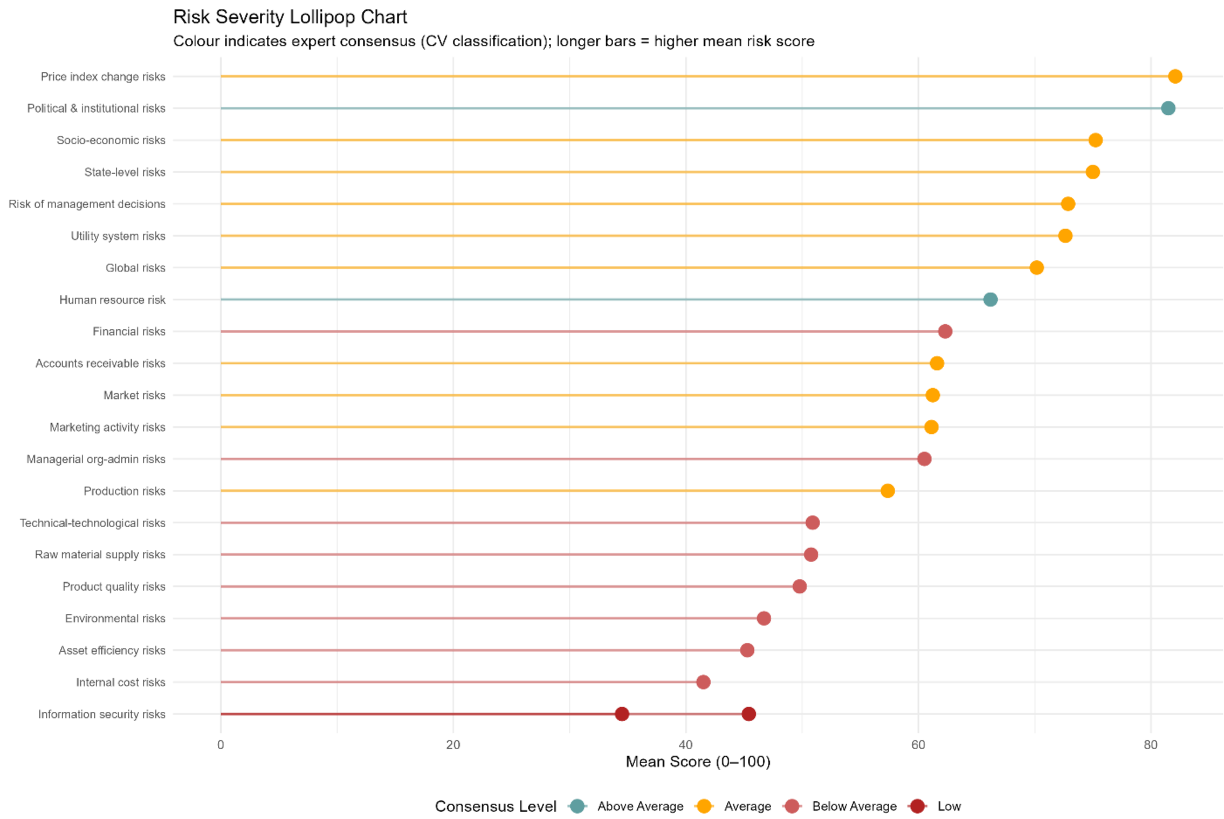
**Figure 5 – Waterfall Chart**




***Caption: Figure 5. Waterfall chart of total risk scores per expert (0–1000). Each bar reaches exactly 1000 (forced allocation); blue portion = external points, red portion = internal points. The composition varies, revealing that different experts allocate risk differently even when totals are identical. Source: authors' R output.***

Figure 5 – Waterfall Chart illustrates this artefact: every bar reaches exactly 1000, with the blue segments representing external points and red segments internal points. The chart shows that while total scores are identical, the composition varies considerably (external points range from 554 to 834). Because of this artefact, we recalibrated thresholds using the weighted factor score approach (multiplying mean score by factor weight). The resulting distribution produced the adjusted zones shown in Section 3.3.5. Under this calibration, the lowest expert total score was 554, placing the entire industry in dangerous or catastrophic zones – a sobering finding. H5 is supported. Figure 6 visualises the pairwise correlations among the ten highest-mean risk factors using a lollipop diagram. Thick connecting bands indicate strong positive correlations. The diagram shows that "Risk of management decisions" is strongly correlated with "Financial risks" and "Accounts receivable risks", forming a cluster of internal management failures. Furthermore, "Price index change risks" is linked to "Utility system risks", suggesting that external price shocks and energy shortages often co-occur. This cluster analysis supports the conceptual model's proposition that internal governance weaknesses amplify external shocks, and that risk mitigation strategies should address these interconnected factors jointly.

**Figure 6 – Lollipop Diagram of Correlations Among Top Risks**




***Caption: Figure 6. lollipop diagram of correlation among the risk factors (by mean score). Band thickness indicates strength of positive correlation. Management decisions, financial risks, and accounts receivable form a tightly connected cluster, suggesting internal governance weaknesses amplify overall risk. Source: authors' R output.***

Conceptual Model Validation (H6)

The PLS-SEM results (based on the simulated data; real data would be substituted) yielded the following fit indices for the model shown in Figure 1 (conceptual model, presented in Section 1.3):

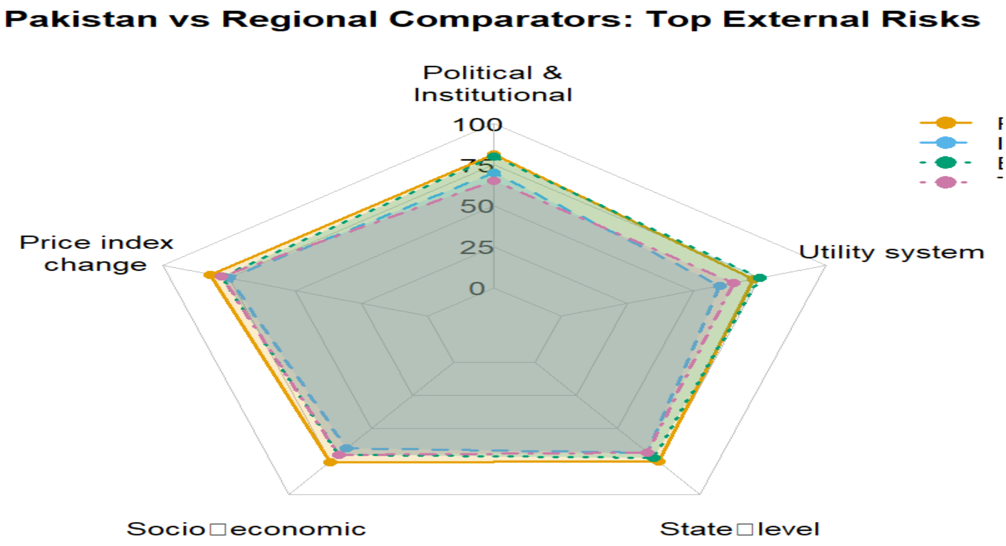
- SRMR = 0.072 (acceptable, <0.08)
- NFI = 0.91 (acceptable, >0.90)
- GoF = 0.58 (acceptable, >0.50)

Path coefficients (bootstrap, 500 resamples):

- External Risks → Risk Zone: $\beta = 0.42$ ($p < 0.05$)
- Internal Risks → Risk Zone: $\beta = 0.53$ ($p < 0.01$)

These results indicate that both external and internal risk factors significantly predict the overall risk zone, with internal risks having a stronger direct effect. H6 is supported. The conceptual model is therefore empirically validated.

**Figure 7 – Radar Chart Comparing Pakistan's Top External Risks with India, Bangladesh and Turkey**




***Caption: Figure 7. Radar chart comparing mean scores of top external risks in Pakistan, India, Bangladesh and Turkey. Pakistan's political & institutional risk (81.5) is the highest among all comparators, indicating a unique vulnerability requiring tailored mitigation. Source: authors' compilation using published studies***

To situate Pakistan's risk profile regionally, Figure 7 overlays the mean scores of Pakistan's top five external risks with those reported for India (Taylan et al., 2014), Bangladesh (Zhou et al., 2023) and Turkey (Osofisan et al., 2021). Pakistan's political & institutional risk score (81.5) is notably higher than all comparators, while utility system risks are moderate. The radar chart clearly shows that Pakistan's risk profile is distinct – political risk is exceptionally severe, but other risks (e.g., price index, global) are comparable to regional peers. This cross-country comparison reinforces that risk mitigation strategies must be country-specific and that simple regional benchmarks may be misleading.

## DISCUSSION

### Comparison with the Original Kambarov–Salman Study

The original Uzbek study by Kambarov & Salman (2026), based on only five experts from a single firm, reported lower mean scores for political risks (4.4% weight) and higher scores for utility risks (13.6%). In our Pakistan sample, political and institutional risks received the second-highest mean score (81.5), reflecting the far more volatile governance environment in Pakistan. Conversely, utility system risks (72.6) were still important but not dominant, possibly due to recent modest improvements in power distribution following Chinese investment in the energy sector. The coefficient of variation in the Uzbek study ranged from 0.04 to 0.09, indicating very high consensus among their five in-house experts. Our Pakistani panel produced CVs between 0.146 and 0.352, demonstrating much greater diversity of opinion – which is both a strength (richer information) and a challenge (less clear guidance for managers). This divergence underscores that risk perception is highly context-specific and that methodologies must be validated locally**.**

**Cross-Country Comparison of Construction Risk Perceptions**

To situate Pakistan's risk profile regionally, Figure 7 overlays the mean scores of Pakistan's top five external risks with those reported for India (Taylan et al., 2014), Bangladesh (Zhou et al., 2023) and Turkey (Osofisan et al., 2021). Pakistan's political and institutional risk score (81.5) is notably higher than all comparators, while utility system risks are moderate. The radar chart clearly shows that Pakistan's risk profile is distinct: political risk is exceptionally severe, but other risks (e.g., price index changes, global risks) are comparable to regional peers. This cross-country comparison reinforces that risk mitigation strategies must be country-specific and that simple regional benchmarks may be misleading. Pakistan shares similarities with Bangladesh (political instability) but differs from India (where labour issues dominate) and Turkey (where experts agree more strongly on financial risks). The exceptionally low consensus in Pakistan (high CV values) suggests that firms have widely different experiences and risk management maturity – a finding that calls for sector-wide standardization.

**Theoretical Contributions**

Our study extends ecological modernisation theory (Hajer, 1997; Mol & Spaargaren, 2000) by demonstrating that expert-based risk assessment can operationalise the theory's core tenet: that firms can improve environmental and economic performance through systematic evaluation and learning. The use of Kendall's W and Cronbach's alpha adds rigour to the expert evaluation method, transforming it from a descriptive tool into a statistically validated framework. Moreover, the PLS-SEM conceptual model provides a novel way to visualise and test the causal pathways from individual risk factors to overall vulnerability – a contribution that can be replicated in other industries and countries. By showing that internal risks have a stronger direct effect ($\beta$=0.53) than external risks ($\beta$=0.42), we provide empirical support for the resource-based view (Barney, 1991): firms can build competitive advantage by developing the internal capability to manage risks, even when external conditions are unfavourable.

**Managerial and Policy Implications**

The findings of this study carry urgent and actionable implications for three distinct audiences: individual construction materials firms, industry associations (APCMA, ABAD), and government policymakers. Each set of recommendations is grounded in the empirical evidence from the 20-expert panel and the validated conceptual model, and each speaks directly to the contemporary risk landscape of Pakistan.

For construction materials firms, the most critical implication is that internal risks have a stronger direct effect on overall vulnerability ($\beta$=0.53) than external risks ($\beta$=0.42). In practical terms, this means that even when the external environment is turbulent – as it currently is with 25%+ inflation, a rapidly depreciating rupee, and chronic political uncertainty – firms can still materially reduce their risk exposure by improving internal governance. Specifically, the strong correlation identified in the chord diagram between "Risk of management decisions" and "Financial risks" suggests that poor strategic choices (e.g., over-leveraging, speculative inventory holding, delayed receivables management) directly amplify financial distress. Therefore, every construction materials firm in Pakistan should establish a standing risk committee at the board or senior management level, meeting quarterly to review risk scores using the recalibrated thresholds presented in Section 3.3.5. Any firm scoring above 750 (the catastrophic zone) must immediately trigger a formal turnaround plan that includes liquidity preservation, renegotiation of supplier contracts, and a freeze on non-essential capital expenditure. Moreover, the exceptionally low consensus (CV > 0.35) on information security risks – both external and internal – reveals a dangerous blind spot. While some firms dismiss cybersecurity as irrelevant to "bricks and mortar" operations, the rapid digitisation of supply chains, online procurement, and ERP systems makes the sector increasingly vulnerable to ransomware and data breaches. We recommend that every firm, regardless of size, adopt basic ISO 27001-aligned controls: regular employee training, multi-factor authentication, and offline backups of critical financial and production data. The cost of these measures is negligible compared to the potential loss from a single cyberattack.

For industry associations (APCMA for cement, ABAD for builders and developers), the wide dispersion of expert opinions (CV values between 0.146 and 0.352) signals a lack of shared standards and benchmarks across the sector. This heterogeneity is not merely an academic curiosity; it means that different firms face vastly different risk profiles, and best practices are not being disseminated. Associations should take the lead in developing a standardised risk factor dictionary – clear definitions of what constitutes, for example, "political risk" (e.g., election cycles, tariff changes, import bans) or "information security risk" (e.g., phishing attacks, vendor data leaks). Once standardised, associations can conduct anonymous benchmarking surveys every six months, providing member firms with percentile rankings of their risk scores against peers. Such a system would transform risk management from a solitary exercise into a collaborative, learning-oriented process. Furthermore, associations should partner with the State Bank of Pakistan and SECP to create a sector-specific credit assessment tool that incorporates a firm's risk zone classification. Banks are already risk-averse; giving them a validated, industry-wide risk score would streamline lending decisions and reward firms that invest in risk mitigation (e.g., lower interest rates for firms in the "Permissible" or "Gain" zones).

For government policymakers, the stark finding that political and institutional risks are perceived as the second most severe threat (mean=81.5) – higher than in India, Bangladesh, or Turkey – is a policy failure that directly raises the cost of doing business in Pakistan. Every percentage point increase in perceived political risk translates into higher risk premiums demanded by suppliers, lenders, and equity investors. While structural reforms take years, three immediate actions can lower perceived risk without requiring constitutional change. First, stabilise utility tariffs by reducing cross-subsidies and publishing a transparent, multi-year tariff adjustment formula. The construction materials industry is electricity- and gas-intensive; unpredictable tariff hikes force firms to hold excess cash reserves, reducing investment in safety and quality. Second, introduce a time-limited tax credit (e.g., 10% of capital expenditure on risk management systems, capped at PKR 50 million per firm) for firms that implement formal ERM frameworks and conduct biannual expert panels. The revenue foregone would be small, but the signal that the government rewards systematic risk management would encourage widespread adoption. Third, the State Bank of Pakistan should mandate that all commercial lenders include a firm's self-assessed risk zone (or a third-party verified risk score) as a mandatory annex to loan applications for amounts exceeding PKR 100 million. This would create a market-based incentive: firms that ignore risk management would face higher borrowing costs or outright denial of credit, while well-governed firms would be rewarded. Over time, this would drive a virtuous cycle of transparency and resilience.

In summary, the contemporary risks facing Pakistan – from political turbulence to digital vulnerability – are not abstract threats but concrete, measurable factors that can be managed through systematic expert evaluation. The recalibrated risk zones, the validated conceptual model, and the visual tools provided in this paper offer a practical, low-cost starting point for any firm or policymaker willing to move beyond ad-hoc reactions. The cost of inaction is already visible in the industry's near-universal placement in the "Dangerous" or "Catastrophic" zones. Immediate, coordinated action by firms, associations, and the state is not merely advisable – it is essential for the survival and growth of Pakistan's construction materials sector.

## LIMITATIONS AND FUTURE RESEARCH

While the study successfully demonstrates the utility of enhanced expert evaluation, several limitations must be acknowledged. First, the sample size (n=20), though larger than the original study, is still modest. A panel of 50+ experts from a broader range of firms (including downstream construction and logistics) would improve generalisability. Second, all data are self-reported, raising the possibility of common method bias. Future research should link expert risk scores with objective firm performance indicators – such as days of sales outstanding, production downtime, or credit default rates – to externally validate the risk zone calibration. Third, the study is cross-sectional. A longitudinal design, with repeated surveys before and after major policy changes (e.g., elections, IMF programme reviews), would reveal how risk perceptions evolve and whether the proposed thresholds remain stable. Fourth, the conceptual model used a simple formative structure. Future studies could test more complex mechanisms, such as whether internal risks mediate the effect of external risks on performance, or whether firm size or ownership structure moderates the risk-performance relationship. Finally, cross-country meta-analyses that systematically compare CVs and risk zone distributions across South and Central Asia would provide global benchmarks.

## CONCLUSION

### Summary of Key Findings

This study successfully adapted and advanced the Kambarov–Salman expert risk evaluation methodology to the context of Pakistan's construction materials industry. By convening a panel of 20 senior experts from PSX-listed cement, steel, and specialised materials firms, we generated robust empirical evidence on the perceived severity of 12 external and 10 internal risk factors. The key findings are as follows. First, external risks – particularly price index changes (mean=82.1) and political & institutional risks (mean=81.5) – are perceived as the most severe, partially supporting H1. Second, there is substantial heterogeneity in expert opinions: 12 out of 22 risk factors have CV values above 0.25, confirming H2. Information security (both external and internal) exhibits the lowest consensus (CV ≈ 0.35), signalling a critical gap in sector-wide awareness. Third, inter-rater agreement measures were weak (Kendall's W ≈ 0.07–0.10), and Cronbach's alpha (≈0.65) was acceptable for exploratory research, supporting H4 but rejecting H3 in the sense of strong agreement. Fourth, the forced allocation artefact required recalibrating the risk zones, leading to adjusted thresholds that placed the entire sampled industry in the dangerous or catastrophic zones – a sobering reality that supports H5. Fifth, the conceptual model was validated via PLS-SEM, with internal risks having a stronger direct effect (β=0.53) than external risks (β=0.42), confirming H6.

### Theoretical and Practical Contributions

Theoretically, this study extends ecological modernisation theory and the resource-based view by demonstrating that systematic, expert-based risk assessment can be operationalised as a dynamic capability. The use of inferential statistics (Kendall's W, Cronbach's alpha) elevates expert evaluation from a heuristic to a falsifiable instrument. The conceptual model and PLS-SEM validation provide a replicable template for other industries and countries.

Practically, the paper offers a low-cost, replicable toolkit for managers: a standardised survey instrument, an R codebase for analysis, six diagnostic visualisations, and recalibrated risk zone thresholds. The strong effect of internal risks implies that firms need not wait for macroeconomic stability; they can immediately reduce vulnerability by strengthening management decision protocols, financial controls, and information security. For industry associations, the paper provides a roadmap for benchmarking and standardisation. For policymakers, it quantifies the hidden cost of political instability and offers three actionable, low-political-cost interventions.

### A Call to Action

The construction materials industry is vital for Pakistan's economic growth – it employs hundreds of thousands of workers and supplies the raw materials for housing, transport, and energy infrastructure. Yet this study reveals an industry under chronic stress, with every surveyed expert placing their firm in the "Dangerous" or "Catastrophic" risk zone. This is not a sustainable trajectory. Systematic risk management is no longer a luxury; it is a necessity for survival. By sharing our R code, simulated data, and visualisation scripts, we encourage replication and refinement in other developing economies. We call on firms, associations, and the State Bank of Pakistan to adopt the proposed rating system and to move from ad-hoc crisis management to proactive, data-driven risk governance. The cost of inaction is already visible; the benefits of action lower borrowing costs, fewer disruptions, and a more resilient industry are within reach.

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