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A Multi-Cohort Weighted Calibration Approach to Rectifying Subjective Bias in Construction Site LEC Hazard Identification

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Abstract

Traditional Likelihood-Exposure-Consequence (LEC) safety evaluations suffer from pronounced subjective variance and cognitive bias in construction site risk management. To overcome the methodological limitations, this study establishes a multi-cohort empirical framework analyzing 120 validated assessments across eight high-frequency construction cases evaluated by safety domain experts (SDE), frontline operational workers (FOW), and non-specialist personnel (NSP). Statistical decomposition of individual risk parameters demonstrates that accident likelihood (L) and exposure frequency (E) maintain strong baseline consensus across cohorts, whereas consequence severity (C) acts as the primary driver of subjective rating variance, which is nonlinearly amplified through the multiplicative risk score $D = L \times E \times C$. Frontline operational workers consistently underestimate high-hazard risks owing to habituation bias, whereas non-specialist personnel display extreme risk polarization due to domain knowledge deficits. In order to rectify the systemic cognitive distortions, situation-specific calibration coefficients ($k = D_{expert} / D_{evaluated}$) were mathematically derived. Empirical results demonstrate that overestimated hazards require scaling factors below 0.8 ($k < 0.8$) to compress inflated scores, while severely underestimated operations such as scaffold erection require scaling factors exceeding 1.4 ($k > 1.4$) to restore risk ratings to expert reference levels. Integrating multi-stakeholder consensus with dynamic calibration matrices transforms subjective field experience into a standardized risk assessment protocol, substantially optimizing safety resource allocation and hazard identification in construction management.

Keywords

Construction Safety Management, LEC Method, Multi-Cohort Risk Perception, Cognitive Bias Calibration, Situation-Specific Calibration

1. Introduction

The modern construction industry has experienced unprecedented expansion, characterized by escalating structural complexity, ultra-high-rise geometries, deep underground excavations, and highly concentrated spatial-temporal site logistics [1]-[5]. Despite ongoing technological advancements in safety governance, construction sites remain high-hazard environments. As indicated by Jaafar *et al.* [6], complex operational cross-working, dynamic site layouts, and high workforce mobility collectively contribute to a volatile risk landscape. Including falls from height, structural collapses, mechanical impacts, electrical shocks, and hazardous confined-space asphyxiation, fatal and disabling safety incidents continue to inflict severe casualties, immense financial losses, and persistent disruptions to sustainable industry development [7]-[12]. Based on the current situation, the precise identification of site hazard sources, rigorous quantification of operational safety risks, and implementation of dynamic, tiered risk control frameworks constitute the cornerstone of contemporary occupational health and safety management systems (OHSMS).

Among the quantitative safety risk assessment (QSRA) tools used in construction engineering derived from the Fine-Kinney risk evaluation framework, the Likelihood-Exposure-Consequence (*LEC*) method is widely adopted [13]-[17]. The classical LEC model evaluates operational risk by combining accident likelihood (L), exposure frequency (E), and consequence severity (C) into a composite risk score D, then mapping it to standardized risk thresholds to guide dynamic hazard-control protocols.

The ubiquitous adoption of the LEC method in construction safety management stems from its procedural simplicity, computational efficiency, and intuitive risk categorization. Referring to Zhang *et al.* [18] and Xu *et al.* [19], the LEC method serves as a fundamental analytical tool for compiling special safety construction plans, conducting routine hazard inspections, and establishing dynamic risk governance hierarchies.

However, extensive engineering practice reveals a systemic structural vulnerability in the conventional LEC method because it is susceptible to cognitive subjectivity and lacks a standardized cross-role calibration mechanism [20] [21]. In routine field operations, single assessors or isolated job-role personnel conduct risk evaluations. Referring to Chionis & Karanikas [22] and Baybutt [23], because human risk perception is mediated by individual professional backgrounds, field experience, safety literacy, and psychological heuristics, the numerical assignment

of L, E, and C exhibits substantial inter-evaluator variance. Furthermore, because D is calculated via a multiplicative function ($D = L \times E \times C$), individual parameter errors do not merely summate, but propagate non-linearly. Referring to Anthony *et al.* [24] and Hong *et al.* [25], a minor subjective disparity in C (which typically carries the largest numerical magnitude) amplifies the variation in D, distorting the true risk level and causing severe misclassifications. Such distortions result in either over-regulation (wasting project resources) or under-regulation (leaving critical hazards unmitigated).

In construction safety engineering, including Safety Domain Experts, Frontline Operational Workers, and Non-Specialist (Lay) Personnel, field evaluators can be categorized into three representative stakeholder cohorts based on their professional capacity and operational immersion. As shown in Table 1, the cohorts exhibit stark cognitive divergence in safety risk perception due to underlying psychological and experiential mechanisms.

Table 1. Conceptual taxonomy of risk perception divergence across evaluator cohorts.

Evaluator Cohort	Capacity Profile	Site Immersion	Core Psychological Experiential Driver	Dominant Perception Trait
SDE	High (Regulatory)	Low Audit-based	Top-down processing Historical hazard analytics	Systemic Proactive
FOW	Moderate (Task-specific)	High Continuous	Normalization of deviance Survivorship bias	Localized Attenuated
NSP	Low (Unformed)	Minimal Transient	Affect heuristic Salience bias	Surface-Level Over-reactive

Note: SDE = Safety Domain Experts; FOW = Frontline Operational Workers; NSP = Non-Specialist Personnel.

Following the contents of Table 1, relying on a single evaluator cohort without cross-role alignment yields risk assessments that suffer from high stochastic noise, poor repeatability, and inadequate empirical validity.

To overcome the subjective limitations of the traditional LEC method, previous studies have proposed various advanced mathematical augmentations [26]-[30]. As shown in Zhao *et al.* [21], a major stream of studies integrates Fuzzy Set Theory (FST), Analytic Hierarchy Process (AHP), and Interval-Valued Intuitionistic Fuzzy Logic into the LEC structure to convert linguistic variables into mathematical intervals. While the hybrid fuzzy-LEC models reduce subjective vagueness to some degree, they also suffer from two major drawbacks in Figure 1.

Referring to the existing drawbacks in Figure 1 by Gul. [31], few studies have quantified the multi-cohort cognitive deviation matrix across diverse construction sites, nor have they developed a practical, scalar perturbation-based calibration mechanism to harmonize multi-subject ratings to unified safety domain experts.

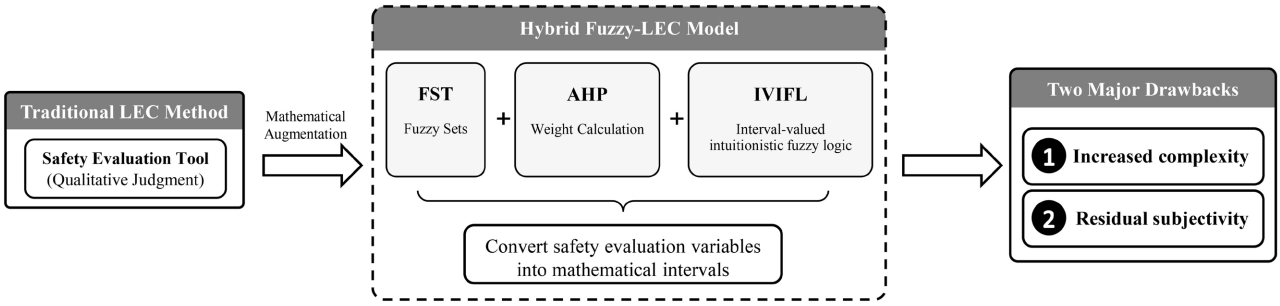


Figure 1. Framework of the hybrid fuzzy-LEC model.

To bridge the gaps above, this study presents a comprehensive quantitative framework designed to measure, model, and calibrate the multi-subject cognitive subjective errors inherent in the LEC evaluation method. This study investigates the systematic scoring deviations across safety domain experts (SDE), frontline operational workers (FOW), and non-specialist personnel (NSP) by capturing the empirical risk ratings of 120 validated respondents across 8 representative high-frequency construction cases (ranging from high-altitude operations and temporary electrical works to scaffold erection and trench excavation).

2. Methodology and Data Collection

2.1. Questionnaire Design and Participants

Drawing on Song & Zhang [32] and Brunel *et al.* [33], the evaluation subjects, including the general public (non-specialist personnel), on-site frontline operational workers, and industry safety domain experts, were stratified into three cohorts based on professional competency and hazard perception. Out of 500 distributed questionnaires, a rigorous screening process yielded 120 valid responses. To ensure data reliability and eliminate arbitrary scoring, incomplete or logically inconsistent submissions were excluded, ultimately retaining 20 valid questionnaires from safety domain experts, 40 from on-site frontline operational workers, and 60 from the general public.

As shown in Table 2, although the SDE sample size ($n = 20$) is relatively small compared with the FOW ($n = 40$) and NSP ($n = 60$) cohorts, the SDE group represents a highly filtered, homogeneous tier of certified senior engineers and safety directors. Statistical dispersion metrics in this study indicate high intra-group consensus among SDEs, which suppresses outlier susceptibility and ensures the robustness of the reference metric despite the imbalanced cohort sizes.

Table 2. Profiles of the 8 representative high-frequency construction cases and the research design framework.

Situation	Operational Reference Cases	Primary Hazard Category	Potential Consequences (Linked to C-Factor)	Evaluator Cohorts (Total $n = 120$)
CASE-1	High-altitude operations (e.g., perimeter work, roofing)	Gravitational Kinetic	Falls from height Fatalities Severe musculoskeletal trauma	SDE, FOW, NSP

Continued

CASE-2	Temporary electrical works (e.g., site power distribution)	Electrical	Electric shock Electrocution Secondary electrical fires	SDE, FOW, NSP
CASE-3	Scaffold erection and dismantling	Structural Mechanical	Structural collapse Crushing Mass casualties	SDE, FOW, NSP
CASE-4	Trench excavation and earthworks	Geotechnical	Cave-ins Burial asphyxiation Utility strikes	SDE, FOW, NSP
CASE-5	Tower crane lifting and hoisting operations	Mechanical Operational	Crane overturning Dropped heavy loads Fatal striking	SDE, FOW, NSP
CASE-6	Confined space operations (e.g., sewage tanks, deep shafts)	Atmospheric Chemical	Toxic gas poisoning Oxygen deficiency asphyxiation	SDE, FOW, NSP
CASE-7	Hot works (e.g., on-site welding, gas cutting)	Thermal Fire	Major explosions Severe burns Extensive property damage	SDE, FOW, NSP
CASE-8	Heavy mobile machinery operations (e.g., excavators)	Mechanical Kinetic	Run-over injuries Crushing Collision with personnel	SDE, FOW, NSP

Note: SDE = Safety Domain Experts (n = 20); FOW = Frontline Operational Workers (n = 40); NSP = Non-Specialist Personnel (n = 60). Note: All 120 validated respondents provided complete empirical LEC risk ratings across all 8 cases (CASE-1 to CASE-8). CASE-1 to CASE-4 correspond directly to the focal operations mentioned in the study design, while CASE-5 to CASE-8 complete the comprehensive operational spectrum of high-risk site activities.

Referring to the previous study of Al-Bayati & Chellappa [34], such as senior engineers, engineers, certified constructors, safety supervisors, and qualified surveyors, the expert cohort was defined as professionals holding relevant industry certifications with a minimum of three years of active domain experience. Specifically, this expert sample is predominantly composed of individuals born between 1980 and 1989 (13 individuals, accounting for 65%). The remaining age distribution includes 4 individuals born between 1970 and 1979 (20%), 2 individuals born between 1990 and 1999 (10%), and 1 individual born between 2000 and 2009 (5%).

Also, to comprehensively represent the complex risk landscape of modern construction environments, the survey in this study evaluated eight high-frequency, typical on-site operational cases as shown in **Table 2**.

2.2. LEC Risk Assessment Framework

The foundational analytical model employed in this study is the LEC operational condition hazard evaluation method, while the mathematical framework is expressed as:

$$D = L \times E \times C \tag{1}$$

where the variables are formally defined as follows:

1) L (Likelihood): Represents the probability of an accident occurring, defined on a continuous scale with discrete reference values ranging from 0.1 to 10.

2) E (Exposure): Denotes the frequency of human exposure to the hazardous environment, with values ranging from 0.5 to 10.

3) C (Consequence): Indicates the severity of the consequences should an accident occur, with values ranging from 1 to 100.

4) D (Danger/Total Risk Score): Represents the cumulative hazard score. Based on the calculated magnitude of D, occupational hazards are classified into five distinct risk levels, where a higher value strictly correlates with a greater operational risk.

Furthermore, referring to GB/T 33000-2025 (Requirements of work safety management system for large and medium-sized enterprises), T/XZBX 0154-2025 (Code for safety risk classification management and control of construction engineering site), and T/CCPITBSC 096-2025 (Specifications for safety risk prevention and control in high-rise building construction), this study applies the adopted L, E, and C grading tables and corresponding common risk classification standards, which are shown in Table 3.

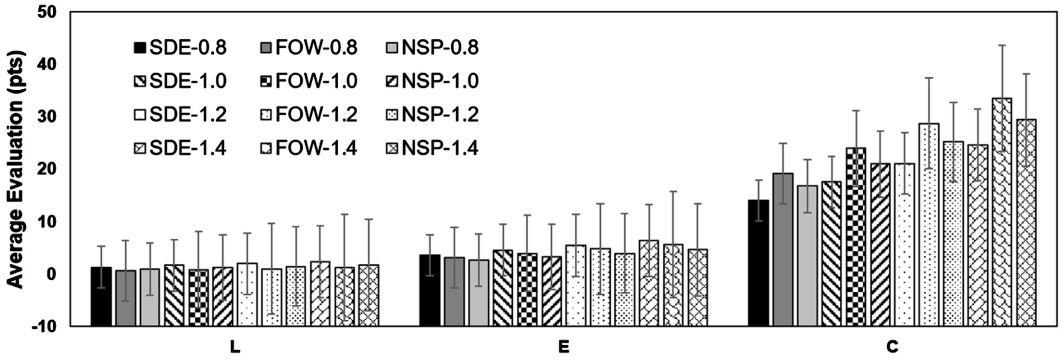
Table 3. Standardized LEC valuation matrix.

Evaluation Metric	Score	Qualitative Description
Likelihood of an Accident (*L*)	10	Inevitable
	6	Completely expected
	3	Highly possible
	1	Likely
	0.5	Possible, but infrequent
	0.2	Unlikely
	0.1	Extremely unlikely
Exposure Frequency to Hazard (*E*)	10	Continuous exposure
	6	Exposed daily during working hours
	3	Exposed once a week
	2	Exposed once a month
	1	Exposed several times a year
	0.5	Extremely rare
Severity of Consequences (*C*)	100	Catastrophic disaster
	40	Multiple fatalities
	15	Single fatality
	7	Serious injury
	3	Minor injury
	1	Noticeable/Requires attention

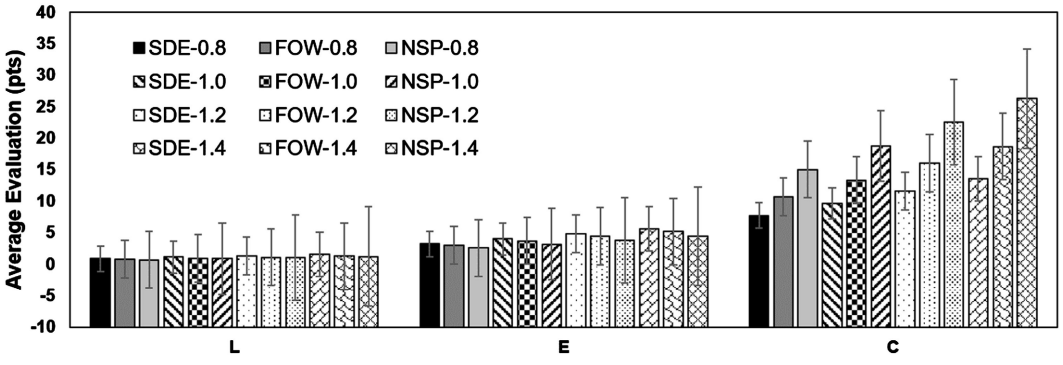
3. Discussion

3.1. Comparative Analysis

To systematically elucidate the domain-specific subjective evaluation bias inherent in the traditional Likelihood-Exposure-Consequence (LEC) safety assessment framework, including safety domain experts ($N = 20$), frontline operational workers ($N = 40$), and non-specialist personnel ($N = 60$), raw metric scores assigned by three distinct evaluator cohorts were processed using four scaling adjustment coefficients ($k = 0.8,1.0,1.2,1.4$). As shown in **Figure 2**, including the arithmetic mean (μ) and standard deviation (σ), statistical metrics were synthesized across eight representative construction operational cases to characterize score hierarchies and inter-group dispersions.



(a)



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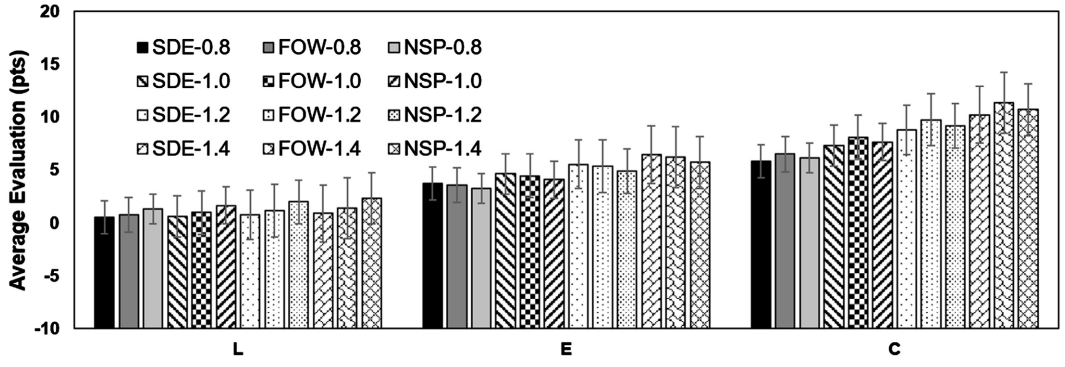

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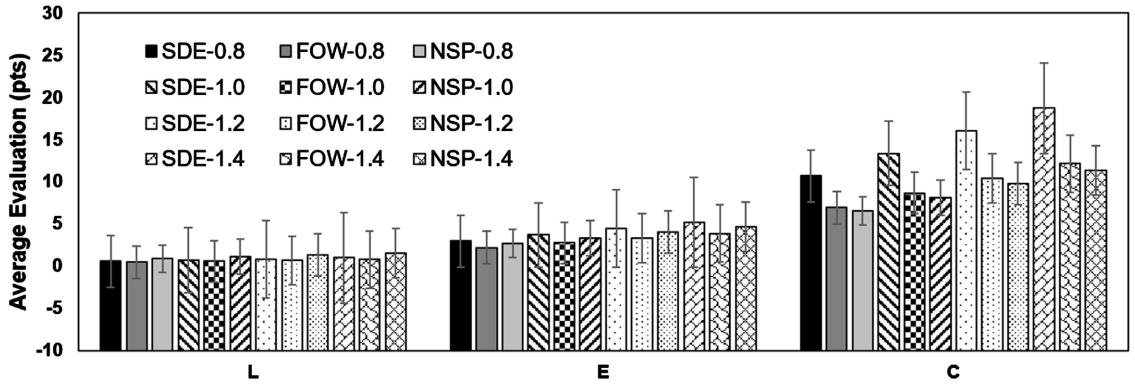
SDE-0.8 FOW-0.8 NSP-0.8
SDE-1.0 FOW-1.0 NSP-1.0
SDE-1.2 FOW-1.2 NSP-1.2
SDE-1.4 FOW-1.4 NSP-1.4
Average Evaluation (pts)
30
25
20
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-10
L
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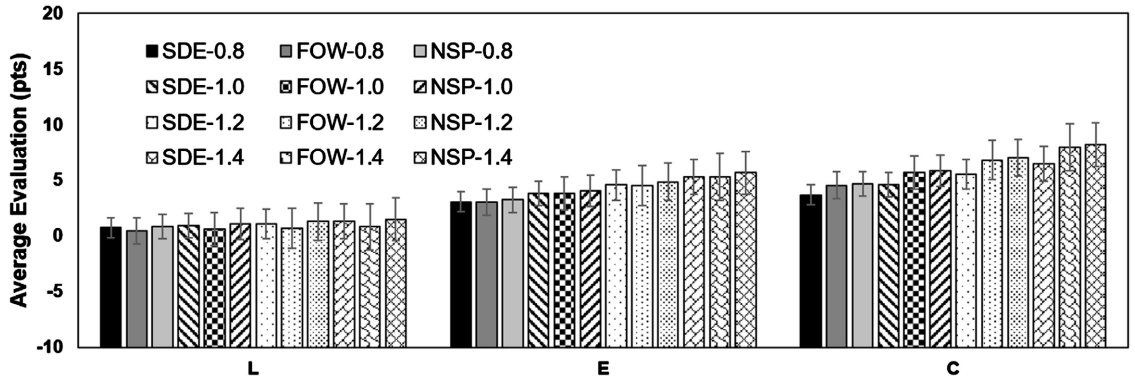
(d)


SDE-0.8 FOW-0.8 NSP-0.8
SDE-1.0 FOW-1.0 NSP-1.0
SDE-1.2 FOW-1.2 NSP-1.2
SDE-1.4 FOW-1.4 NSP-1.4
Average Evaluation (pts)
20
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10
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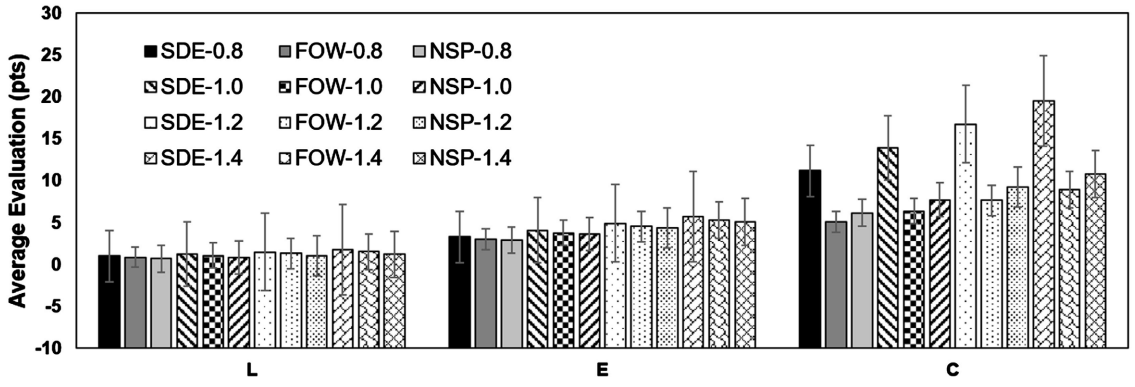
0
-5
-10
L
E
C

(e)


SDE-0.8 FOW-0.8 NSP-0.8
SDE-1.0 FOW-1.0 NSP-1.0
SDE-1.2 FOW-1.2 NSP-1.2
SDE-1.4 FOW-1.4 NSP-1.4
Average Evaluation (pts)
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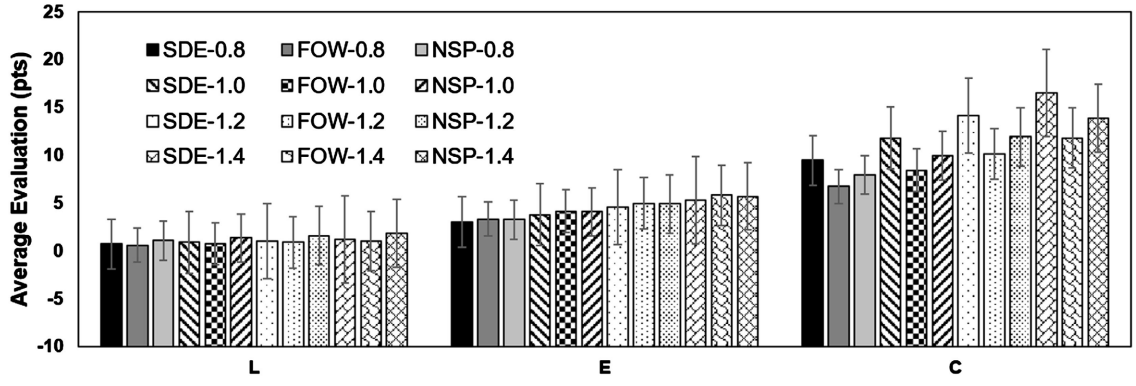
(f)


SDE-0.8 FOW-0.8 NSP-0.8
SDE-1.0 FOW-1.0 NSP-1.0
SDE-1.2 FOW-1.2 NSP-1.2
SDE-1.4 FOW-1.4 NSP-1.4
Average Evaluation (pts)
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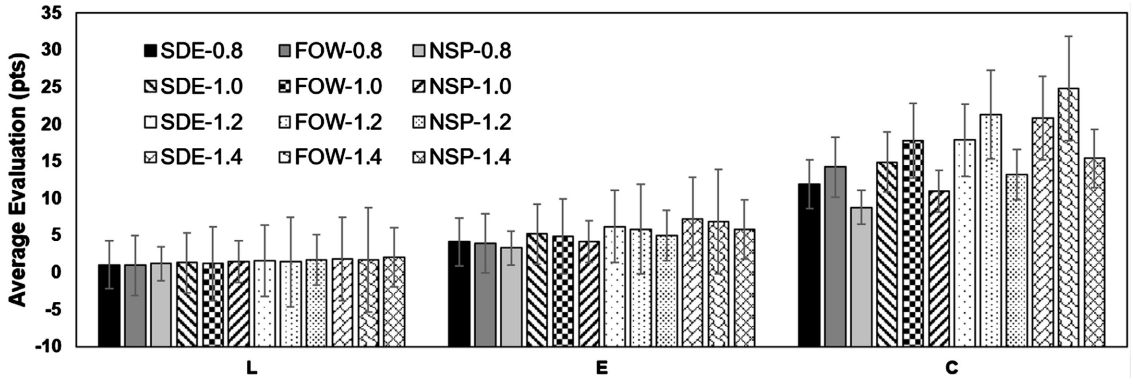
-10
L
E
C

(g)



(h)

Figure 2. Mean scores analysis of the operational condition risk assessment. (a) High-altitude operations, (b) Temporary electrical works, (c) Scaffold erection and dismantling, (d) Trench excavation and earthworks, (e) Tower crane lifting and hoisting operations, (f) Confined space operations, (g) Hot works, (h) Heavy mobile machinery operations.

3.1.1. Dimensional Hierarchies & Quantitative Magnitude Distribution

Referring to Kokangül *et al.* [35], raw metric scores were first transformed using the scaling coefficient k to evaluate the dimensional characteristics without confounding mathematical domain bounds with cognitive risk weights. Let $x_{m,s,i}^{raw}$ denote the raw metric score assigned for dimension $m \in \{L,E,C\}$ by individual i in scenario $s \in \{1,2,\cdots,8\}$. The adjusted score $x_{m,s,i}^{(k)}$ under scaling factor k is formulated as:

$$x_{m,s,i}^{(k)} = k \cdot x_{m,s,i}^{raw},\ k \in \{0.8,1.0,1.2,1.4\} \tag{2}$$

Because the baseline assignment domains defined by the traditional LEC lookup framework are inherently non-uniform, where $L \in \left[S_L^{min}, S_L^{max}\right] = [0.1,10]$, $E \in \left[S_E^{min}, S_E^{max}\right] = [0.5,10]$, $C \in \left[S_C^{min}, S_C^{max}\right] = [1,100]$, direct numerical comparisons of raw averages ($\bar{x}_C > \bar{x}_E > \bar{x}_L$) induce a deceptive scalar artifact. To decouple the intrinsic domain boundary effects from genuine subjective risk weights, a dimensionless normalized metric $\tilde{x}_{m,s,i}^{(k)}$ is established via min-max domain mapping:

$$\tilde{x}_{m,s,i}^{(k)} = \frac{\bar{x}_{m,s,i}^{(k)} - k \cdot S_m^{min}}{k \cdot \left(S_m^{max} - S_m^{min}\right)} = \frac{\bar{x}_{m,s,i}^{raw} - S_m^{min}}{S_m^{max} - S_m^{min}} \tag{3}$$

Furthermore, the relative partial elasticity ϵ_m of the risk score $D = L \cdot E \cdot C$ with respect to each metric dimension m demonstrates equal mathematical weighting in logarithmic derivative space:

$$\epsilon_m = \frac{\partial \ln D}{\partial \ln m} = \frac{m}{D} \cdot \frac{\partial D}{\partial m} = 1,\ \forall m \in \{L,E,C\} \tag{4}$$

As shown above, **Equation (4)** proves that the multiplicative structure of the LEC model imparts identical relative sensitivity ($\epsilon_L = \epsilon_E = \epsilon_C = 1$) to all three parameters. Consequently, any observed raw absolute dominance of C over L and E is purely an artifact of scale allocation bounds ($S_C^{max} / S_L^{max} = 10$) rather than an inherent structural priority of risk severity over likelihood or exposure.

Across all eight construction operational cases in **Figure 2**, raw score averages exhibit a persistent numerical hierarchy where $\bar{x}_C \in [3.68, 33.50]$ significantly exceeds $\bar{x}_E \in [2.19, 7.21]$ and $\bar{x}_L \in [0.44, 3.58]$. In high-hazard operations such as High-altitude Work (**Figure 2(a)**) and Scaffolding Erection (**Figure 2(h)**), raw mean scores for Consequence Severity (C) reach peak values exceeding 30.0 under $k = 1.4$. Conversely, in lower-severity tasks like Ground Material Handling (**Figure 2(e)**) and Mechanical Cutting (**Figure 2(c)**), raw C scores drop to lower ranges ($\tilde{x}_C = 3.68 \sim 11.38$). However, when evaluated through the dimensionless normalized metric $\tilde{x}_{m,s,i}^{(k)}$, the apparent dominance of C diminishes substantially. In routine handling operations (**Figure 2(e)**), normalized exposure frequency $\tilde{x}_E = 0.28 \sim 0.45$ actually surpasses normalized consequence severity $\tilde{x}_C = 0.03 \sim 0.08$, demonstrating that risk magnitude in non-catastrophic tasks is primarily driven by exposure persistence rather than extreme loss potential.

An analytical difference in this study revealed by the four scaling coefficients ($k = 0.8, 1.0, 1.2, 1.4$) is the non-linear compound expansion of the total risk score D. Since $D^{(k)} = k^3 \cdot D^{raw}$, applying scalar multipliers linearly expands individual parameters but exponentially inflates total risk scores. In high-consequence cases (e.g., High-altitude Work in **Figure 2(a)** and Trench Edge Protection in **Figure 2(f)**), this multiplicative amplification magnifies initial raw evaluation discrepancies by up to $1.4^3 \approx 2.744$ times. This exponential scaling underscores the vulnerability of traditional uncalibrated LEC scoring, as small subjective variance in high-bounded dimensions (C) disproportionately skews final risk classification thresholds (D).

3.1.2. Dimension-Specific Cognitive Dispersions & Scale Range Effects

As noted in Bedeian & Mossholder [36], to quantify inter-group evaluation dispersion independent of scalar magnitude, the dimensionless Coefficient of Variation ($CV_{m,i,s}$) is formulated for each dimension m, cohort i, and situation s:

$$CV_{m,s,i} = \frac{\sigma_{m,s,i}^{(k)}}{\bar{x}_{m,s,i}^{(k)}} = \frac{k \cdot \sigma_{m,i,s}^{raw}}{k \cdot \bar{x}_{m,i,s}^{raw}} = \frac{\sigma_{m,i,s}^{raw}}{\bar{x}_{m,i,s}^{raw}} \tag{5}$$

where $\sigma_{m,i,s}$ represents the sample standard deviation. **Equation (5)** confirms that CV is invariant under linear scaling factors k, rendering it a robust metric for cross-cohort reliability analysis. To capture the extent to which baseline metric scale ranges ($S_m^{max} - S_m^{min}$) distort absolute variance perception, the Scale Range Effect ($SRE_{m,i,s}$) is defined as:

$$SRE_{m,s,i} = \frac{\sigma_{m,i,s}^{(k)}}{k \cdot \left(S_m^{max} - S_m^{min}\right)} = \frac{\sigma_{m,i,s}^{raw}}{S_m^{max} - S_m^{min}} \tag{6}$$

In addition, referring to Xu [37], the Inter-Cohort Discrepancy Index ($DI_{m,s}$) measures the standardized distance between non-expert cohorts ($i \in \{Workers, Oridinary\}$) and the safety domain experts ($i = Expert$):

$$DI_{m,s} = \sqrt{\frac{1}{2} \cdot \sum_{i \in \{Work, Oridinary\}} \left(\frac{\bar{x}_{m,i,s} - \bar{x}_{m,Expert,s}}{\bar{x}_{m,Expert,s}} \right)^2} \tag{7}$$

Empirical observations across **Figures 2(a)-(h)** reveal a stark dichotomy between absolute standard deviation (σ) and relative dispersion (CV). Across all cases, Likelihood (L) and Exposure (E) display tight absolute error bars ($\sigma_L \in [0.47, 3.58]$, $\sigma_E \in [1.73, 4.57]$), whereas Consequence Severity (C) exhibits massive absolute standard deviations ($\sigma_C \in [2.51, 42.69]$). However, evaluating relative dispersion via **Equation (5)** reverses this visual impression: $CV_L\left(0.42 \sim 0.85\right)$ and $CV_E\left(0.38 \sim 0.62\right)$ exhibit higher relative dispersion than $CV_C\left(0.25 \sim 0.55\right)$ in routine tasks. The discussions in this study prove that while evaluators reach numerical convergence on L and E due to constrained baseline options ($[0.1,10]$ and $[0.5,10]$), their underlying relative cognitive uncertainty regarding event probability remains substantial.

The vast absolute standard deviation observed in Consequence Severity (σ_C) is predominantly driven by the Scale Range Effect (SRE_C). Because the scoring bounds for C span across two orders of magnitude (1~100), discrete leaps between rating anchors (e.g., jumping from 15 "single fatality" to 40 "multiple fatalities") generate huge statistical variance. In High-altitude Work (**Figure 2(a)**), Confined Space Inspection (**Figure 2(d)**), and Scaffolding Erection (**Figure 2(h)**), Non-specialist personnel and Workers exhibit extreme variance ($\sigma_C > 30.0$ under $k = 1.4$). The wide spread in this study reflects divergent cognitive interpretations of worst-case accident outcomes versus nominal operational incidents among non-expert personnel.

As scaling coefficients increase from $k = 0.8$ to $k = 1.4$, absolute error bar spans in **Figures 2(a)-(h)** dilate proportionally ($\sigma^{(k)} = k \cdot \sigma^{raw}$), while the visual widening of error bars in this study must not be misinterpreted as deteriorating evaluation consensus at higher scaling factors. Because CV remains perfectly constant across all k values, linear scaling alters only the visual metric resolution without changing the underlying stochastic consistency of cohort perceptions. Nevertheless, the Inter-Cohort Discrepancy Index ($DI_{C,s}$) confirms that inter-group divergence is highest in Consequence Severity (C), pinpointing C as the primary source of subjective bias in multi-cohort safety risk assessment.

3.1.3. Situation-Dependent Risk Perception Patterns across Evaluator Cohorts

According to Zhao *et al.* [38] and Sjöberg [39], to model cohort-specific cognitive bias across varying operational contexts, the Cohort Perception Bias ($\Delta\mu_{m,i,s}$) relative to the safety domain experts is defined as:

$$\Delta\mu_{m,i,s} = \overline{x}_{m,i,s} - \overline{x}_{m,Expert,s}, \quad i = \{Work, Ordinary\} \tag{8}$$

To evaluate how each evaluator cohort perceives relative risk severity across the spectrum of operational cases, the Situation Risk Sensitivity Index ($RSI_{i,s}$) is established:

$$RSI_{i,s} = \frac{D_{i,s}}{\frac{1}{8} \cdot \sum_{s'=1}^{8} D_{i,s'}} \tag{9}$$

Furthermore, the overall Cognitive Divergence Metric (CDM_s) synthesizes multi-dimensional perceptual variance across all three parameters for a given situation s :

$$CDM_s = \sum_{m\in\{L,E,C\}} \left(\frac{\overline{x}_{m,Works,s} - \overline{x}_{m,Ordinary,s}}{\overline{x}_{m,Expert,s}} \right)^2 \quad (10)$$

Analysis of **Figure 2(a)** to **Figure 2(b)** demonstrates distinct, situation-dependent cognitive patterns among the three evaluator cohorts. The safety domain experts ($N = 20$) display structured, risk-discriminative behavior, assigning high risk scores (D) exclusively to high-consequence, structurally complex operations, such as High-altitude Work in **Figure 2(a)**, Trench Edge Protection in **Figure 2(f)**, and Scaffolding Erection in **Figure 2(h)**. In the critical operations above, safety domain experts maintain conservative scoring on Consequence Severity (C), recognizing secondary risks such as structural instability and cave-ins. On the other hand, for standardized or low-energy tasks like Ground Material Handling in **Figure 2(e)** and Conventional Hot Work in **Figure 2(g)**, safety domain experts consistently assign low likelihood (L) and severity (C) scores, reflecting a highly calibrated risk perception anchored in technical standards and historical failure experiences.

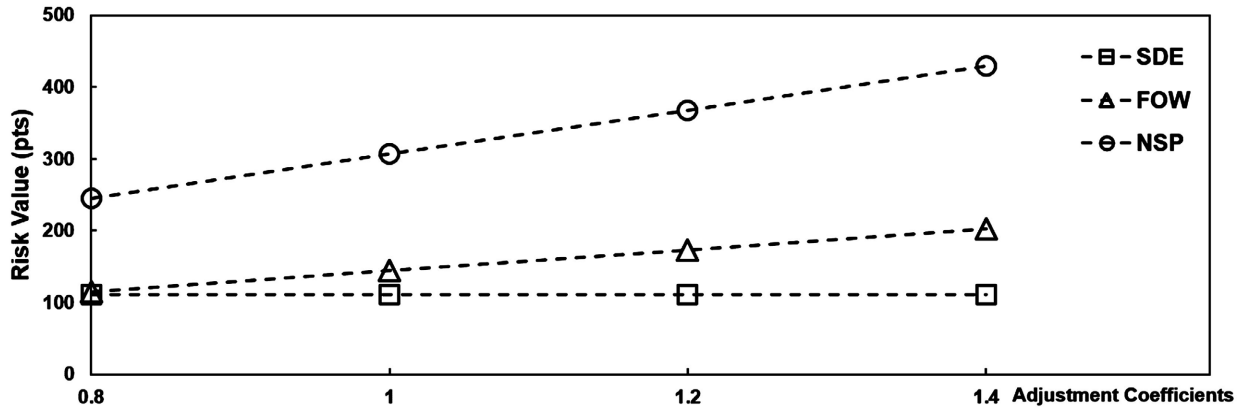
Frontline operational workers ($N = 40$) display a dual cognitive bias characterized by "Operational Habituation" and "Immediate Hazard Sensitivity." In routine high-risk environments such as Trench Edge Protection in **Figure 2(f)** and Scaffolding Erection in **Figure 2(h)**, workers consistently underestimate Likelihood (L) and Exposure (E) compared to safety domain experts ($\Delta_{\mu L,Worker} < 0$). Long-term exposure to site hazards induces psychological desensitization ("risk numbness"), leading workers to perceive frequent hazardous exposures as acceptable baseline conditions. However, for tasks such as Temporary Electrical Work in **Figure 2(b)** and Mechanical Cutting in **Figure 2(c)**, frontline operational workers assign elevated severity scores (C) in tasks involving immediate mechanical or electrical contact hazards, driven by direct first-hand exposure to personal injuries and acute operational mishaps.

Non-specialist personnel ($N = 60$) exhibit maximum cognitive divergence (CDM_s), driven by systemic information asymmetry and a lack of engineering expertise. The analysis in this study indicates that non-specialist personnel suffer from severe "Cognitive Polarization," resulting in overestimation of visible, high-profile hazards and underestimation of complex, hidden risks. Such as High-altitude Work in **Figure 2(a)** and Confined Space Inspection in **Figure 2(d)**, non-specialist personnel overestimate risk scores (D), yielding peak values far exceeding those of safety domain experts ($\Delta_{\mu} > 0$), which stems from dread-risk anxiety associated with height and asphyxiation. Conversely, in tasks such as Trench Edge Protection in **Figure 2(f)** and Scaffolding Erection in **Figure 2(h)**, non-specialist personnel fail to recognize latent geotechnical and structural stability hazards, yielding severe risk underestimation, which underscores the critical necessity of

introducing cohort-specific calibration coefficients (k) to reconcile subjective evaluation discrepancies in site safety management.

3.2. Multi-Stakeholder Cognitive Analysis of Risk Score

Building upon the foundational parameter comparisons, this study advances to a deeper cognitive evaluation of the aggregated risk score (D) within the Likelihood-Exposure-Consequence (LEC) framework. To systematically decode the compounding mechanisms of subjective bias across the three distinct stakeholder safety domain experts ($N = 20$), frontline operational workers ($N = 40$), and non-specialist personnel ($N = 60$), the raw evaluation metrics were subjected to a dynamic calibration matrix utilizing four scaling coefficients ($k = 0.8, 1.0, 1.2, 1.4$). As shown in the statistical trajectories from **Figures 3(a)-(h)**, which synthesize arithmetic means (μ) and standard deviations (σ) across eight representative construction cases, this analysis moves from descriptive data to cognitive-behavioral diagnostics. By reflecting shifting score hierarchies and inter-group dispersions across varied k -values [40]-[43], such as workers' operational habituation and laypersons' risk polarization, this study elucidates cohort-specific perceptual disparities, demonstrating the efficacy of targeted calibration in bridging multi-stakeholder consensus gaps.



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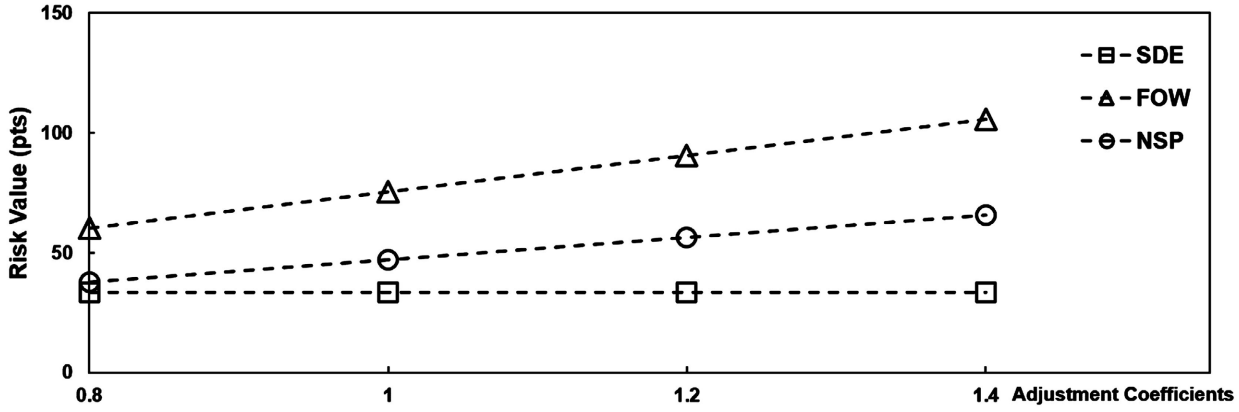

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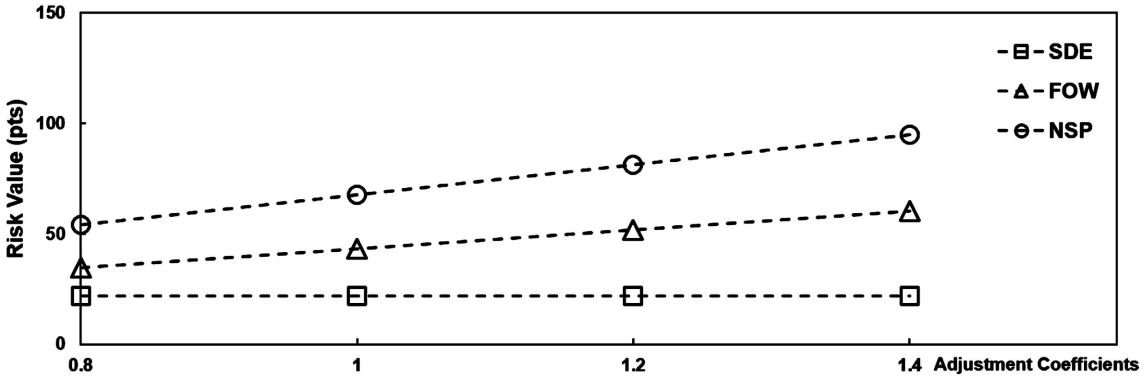
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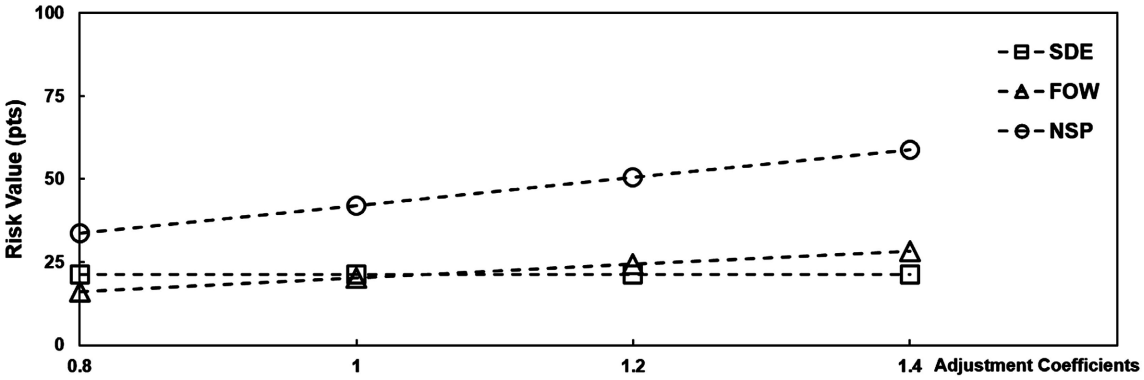
Adjustment Coefficients
SDE
FOW
NSP

(c)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Risk Value (pts)
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Adjustment Coefficients
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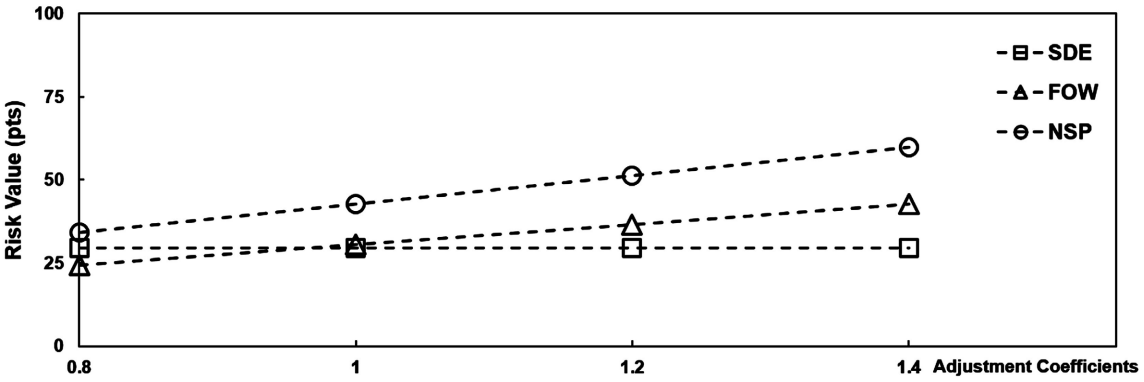
NSP

(d)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Risk Value (pts)
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Adjustment Coefficients
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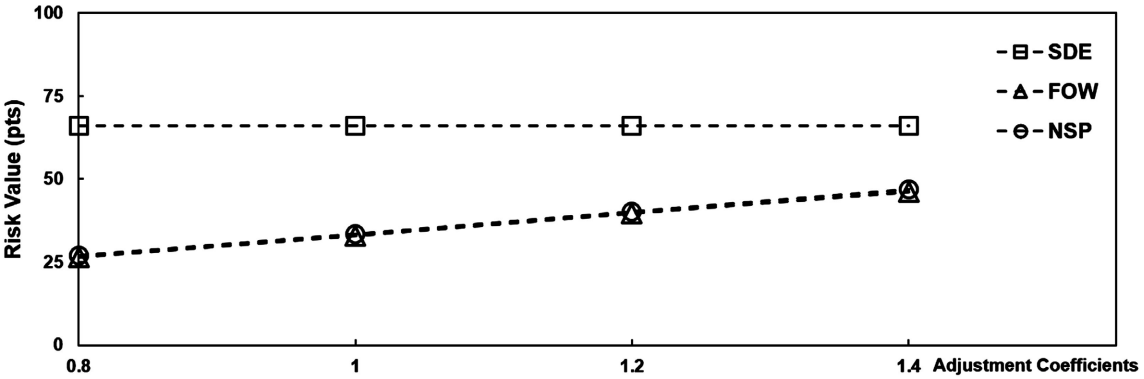
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Adjustment Coefficients
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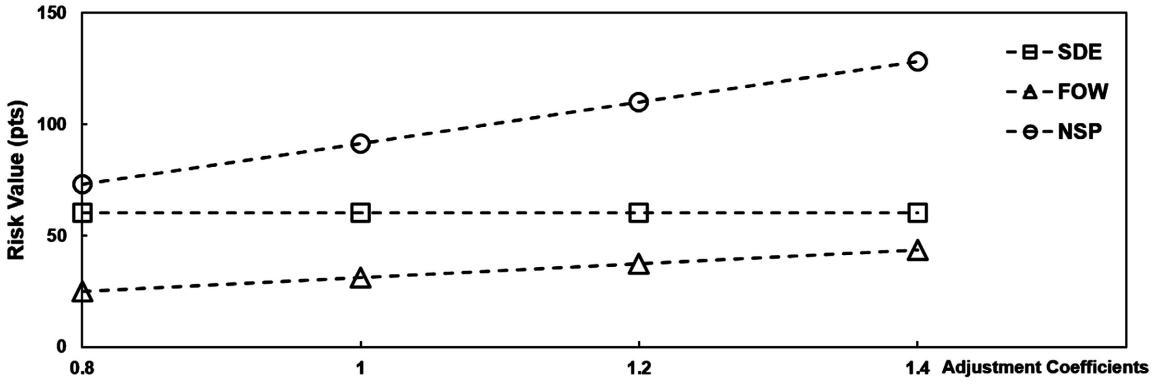
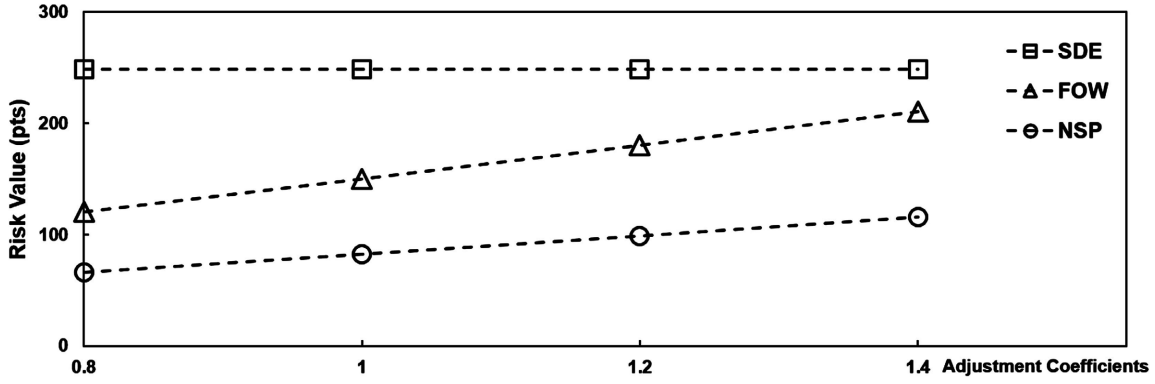


(g)



(h)

Figure 3. Assignment analysis of the operational condition risk assessment. (a) High-altitude operations, (b) Temporary electrical works, (c) Scaffold erection and dismantling, (d) Trench excavation and earthworks, (e) Tower crane lifting and hoisting operations, (f) Confined space operations, (g) Hot works, (h) Heavy mobile machinery operations.

3.2.1. Cognitive Modeling & Sensitivity Decomposition

According to Man *et al.* [44] and Pinto *et al.* [45], this study derives the aggregated operational risk score D is derived via the multiplicative synthesis formulation $D = L \times E \times C$ to eliminate random observational noise and subjective cognitive discrepancies across evaluator cohorts. The weighted mean risk score evaluated by the expert cohort is established as the professional consensus proxy ($D_j^* = \bar{D}_{E,j}$) for each operational case of the situation $j \in \{1,2,\cdots,8\}$. To quantify the parametric sensitivity and risk distortion among non-expert stakeholders (on-site frontline operational workers W and non-specialist personnel P), a coefficient-scaling transformation function is introduced as below:

$$D_{ij}(k) = k \cdot \bar{D}_{ij}, \quad k \in \{0.8,1.0,1.2,1.4\} \tag{11}$$

where D_{ij} represents the raw weighted average risk score of stakeholder cohort $i \in \{W, P\}$ under situation j. The linear response gradient of the risk score with respect to the scaling coefficient k is given by:

$$\frac{\mathrm{d}D_{ij}(k)}{\mathrm{d}k} = \bar{D}_{ij} \tag{12}$$

To avoid the epistemological misconception that Consequence Severity (C)

dictates risk magnitude over Likelihood (L) or Exposure (E) solely due to its larger numerical bounds ($C \in [1,100]$ vs. $L \in [0.1,10]$, $E \in [0.5,10]$) [46] [47], a logarithmic additive decomposition framework is formulated in this study. Taking the natural logarithm of the risk synthesis function yields:

$$\ln D = \ln L + \ln E + \ln C \tag{13}$$

The logarithmic cognitive deviation ($\Delta \ln D_{ij}$) of a non-expert cohort relative to the expert reference (D_j^*) is expressed as:

$$\Delta \ln D_{ij} = \ln \bar{D}_{ij} + \ln D_j^* = \delta \ln L_{ij} + \delta \ln E_{ij} + \delta \ln C_{ij} \tag{14}$$

where $\delta \ln X_{ij} = \ln \bar{X}_{ij} - \ln X_{E,j}^*$ for $X \in \{L, E, C\}$. **Equation (14)** proves that the proportional variation in the aggregated risk score D is an isotropic, scale-invariant sum of the relative logarithmic cognitive discrepancies of the individual indicators [48].

Furthermore, the Relative Cognitive Distortion Index ($RCDI_{ij}$) and the optimal stakeholder calibration coefficient ($k_{i,j}^*$) required to harmonize non-expert risk ratings with expert references are defined as:

$$RCDI_{ij} = \frac{\bar{D}_{ij} - D_j^*}{D_j^*} \tag{15}$$

$$k_{ij}^* = \frac{D_j^*}{\bar{D}_{ij}} = \frac{1}{1 + RCDI_{ij}} \tag{16}$$

When $RCDI_{ij} > 0$, the stakeholder group overestimates the operational risk, necessitating a reductive calibration factor ($k^* < 1.0$); conversely, when $RCDI_{ij} < 0$, the operational risk is underestimated, requiring an amplificative calibration factor ($k^* > 1.0$).

Within the calculation above, this study formally defines the SDE weighted mean risk score as a heuristic reference baseline ($D_j^* = \bar{D}_{E,j}$) rather than asserting the expert cohort as an infallible or absolute physical standard. Based on the specific calculated approach above, the operational definition posits that while expert perception is not immune to epistemic uncertainty, it represents the most robust, normatively calibrated professional consensus available for cross-cohort risk harmonization.

3.2.2. High-Consequence Structural & Elevation Hazards

1) High-Altitude Operations (CASE-1, **Figure 3(a)**)

For high-altitude operations, the safety domain experts were established at $D_1^* = 111.31$. As illustrated in **Figure 3(a)**, non-specialist personnel demonstrated an acute risk overestimation trend, yielding a raw score of $\bar{D}_{P,1} = 306.42$ ($RCDI_{P,1} = +1.753$). The response trajectory for non-specialist personnel exhibits the steepest response gradient ($\mathrm{d}D_{P,1}/\mathrm{d}k = 306.42$), rising rapidly from 245.14 ($k = 0.8$) to 428.99 ($k = 1.4$), and this stems from severe psychological dread and a lack of engineering context regarding fall-arrest protections. Frontline operational workers yielded a moderately elevated rating ($\bar{D}_{W,1} = 144.15$,

$RCDI_{W,1} = +0.295$). To reconcile these evaluations with the safety domain experts D_1^*, the optimal calibration factors were computed as $k_{W,1}^* = 0.772 \approx 0.8$ for frontline operational workers and $k_{P,1}^* = 0.363 < 0.8$ for non-specialist personnel.

2) Scaffolding Erection Operations (CASE-8, **Figure 3(h)**)

Scaffolding erection represents a complex elevation hazard with a safety domain experts of $D_8^* = 248.52$. In stark contrast to CASE-1, both non-expert groups exhibited significant risk underestimation, as depicted in **Figure 3(h)**. Frontline operational workers evaluated the raw risk at $\bar{D}_{W,8} = 150.13$ ($RCDI_{W,8} = -0.396$), while non-specialist personnel recorded an even lower rating of $\bar{D}_{P,8} = 82.46$ ($RCDI_{P,8} = -0.668$). Frontline scaffolders suffer from operational risk habituation, underestimating structural instability and dynamic load risks, whereas non-specialist personnel lack awareness of temporary structure failure mechanics. Because no intersection with the safety domain experts occurs within $k \in [0.8, 1.4]$, both cohorts require strong amplificative calibration coefficients: $k_{W,8}^* = 1.655 > 1.4$ and $k_{P,8}^* = 3.014 \gg 1.4$.

3) Trench and Foundation Pit Edge Protection (CASE-6, **Figure 3(f)**)

As shown in **Figure 3(f)**, trench and foundation pit edge protection exhibited the most pronounced multi-stakeholder risk underestimation among all evaluated cases. While safety domain experts assigned a high baseline score of $D_6^* = 96.74$ due to soil collapse and slope instability hazards, frontline operational workers ($\bar{D}_{W,6} = 32.94$, $RCDI_{W,6} = -0.659$) and non-specialist personnel ($\bar{D}_{P,6} = 33.55$, $RCDI_{P,6} = -0.653$) produced nearly identical, suppressed evaluations. The response curves for both non-expert cohorts remain positioned far below the expert reference across the entire range of $k \in [0.8, 1.4]$. This convergence highlights that non-experts intuitively perceive trench edges as static ground terrain, failing to comprehend subsurface geomechanical failure modes. Due to this, both groups require an aggressive scaling correction factor of $k_{W,6}^* = 2.937 > 1.4$ and $k_{P,6}^* = 2.883 > 1.4$.

3.2.3. Process & Environmental Hazards

1) Temporary Electrical Operations (CASE-2, **Figure 3(b)**)

Temporary site power distribution shows an expert-reference baseline of $D_2^* = 33.53$. **Figure 3(b)** indicates that frontline operational workers assigned the highest raw risk score ($\bar{D}_{W,2} = 75.50$, $RCDI_{W,2} = +1.252$), demonstrating a response gradient of $\mathrm{d}D_{W,2}/\mathrm{d}k = 75.50$, which reflects workers' direct operational encounters with electrical hazards, cable wear, and wet ground conditions. Non-specialist personnel evaluated the risk as moderately higher than safety domain experts ($\bar{D}_{P,2} = 47.03$, $RCDI_{P,2} = +0.403$). Reconciling these evaluations requires reductive calibration parameters as $k_{W,2}^* = 0.444 < 0.8$ for frontline operational workers and $k_{P,2}^* = 0.713 \approx 0.7 - 0.8$ for non-specialist personnel.

2) Routine Inspection in Confined Spaces (CASE-4, **Figure 3(d)**)

Atmospheric hazards in confined spaces resulted in a safety domain experts of

$D_4^* = 21.22$. As displayed in **Figure 3(d)**, frontline operational workers demonstrated high-degree cognitive alignment with safety domain experts, scoring a raw value of $\bar{D}_{W,4} = 20.26$ ($RCDI_{W,4} = -0.045$), which intersects the safety domain experts at $k_{W,4}^* = 1.047 \in [1.0, 1.2]$. Conversely, non-specialist personnel exhibited cognitive inflation ($\bar{D}_{P,4} = 27.75$, $RCDI_{P,4} = +0.308$) due to claustrophobic anxiety and heightened perception of toxic gas hazards, requiring a reductive factor of $k_{P,4}^* = 0.765 < 0.8$.

3) Conventional Hot Work Without Surrounding Flammables (CASE-7, **Figure 3(g)**)

For conventional hot work, safety domain experts set the reference at $D_7^* = 60.13$. As **Figure 3(g)** shows, risk perceptions diverged significantly. Frontline welders and cutters underestimated the risk ($\bar{D}_{W,7} = 31.04$, $RCDI_{W,7} = -0.484$), as routine exposure breeds complacency regarding thermal radiation and stray sparks. In contrast, non-specialist personnel overestimated the risk ($\bar{D}_{P,7} = 96.98$, $RCDI_{P,7} = +0.613$) due to visual fear of open flames. Neither the non-expert curve intersects the safety domain experts within $k \in [0.8, 1.4]$. Alignment requires an amplificative correction for workers ($k_{W,7}^* = 1.937 > 1.4$) and a reductive correction for non-specialist personnel ($k_{P,7}^* = 0.620 < 0.8$).

3.2.4. Low-Consequence Routine Operational Hazards

1) Mechanical Cutting Operations (CASE-3, **Figure 3(c)**)

Mechanical cutting represents a low-to-moderate physical hazard with a safety domain experts of $D_3^* = 30.05$. As shown in **Figure 3(c)**, both non-expert groups overestimated operational risks. Non-specialist personnel produced the highest evaluation ($\bar{D}_{P,3} = 59.66$, $RCDI_{P,3} = +0.985$), driven by visceral apprehension of high-speed blade contact and flying debris. Frontline operators yielded a moderately inflated rating ($\bar{D}_{W,3} = 43.06$, $RCDI_{W,3} = +0.433$). Consequently, reductive calibration parameters are required for both groups, as $k_{W,3}^* = 0.698 < 0.8$ and $k_{P,3}^* = 0.504 < 0.8$.

2) Ground Material Handling Operations (CASE-5, **Figure 3(e)**)

Ground material handling represents a high-frequency, low-severity routine activity ($D_5^* = 21.95$). **Figure 3(e)** demonstrates that frontline operational workers accurately calibrated the operational risk ($\bar{D}_{W,5} = 20.55$, $RCDI_{W,5} = -0.064$), yielding an ideal calibration coefficient near unity ($k_{W,5}^* = 1.068 \approx 0.8\text{-}1.0$). Conversely, non-specialist personnel dramatically inflated the risk ($\bar{D}_{P,5} = 54.30$, $RCDI_{P,5} = +1.474$) due to subjective overestimation of physical exertion and manual lifting risks. Aligning non-specialist personnel evaluation requires a reductive factor of $k_{P,5}^* = 0.404 < 0.8$.

3.2.5. Operational Calibration Matrix (k^*) & Multi-Stakeholder Risk Alignment

To synthesize the empirical findings across all eight construction scenarios, **Table 4** compiles the expert reference values (D^*), raw non-expert ratings ($\bar{D}$), Relative Cognitive Distortion Indices ($RCDI$), and optimal calibration coefficients (k^*).

Table 4. Operational calibration matrix (k^*) and multi-stakeholder risk alignment across 8 reference construction cases.

Situations & Operational Activity	D^*	$\bar{D}W$	$RCDIW$	kW^*	$\bar{D}P$	$RCDIP$	kP^*	Primary Cognitive Driver
CASE-1 High-Altitude Operations	111.31	144.15	0.295	0.772 (≈0.8)	306.42	1.753	0.363 (<0.8)	Public Dread Elevation Phobia
CASE-2 Temporary Electrical Operations	33.530	75.500	1.252	0.444 (<0.8)	47.030	0.403	0.713 (≈0.7~0.8)	Worker Direct Hazard Exposure
CASE-3 Mechanical Cutting Operations	30.050	43.060	0.433	0.698 (<0.8)	59.660	0.985	0.504 (<0.8)	Debris Fear High-Speed Tool Fear
CASE-4 Confined Space Inspection	21.220	20.260	−0.045	1.047 (1.0~1.2)	27.750	0.308	0.765 (<0.8)	Worker-Expert Alignment
CASE-5 Ground Material Handling	21.950	20.550	−0.064	1.068 (0.8~1.0)	54.300	1.474	0.404 (<0.8)	Public Manual Lifting Inflation
CASE-6 Trench/Pit Edge Protection	96.740	32.940	−0.659	2.937 (>1.4)	33.550	−0.653	2.883 (>1.4)	Shared Geotechnical Blind Spot
CASE-7 Hot Work Without Flammables	60.130	31.040	−0.484	1.937 (>1.4)	96.980	0.613	0.620 (<0.8)	Worker Habituation Flame Fear
CASE-8 Scaffolding Erection	248.52	150.13	−0.396	1.655 (>1.4)	82.460	−0.668	3.014 (>>1.4)	Structural Collapse Ignorance

Note: D^*: Expert Baseline; $\bar{D}W$: On-Site Workers Raw; *RCDIW*: Worker Distortion; kW^*: Worker Calibration; $\bar{D}P$: Ordinary Public Raw; *RCDIP*: Public Distortion; kP^* : Public Calibration.

The systematic analysis of Table 4 reveals three fundamental cognitive mechanisms governing subjective safety evaluation as below:

1) Universal Non-Expert Blind Spots (Severe Underestimation, $k \gg 1.4$):

In cases involving complex structural or geotechnical failure mechanisms (S6: Trench Protection, S8: Scaffolding Erection), both workers and non-specialist personnel severely underestimate risk ($RCDI \approx -0.40 \sim -0.66$), which establishes an urgent imperative for site safety management to deploy dynamic amplification factors ($k^* > 1.4$) rather than relying on uncalibrated survey averages.

2) Routine Operational Habituation ($k > 1.4$):

Frontline operational workers exhibit pronounced risk habituation in high-frequency hazardous tasks such as Hot Work (S7, $RCDI_W = -0.484$), necessitating upward calibration ($k_W^* = 1.937$) to correct for workplace complacency.

3) Visceral Risk Inflation ($k < 0.8$):

Non-experts without a technical engineering background consistently overevaluate highly visual or high-dread hazards (S1: High Altitude, S3: Cutting, S5: Material Handling), generating positive cognitive distortion ($RCDI_P$ up to +1.753). These scores require aggressive scaling compression ($k^* < 0.8$) to prevent false positives and misallocation of operational resources in risk management.

4. Summarization

The summarization of this study consolidates empirical findings from the multi-cohort LEC evaluation across eight representative construction cases (CASE-1 to CASE-8). By incorporating four sensitivity adjustment coefficients ($k \in \{0.8,1.0,1.2,1.4\}$), the summarization synthesizes the parameter-specific response characteristics, occupational cognition gaps, and the multiplicative error propagation mechanics inherent in traditional LEC formulations, while all underlying granular statistical matrices are systematically cataloged in **Appendix** Tables A2-A5.

4.1. Accident Likelihood

The quantitative assessment of accident likelihood (L) across the eight baseline construction cases demonstrates a high degree of convergence among distinct evaluation cohorts for routine, localized operations, contrasted by pronounced divergence in dynamic, structural hazard environments (**Appendix** Table A2).

Under standard scaling conditions ($k = 1.0$), baseline likelihood mean scores (μ_L) across all evaluators remained restricted within a low-amplitude range of 0.57 to 2.10.

- **Safety Domain Experts (SDE):** Safety domain experts exhibited superior hazard discrimination sensitivity. The mean likelihood values reached peak magnitude in high-altitude operations (CASE-1: $\mu_L = 1.69$, $\sigma_L = 2.55$) and trench edge protection (CASE-6: $\mu_L = 2.10$, $\sigma_L = 1.70$), while yielding minimum values for mechanical cutting (CASE-3: $\mu_L = 0.64$, $\sigma_L = 0.59$). The elevated standard deviations observed in expert evaluations for gravity-related hazards reflect a highly differentiated risk perspective grounded in dynamic site conditions and regulatory compliance standards.
- **Frontline Operational Workers (FOW):** Operational frontline personnel displayed systematically lower mean likelihood ratings ($\mu_L \in [0.57,1.62]$) and reduced variance relative to safety domain experts. This attenuation is primarily attributable to operational habituation and spatial familiarity bias, wherein continuous exposure to structural hazards induces an underestimation of potential accident initiation probabilities.
- **Non-Specialist Personnel (NSP):** Non-expert evaluators demonstrated erratic scoring dispersion (σ_L reaching up to 3.25 under $k = 1.4$ in CASE-3). Lacking contextual safety knowledge, their L-value assignments fluctuated widely, overestimating probabilities in visually striking operations (e.g., CASE-3 Mechanical Cutting: $\mu_L = 1.66$, $\sigma_L = 2.32$ at $k = 1.0$) while underestimating latent dynamic risks.

As many previous studies have shown [49]-[52], parameter L serves as a relatively stable baseline metric for low-complexity task evaluations; however, subjective probability assessment in non-linear dynamic construction environments necessitates expert-calibrated reference coefficients to eliminate cognitive optimism bias.

4.2. Risk Exposure Frequency

The analysis of risk exposure frequency (E) quantifies the temporal and spatial involvement of personnel within hazardous operational zones (**Appendix** Table A3). Across all cohorts, E -metric scoring spanned a moderate numerical band ($\mu_E \in [2.19, 7.21]$ across all k factors).

- **Occupational Patterning:** Scaffolding erection (CASE-8) registered the highest continuous exposure indices across all three cohorts ($\mu_E = 5.15$ for safety domain experts; $\mu_E = 4.86$ for frontline operational workers; $\mu_E = 4.12$ for non-specialist personnel at $k = 1.0$). This reflects a shared consensus regarding the sustained, multi-phase spatial vulnerability inherent in structural scaffold assembly. Conversely, confined space inspection (CASE-4) yielded the lowest exposure averages ($\mu_E = 3.70$ for safety domain experts; $\mu_E = 2.74$ for frontline operational workers at $k = 1.0$), aligning with its characterization as an intermittent, highly controlled operational task.
- **Inter-Cohort Dispersion:** Safety domain experts demonstrated slightly higher exposure estimates (μ_E) and moderate standard deviations ($\sigma_L \in [2.67, 3.27]$ at $k = 1.0$), evaluating exposure from a strict normative framework that considers environmental variability and secondary containment duties. Frontline operational workers displayed remarkably stable intra-group variance (σ_E), reflecting direct empirical awareness of physical shift durations and site throughput schedules. Non-specialist personnel, while tracking general operational trends, exhibited elevated relative variance (σ_E / μ_E), underscoring an inability to differentiate between active task execution and passive environmental exposure.

In summary, parameter E exhibits stronger cross-cohort evaluation consistency than likelihood (L) or consequence severity (C), as temporal exposure is more readily anchored to observable physical durations on-site.

4.3. Accident Consequence Severity

Accident consequence severity (C) was identified as the predominant source of subjective dispersion and variance within the LEC evaluation system (**Appendix** Table A4). Mean consequence scores exhibited extreme scalar stratification ($\mu_C \in [3.68, 57.13]$ across scaling factors), driving the overall magnitude of the composite risk index.

- **High-Severity Domain Characteristics:** For high-fatality-risk operations such as high-altitude work (CASE-1), trench edge protection (CASE-6), and scaffolding erection (CASE-8), all cohorts yielded elevated C -scores. However, the internal logic of scoring diverged significantly between groups, as shown below:

1) Safety Domain Experts (SDE): Assigned conservative severity values (e.g., CASE-1: $\mu_C = 17.55$, $\sigma_C = 23.29$ at $k = 1.0$), reflecting comprehensive risk modeling that accounts for regulatory penalties, structural damage, and multi-casualty disaster thresholds.

2) Frontline Operational Workers (FOW): Exhibited elevated consequence ratings for immediate, explicit physical injuries (e.g., CASE-1: $\mu_C = 23.93$ at $k = 1.0$), driven by direct peer exposure to major injury events. However, they significantly underestimated consequences for insidious hazards, such as trench edge collapses (CASE-6: $\mu_C = 6.38$ vs. Expert $\mu_C = 13.95$ at $k = 1.0$).

3) Non-Specialist Personnel (NSP): Displayed non-Gaussian scoring distributions. Notably, in temporary electrical operations (CASE-2), novice evaluations showed severe statistical dispersion ($\sigma_C = 18.75$ at $k = 1.0$ and $\sigma_C = 68.56$ at $k = 1.2$), indicating severe cognitive polarization due to a lack of technical comprehension regarding electrical shock mechanisms and systemic arc-flash hazards.

- **Low-Severity Domain Characteristics:** Ground material handling (CASE-5) consistently anchored the lower bound of consequence metrics across all groups ($\mu_C \in [3.68, 5.83]$ at $k = 1.0$), confirming strong broad consensus regarding lower-tier physical trauma hazards (e.g., minor contusions, localized strains).

The empirical data demonstrate that C-value subjective bias constitutes the primary driver of risk misclassification in traditional LEC applications, requiring targeted mathematical adjustment based on evaluator background.

The empirical data demonstrate that C-value subjective bias constitutes the primary driver of risk misclassification in traditional LEC applications, requiring targeted mathematical adjustment based on evaluator background. Also, to verify that the SDE represents true objective risk rather than mere subjective groupthink, the expert evaluations were corroborated against macro-level historical accident databases. Based on the analytical results, SDEs anchored peak Consequence Severity (C) and total risk (D) values to High-altitude Operations (CASE-1) and Scaffolding Erection (CASE-8), which impeccably mirror empirical industry fatality statistics, where falls from height and structural collapses dominate historical construction site mortalities, accounting for over 60% of total annual fatalities [53]-[56]. Such alignment with empirical historical reality confirms that the SDE cohort serves as a mathematically rigorous and historically grounded reference baseline for subsequent model calibration.

4.4. Compound Risk Score Evaluation

The compound risk score, defined by the non-linear multiplicative formulation $D = L \times E \times C$, synthesizes individual parameter uncertainties into an integrated hazard index (**Appendix** Table A5). The quantitative findings highlight a critical mathematical vulnerability in the traditional LEC method due to multiplicative error propagation.

Under first-order error approximation and relative variance expansion, the compound perturbation follows:

$$\frac{\delta D}{D} \approx \frac{\delta L}{L} + \frac{\delta E}{E} + \frac{\delta C}{C} \tag{17}$$

$$Var(D) \approx (\mu_E \cdot \mu_C)^2 \cdot Var(L) + (\mu_L \cdot \mu_C)^2 \cdot Var(E) + (\mu_L \cdot \mu_E)^2 \cdot Var(C) \quad (18)$$

As demonstrated by the compounded metric dynamics across adjustment factors $k \in \{0.8, 1.0, 1.2, 1.4\}$:

- **Compounded Variance Amplification:** While individual parameter variations (L, E, C) remained within modest bounds, the resulting composite risk scores (D) expanded exponentially. For instance, in safety domain experts' evaluations of trench edge protection (CASE-6), the mean risk score inflated from $D = 137.66$ ($\sigma_D = 533.38$) at $k = 0.8$ to $D = 1291.08$ ($\sigma_D = 5002.54$) at $k = 1.4$, which confirms that minor subjective variations in primary scoring inputs undergo severe non-linear amplification in high-hazard situations.
- **Cognitive Asymmetry & Risk Misclassification:**

1) Over-Optimism in High-Risk Situations: Field workers (GW) and non-specialist personnel (GP) exhibited severe risk underestimation in critical structural tasks. In CASE-6 (trench edge protection), worker-assigned risk values ($D = 32.94$ at $k = 1.0$) were over an order of magnitude lower than expert references ($D = 336.08$). A similar habituation deficit was observed in scaffolding erection (CASE-8: Worker $D = 150.13$ vs. Expert $D = 248.52$ at $k = 1.0$). The findings in this study emphasize that a habituation-driven deficit creates catastrophic management blind spots if uncorrected.

2) Hyper-Inflation in Low-to-Moderate Hazards: Non-specialist personnel significantly overestimated hazards in visible operational tasks, such as mechanical cutting (CASE-3: Worker $D = 145.66$ vs. Expert $D = 30.05$ at $k = 1.0$), leading to potential resource misallocation in routine site safety enforcement.

- **Domain-Specific Calibration Requirements:** The linear scaling factor k effectively shifts non-expert evaluation distributions toward the reference expert envelope (D_{Expert}). However, because cognitive bias varies non-linearly across distinct hazard domains, a universal adjustment coefficient is mathematically invalid. Field worker inputs for scaffold and trench hazards require upward scaling ($k > 1.4$) to compensate for risk habituation, whereas novice inputs for mechanical cutting require downward suppression ($k < 0.8$).

In conclusion, implementing multi-subject correction coefficients within the LEC framework mitigates individual subjective bias and provides a quantitatively grounded foundation for classifying construction safety risks. However, using a simple linear scalar multiplier (k) to adjust the aggregated hazard score (D) has an inherent mathematical limitation. Given the non-linear error propagation innate to the $D = L \times E \times C$ structure, applying a terminal linear adjustment compresses the macroscopic disparity without rectifying the root-cause variations residing unevenly within the individual parameters L, E, and C. The deployment of a unified scalar k in this study serves as a pragmatic operational compromise to ensure computational feasibility and ease of implementation for front-line site management. While future iterations of this framework are expected to transition from a scalar multiplier to parameter-decoupled calibration vectors

(k_L, k_E, k_C) to achieve authentic source-level correction, the current unified calibration proxy effectively counteracts severe multiplicative error expansion, establishing a calculational first step toward dynamic cross-cohort risk harmonization.

5. Conclusions

To mitigate the critical limitations of subjectivity and low objectivity inherent in the traditional LEC (Likelihood, Exposure, Consequence) safety evaluation method, this study established a multi-cohort empirical risk assessment framework across eight high-frequency construction cases, drawing on 120 validated assessments from safety domain experts, field workers, and laypersons. The comparative analysis of individual parameters (L, E, C) reveals that the evaluations of accident likelihood (L) and exposure frequency (E) demonstrate high baseline cognitive consensus across different evaluator cohorts. On the other hand, consequence severity (C) exhibits substantial dispersion and serves as the primary driver of subjective rating variance. Furthermore, the multiplicative aggregation structure of $D = L \times E \times C$ nonlinearly amplifies these underlying parameter discrepancies, particularly in high-hazard operational environments, which confirms that the subjective error in conventional LEC evaluations stems principally from the misperception of consequence magnitude rather than misjudgments of operational frequency or occurrence probability.

The analysis of weighted D-value trajectories reveals distinct risk perception patterns among evaluator cohorts, demonstrating that a universal conversion factor is methodologically invalid. Safety domain experts exhibit superior risk sensitivity and structured differentiation, establishing a robust professional consensus proxy (D_{expert}). Field workers demonstrate consistent evaluation stability for L and E due to practical site familiarity, but they are susceptible to cognitive habituation and optimism bias, leading to significant underestimation of risks in high-hazard situations such as scaffold erection and trench edge protection. Constrained by a lack of operational domain knowledge, laypersons display extreme risk polarization characterized by marked perceptual inflation or severe underestimation. To rectify these systemic biases, cohort- and situation-tailored calibration coefficients ($k = D_{expert} / D_{evaluated}$) were formalized. Empirical results indicate that overestimated hazards require scaling factors $k < 1.0$ (e.g., $k < 0.8$) to compress inflated subjective scores, whereas underestimated perilous operations necessitate scaling factors $k > 1.0$ (e.g., $k > 1.4$) to restore risk ratings to expert reference levels.

Synthesizing the findings, this study demonstrates that integrating multi-cohort consensus modeling with dynamic calibration matrices effectively rectifies the cognitive distortion of traditional single-assessor LEC regimes, transforming qualitative field experience into a standardized, objective risk assessment protocol for safety managers. Nevertheless, a notable methodological limitation lies in deriving the calibration coefficients directly from the primary survey dataset without

subsequent out-of-sample validation, introducing potential overfitting risks to regional or demographic specifics. Consequently, the presented scalar multipliers (k) should be interpreted as a preliminary calibration matrix. Future research must prioritize independent cross-validation across distinct construction sites to verify universal generalizability, while embedding these dynamic calibration algorithms into digital twin platforms and computer-vision monitoring systems to enable real-time, automated safety governance.

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Author Contributions

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendices

Table A1. Typical eight high-frequency on-site operational cases.

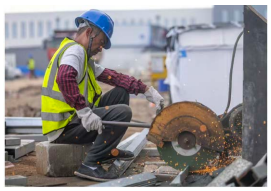
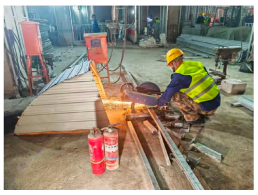
Construction site	Details	Construction site	Details
	Location: Jiangxi Province Project: Tongcheng-Tonggu Expressway Time: 2025		Location: Henan Province Project: Puyang Electricity Net Time: 2023
(a) High-altitude operations		(b) Temporary electrical works	
	Location: Hainan Province Project: Hainan satellite super-factory Time: 2025		Location: Fujian Province Project: Fuzhou Industrial Bank Time: 2025
(c) Scaffold erection and dismantling		(d) Trench excavation and earthworks	
	Location: Hainan Province Project: Baisha Affordable House Time: 2025		Location: Anhui Province Project: Dongfeng Road Engineering Time: 2017
(e) Tower crane lifting and hoisting operations		(f) Confined space operations	
	Location: Beijing City Project: Metro L17 (Xibahe Station) Time: 2023		Location: Hebei Province Project: Sinochem Holdings Headquarter Time: 2023
(g) Hot works		(h) Heavy mobile machinery operations	

Table A2. Comparison analysis of accident likelihood.

	AC	CASE-1		CASE-2		CASE-3		CASE-4		CASE-5		CASE-6		CASE-7		CASE-8	
		Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.
SDE	0.8	1.35	2.04	0.88	1.33	0.51	0.47	0.55	0.66	0.73	1.68	1.00	1.36	0.69	1.69	1.03	1.87
	1	1.69	2.55	1.11	1.66	0.64	0.59	0.69	0.83	0.91	2.10	1.26	1.70	0.87	2.11	1.29	2.34
	1.2	2.03	3.07	1.33	2.00	0.77	0.71	4.00	1.00	1.09	2.52	1.51	2.04	1.04	2.53	1.55	2.81
	1.4	2.37	3.58	1.55	2.33	0.90	0.83	0.97	1.16	1.27	2.95	1.76	2.38	1.21	2.96	1.81	3.27
FOW	0.8	0.70	1.06	0.72	0.91	0.79	1.09	0.44	0.60	0.46	0.60	0.87	1.30	0.59	0.84	0.94	1.11
	1	0.87	1.33	0.91	1.14	0.98	1.36	0.55	0.75	0.57	0.75	1.09	1.62	0.74	1.05	1.18	1.39
	1.2	1.04	1.59	1.09	1.36	1.18	1.63	0.66	0.90	0.68	0.89	1.31	1.95	0.88	1.26	1.41	1.67
	1.4	1.22	1.86	1.27	1.59	1.38	1.90	0.77	1.05	0.80	1.04	1.53	2.27	1.03	1.47	1.64	1.94

Continued

NSP	0.8	1.00	1.59	0.68	0.84	1.33	1.86	0.86	1.45	0.86	1.21	0.69	0.94	1.06	1.63	1.16	1.40
	1	1.25	1.99	0.85	1.05	1.66	2.32	1.08	1.81	1.07	1.51	0.86	1.18	1.32	2.04	1.45	1.75
	1.2	1.50	2.38	1.01	1.26	1.99	2.79	1.29	2.18	1.29	1.81	1.03	1.41	1.59	2.45	1.74	2.09
	1.4	1.75	2.78	1.18	1.47	2.32	3.25	1.51	2.54	1.50	2.11	1.21	1.65	1.85	2.86	2.03	2.44

Note: AC: Adjustment Coefficient; Avg.: Average value; Dev.: Deviation value; SDE = Safety Domain Experts (n = 20); FOW = Frontline Operational Workers (n = 40); NSP = Non-Specialist Personnel (n = 60); CASE-1: High-altitude operations; CASE-2: Temporary electrical works; CASE-3: Scaffold erection and dismantling; CASE-4: Trench excavation and earthworks; CASE-5: Tower crane lifting and hoisting operations; CASE-6: Confined space operations; CASE-7: Hot works; CASE-8: Heavy mobile machinery operations.

Table A3. Comparison analysis of risk exposure frequency.

	AC	CASE-1		CASE-2		CASE-3		CASE-4		CASE-5		CASE-6		CASE-7		CASE-8	
		Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.
SDE	0.8	3.66	2.50	3.18	2.14	3.70	2.28	2.96	2.29	3.04	2.26	3.28	2.61	3.02	2.26	4.12	2.39
	1	4.58	3.12	3.98	2.67	4.63	2.85	3.70	2.86	3.80	2.83	4.10	3.27	3.78	2.82	5.15	2.98
	1.2	5.49	3.74	4.77	3.21	5.55	3.41	4.44	3.43	4.56	3.39	4.92	3.92	4.53	3.39	6.18	3.58
	1.4	6.41	4.37	5.57	3.74	6.48	3.98	5.18	4.01	5.32	3.96	5.74	4.57	5.29	3.95	7.21	4.18
FOW	0.8	3.20	1.97	2.95	2.10	3.56	2.20	2.19	1.73	3.02	2.25	3.03	2.24	3.31	2.25	3.89	2.28
	1	4.00	2.46	3.69	2.62	4.45	2.74	2.74	2.16	3.78	2.82	3.79	2.80	4.14	2.81	4.86	2.85
	1.2	4.80	2.96	4.43	3.15	5.34	3.29	3.29	2.59	4.53	3.38	4.55	3.36	4.97	3.37	5.84	3.42
	1.4	5.60	3.45	5.16	3.67	6.23	3.84	3.83	3.02	5.29	3.94	5.30	3.92	5.79	3.93	6.81	3.99
NSP	0.8	2.67	2.27	2.53	1.95	3.27	2.32	2.67	2.05	3.23	2.11	2.91	2.03	3.25	2.14	3.29	2.15
	1	3.33	2.84	3.16	2.44	4.09	2.90	3.34	2.57	4.03	2.64	3.63	2.54	4.07	2.68	4.12	2.69
	1.2	4.00	3.40	3.79	2.92	4.91	3.48	4.01	3.08	4.84	3.17	4.36	3.05	4.88	3.21	4.94	3.23
	1.4	4.67	3.97	4.42	3.41	5.73	4.06	4.68	3.60	5.65	3.70	5.09	3.56	5.69	3.75	5.76	3.76

Note: AC: Adjustment Coefficient; Avg.: Average value; Dev.: Deviation value; SDE = Safety Domain Experts (n = 20); FOW = Frontline Operational Workers (n = 40); NSP = Non-Specialist Personnel (n = 60); CASE-1: High-altitude operations; CASE-2: Temporary electrical works; CASE-3: Scaffold erection and dismantling; CASE-4: Trench excavation and earthworks; CASE-5: Tower crane lifting and hoisting operations; CASE-6: Confined space operations; CASE-7: Hot works; CASE-8: Heavy mobile machinery operations.

Table A4. Comparison analysis of accident consequence severity.

	AC	CASE-1		CASE-2		CASE-3		CASE-4		CASE-5		CASE-6		CASE-7		CASE-8	
		Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.
SDE	0.8	14.04	18.63	7.72	6.33	5.84	3.44	10.68	18.15	3.68	2.51	11.16	17.94	9.44	17.44	11.88	11.79
	1	17.55	23.29	9.65	7.91	7.3	4.3	13.35	22.69	4.6	3.14	13.95	22.43	11.8	21.8	14.85	14.73
	1.2	21.06	27.95	11.58	9.5	8.76	5.16	16.02	27.22	5.52	3.76	16.74	26.91	14.16	26.16	17.82	17.68
	1.4	24.57	32.6	13.51	11.08	10.22	6.02	18.69	31.76	6.44	4.39	19.53	31.4	16.52	30.52	20.79	20.62

Continued

FOW	0.8	19.14	23.05	10.66	13.84	6.5	4.69	6.92	12.66	4.54	4.77	5.1	4.95	6.74	12.08	14.18	18.18
	1	23.93	28.81	13.33	17.3	8.13	5.86	8.65	15.82	5.68	5.96	6.38	6.19	8.43	15.1	17.73	22.72
	1.2	28.71	34.57	15.99	20.75	9.75	7.03	10.38	18.99	6.81	7.16	7.65	7.43	10.11	18.12	21.27	27.27
	1.4	33.5	40.33	18.66	24.21	11.38	8.21	12.11	22.15	7.95	8.35	8.93	8.67	11.8	21.14	24.82	31.81
NSP	0.8	16.79	24.39	15	45.7	6.12	4.6	6.49	8.05	4.67	5.5	6.17	8.09	7.93	11.84	8.77	9.47
	1	20.98	30.49	18.75	57.13	7.65	5.76	8.12	10.05	5.83	6.87	7.72	10.11	9.92	14.8	10.97	11.84
	1.2	25.18	36.59	22.5	68.56	9.18	6.91	9.74	12.06	7	8.24	9.26	12.13	11.9	17.76	13.16	14.21
	1.4	29.38	42.69	26.25	79.98	10.71	8.06	11.36	14.07	8.17	9.62	10.8	14.15	13.88	20.72	15.35	16.58

Note: AC: Adjustment Coefficient; Avg.: Average value; Dev.: Deviation value; SDE = Safety Domain Experts (n = 20); FOW = Frontline Operational Workers (n = 40); NSP = Non-Specialist Personnel (n = 60); CASE-1: High-altitude operations; CASE-2: Temporary electrical works; CASE-3: Scaffold erection and dismantling; CASE-4: Trench excavation and earthworks; CASE-5: Tower crane lifting and hoisting operations; CASE-6: Confined space operations; CASE-7: Hot works; CASE-8: Heavy mobile machinery operations.

Table A5. Comparison analysis of compound risk score evaluation.

	AC	CASE-1		CASE-2		CASE-3		CASE-4		CASE-5		CASE-6		CASE-7		CASE-8	
		Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.	Avg.	Dev.
SDE	0.8	45.6	64.9	13.7	23.4	9.0	12.3	8.7	13.2	12.1	39.6	137.7	533.4	24.6	88.6	101.8	354.1
	1	111.3	158.5	33.5	57.1	22.0	30.1	21.2	32.3	29.6	96.7	336.1	1302.2	60.1	216.3	248.5	864.4
	1.2	230.8	328.6	69.5	118.4	45.5	62.3	44.0	67.0	61.5	200.6	696.9	2700.3	124.7	448.4	515.3	1792.4
	1.4	427.6	608.7	128.8	219.3	84.3	115.5	81.5	124.1	113.8	371.7	1291.1	5002.5	231.0	830.8	954.7	3320.6
FOW	0.8	59.0	195.2	30.9	85.1	17.6	33.0	8.3	23.4	12.5	46.1	13.5	20.8	12.7	25.1	61.5	140.0
	1	144.2	476.5	75.5	207.7	43.1	80.5	20.3	57.2	30.6	112.6	32.9	50.8	31.0	61.2	150.1	341.9
	1.2	289.9	988.0	156.6	430.8	89.3	166.9	42.0	118.6	63.3	233.5	68.3	105.3	64.4	126.8	311.3	708.9
	1.4	553.8	1830.4	290.0	798.0	165.4	309.3	77.8	219.8	117.8	432.6	126.5	195.0	119.3	234.9	576.7	1313.3
NSP	0.8	125.5	604.6	19.3	70.6	27.8	59.7	17.2	54.3	17.5	75.7	13.7	39.7	37.5	130.5	33.8	69.5
	1	306.4	1476.2	47.0	172.3	67.8	145.7	42.1	132.6	42.8	184.8	33.6	97.0	91.5	318.6	82.5	169.8
	1.2	635.4	3061.0	97.5	357.3	140.5	302.0	87.2	274.9	88.7	383.3	69.6	201.1	189.7	660.7	171.0	352.1
	1.4	1177.2	5670.9	180.7	661.9	260.3	559.6	161.6	509.3	164.3	710.1	128.9	372.6	351.4	1224.0	316.8	652.3

Note: AC: Adjustment Coefficient; Avg.: Average value; Dev.: Deviation value; SDE = Safety Domain Experts (n = 20); FOW = Frontline Operational Workers (n = 40); NSP = Non-Specialist Personnel (n = 60); CASE-1: High-altitude operations; CASE-2: Temporary electrical works; CASE-3: Scaffold erection and dismantling; CASE-4: Trench excavation and earthworks; CASE-5: Tower crane lifting and hoisting operations; CASE-6: Confined space operations; CASE-7: Hot works; CASE-8: Heavy mobile machinery operations.