International Journal of Industrial Ergonomics

ECERI: A Context-Aware Extension of REBA for Elevated Construction Ergonomic Risk

--Manuscript Draft--

Manuscript Number:	ERGON-D-25-00876
Article Type:	Research Paper
Keywords:	Worker safety at height; Construction ergonomics simulation; Computational simulations; Context-aware safety; REBA extension
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Abstract:	Musculoskeletal disorders (MSDs) are prevalent in construction, particularly during elevated tasks where environmental context critically influences risk, yet conventional ergonomic tools like the Rapid Entire Body Assessment (REBA) often overlook these factors. This study introduces and rigorously validates the Elevated Construction Ergonomic Risk Index (ECERI), a context-aware extension of REBA designed specifically for height-exposed work. ECERI integrates four key contextual amplifiers: working height, surface condition, slope angle, and edge proximity, using a theoretically grounded, multiplicative weighting scheme incorporating synergistic interaction effects. Grounded in the Contextual Ergonomic Risk Amplification (C-ERA) framework, ECERI was assessed using a comprehensive multi-tier validation strategy. Theoretical proofs confirmed mathematical consistency, while simulations showed ECERI reclassified 25.1% of scenarios into higher-risk categories. Empirical pilot validation against expert judgments revealed ECERI's significantly improved alignment (R2=0.852 vs. REBA's 0.737, p<0.001) and high-risk sensitivity (0.923 vs. 0.615) without sacrificing specificity (0.917). Key interactions, notably Height-Slope, were confirmed as significant risk drivers.

Highlights

- Existing limitations of traditional ergonomic tools for elevated construction work are reviewed, and a new context-aware framework is introduced.
- A comprehensive taxonomy of contextual ergonomic risk factors is developed and validated through expert input.
- A new model, ECERI, algorithmically reformulates REBA using contextual amplifiers and interaction terms for automated ergonomic risk assessment in elevated construction tasks.
- The ECERI model was developed and validated through a three-tier framework and translated into a functional web-based risk calculator for practical deployment.

ECERI: A Context-Aware Extension of REBA for Elevated Construction Ergonomic Risk

ABSTRACT

Musculoskeletal disorders (MSDs) are prevalent in construction, particularly during elevated tasks where environmental context critically influences risk, yet conventional ergonomic tools like the Rapid Entire Body Assessment (REBA) often overlook these factors. This study introduces and rigorously validates the Elevated Construction Ergonomic Risk Index (ECERI), a context-aware extension of REBA designed specifically for height-exposed work. ECERI integrates four key contextual amplifiers: working height, surface condition, slope angle, and edge proximity, using a theoretically grounded, multiplicative weighting scheme incorporating synergistic interaction effects. Grounded in the Contextual Ergonomic Risk Amplification (C-ERA) framework, ECERI was assessed using a comprehensive multi-tier validation strategy. Theoretical proofs confirmed mathematical consistency, while simulations showed ECERI reclassified 25.1% of scenarios into higher-risk categories. Empirical pilot validation against expert judgments revealed ECERI's significantly improved alignment (R^2=0.852 vs. REBA's 0.737, $p<0.001$) and high-risk sensitivity (0.923 vs. 0.615) without sacrificing specificity (0.917). Key interactions, notably Height-Slope, were confirmed as significant risk drivers.

Keywords: Worker safety at height, Construction ergonomics simulation, Computational simulations, Context-aware safety, REBA extension

1. Introduction

Construction remains one of the most hazardous industries, with dynamic sites exposing workers to significant safety challenges (Awolusi et al., 2018; Lan et al., 2023). Elevated work is common in tasks such as roofing and steel erection and presents a dual risk: acute falls and chronic ergonomic exposures that contribute to musculoskeletal disorders (Ngxesha et al., 2024; Oyeyipo et al., 2025). Construction workers already experience MSDs at rates significantly higher than the general working population, and this disparity is amplified for trades frequently operating at elevation, leading to substantial costs from lost productivity and healthcare expenses (Dale et al., 2015; Gatchel and Schultz, 2014; Song et al., 2017; Dong et al., 2019).

Working at height alters both biomechanical and cognitive demands. Unstable surfaces, inclined planes, restricted spaces, and the perceived risk of falls prompt compensatory strategies such as wider stance, increased co-contraction, and cautious, segmented movement (Gates and Dingwell, 2011; Guo and Xiong, 2020; Simeonov, 2003). These adaptations may improve stability yet often increase static loading, joint strain, and fatigue, which are linked to MSD development (Antwi-Afari et al., 2017; Panariello et al., 2022). Furthermore, the heightened cognitive load associated with maintaining spatial awareness and managing fall risk can detract from optimal ergonomic performance (Habibnezhad et al., 2019; Rezvanizadeh et al., 2023).

Despite these context-dependent demands, widely used ergonomic tools such as Rapid Entire Body Assessment (REBA) were developed for relatively static industrial or clinical settings and may lack sensitivity to multifactorial risks in dynamic, real-world environments (Joshi and Deshpande, 2020; Takala et al., 2010). While such tools provide structured posture scoring, they do not explicitly account for environmental stressors like unstable surfaces, constrained spaces, sloped planes, or proximity to edges (Kee, 2022; Kibria, 2023). By abstracting posture from its surrounding physical context, conventional methods can under-detect exposure in variable work settings and complicate targeted intervention design (Brunner et al., 2022; Kee, 2022).

Enhancements to posture-based assessments have improved precision and automation, but have not fully addressed context as an inherent amplifier of baseline risk. Probabilistic approaches model postural variability and measurement uncertainty (Mumani et al., 2021; Rezvanizadeh et al., 2023). Fuzzy-set methods increase interpretive flexibility and inter-rater agreement (Gada et al., 2024; Golabchi et al., 2016). Machine-learning variants of Rapid Upper Limb Assessment (RULA)/REBA and real-time capture systems deliver more continuous feedback (Yazdani et al., 2022; Wang et al, 2023). While these advancements have increased the precision and automation of ergonomic evaluations, they primarily refine postural analysis or uncertainty handling. They do not integrate environmental state as a structured input that can amplify or moderate risk, which is pivotal for height-exposed work where fall-prevention adaptations interact with ergonomic load.

To bridge this critical gap, this paper introduces the Elevated Construction Ergonomic Risk Index (ECERI), a context-aware enhancement of REBA grounded in the Contextual Ergonomic Risk Amplification (C-ERA) framework. ECERI integrates key environmental factors: working height, surface condition, slope angle, and edge proximity through a multiplicative, interaction-aware formulation that preserves comparability with baseline REBA under neutral context while quantifying amplification when context demands it.

The objective is to develop and validate ECERI as a context-sensitive ergonomic risk model for elevated construction tasks. The study does the following: (i) formalizes the C-ERA framework to guide contextual integration, (ii) defines a taxonomy of height-related risk factors and selects the principal amplifiers, (iii) formulates the ECERI model with justified interaction terms, (iv) validates performance through a three-tier methodology including theoretical, simulation, and empirical expert comparison, and; (v) operationalizes the method using a web-based ECERI Risk Calculator to support field use.

The remainder of the paper presents a review of relevant literature (Section 2), the theoretical background and C-ERA framework (Section 3), model development and validation methodology (Section 4), results across the three tiers (Section 5), discussion of contributions, implications, and limitations (Section 6), and conclusions (Section 7).

2. Literature Review

To contextualize the need for and development of the ECERI model, this section provides a review of established biomechanical and cognitive effects of working at height that necessitate context-sensitive ergonomic assessment.

2.1 Biomechanical and Cognitive Effects of Working at Height

Operating at elevation imposes distinct physiological and psychological demands that differ materially from ground-level work. Recognizing these effects is essential for understanding the limits of context-agnostic assessment tools.

2.1.1. Impaired Postural Stability and Compensatory Adaptations

Maintaining balance is fundamentally more challenging at height. Seminal studies demonstrated that elevated environments, particularly those lacking close visual references or involving unstable surfaces, significantly increase postural sway (Bhattacharya et al., 2003; Simeonov et al., 2001). Increased sway often triggers compensatory muscle activity as workers strive to maintain equilibrium. Modern measurement techniques confirm these findings; inertial sensors show greater center-of-pressure displacement during elevated tasks (Chen et al., 2021), and virtual-reality experiments isolate perceived height as sufficient to alter postural control

(Habibnezhad et al., 2019; Simeonov et al., 2005). These stability constraints prompt compensatory adaptations not typically needed at ground level.

2.1.2. Increased Muscular Loading and Altered Movement Strategies

The drive for stability at height leads to altered muscle activation patterns and movement kinematics. Increased muscle co-contraction, particularly in lower limbs and core stabilizers, is a common protective strategy to stiffen joints and enhance balance (Mochizuki et al., 2024; Simeonov, 2003). While effective for stability, this co-activation significantly increases joint loading, metabolic cost, and fatigue; consequences often overlooked by standard postural assessments (Antwi-Afari et al., 2017).

Motion analysis further reveals that workers at height often adopt more conservative movement strategies: reduced range of motion, increased movement fragmentation, greater reliance on distal joints, fixed stances, and overreaching to avoid repositioning the base of support (Gates and Dingwell, 2011; Panariello et al., 2022). These context-driven adaptations reshape biomechanical loads and increase cumulative trauma risk.

2.1.3 Heightened Cognitive Load and Attentional Demands

Working at height also raises cognitive demands. Continual monitoring of spatial orientation, fall risk, and environmental constraints increases cognitive load (Habibnezhad et al., 2020). Emerging evidence links this load to higher perceived exertion, physiological stress responses, and potential impairments in hazard recognition when attention is divided between task execution and situational awareness (Arachchige et al., 2023; Chen et al., 2021; Umer et al., 2020) . This cognitive load can detract from a worker's ability to adopt or maintain ergonomically optimal postures, further compounding MSD risk (Rezvanizadeh et al., 2023).

Taken together, evidence indicates that elevated work constitutes a distinct ergonomic context: stability is compromised, muscular demands rise due to compensatory strategies, and cognitive load increases. Because traditional tools such as REBA focus primarily on posture without systematically integrating these environmental amplifiers and adaptive responses, they may underestimate true exposure in elevated tasks and complicate targeted intervention design (Brunner et al., 2022; Kee, 2022; Li et al., 2024). These limitations necessitate context-aware assessment methods that can systematically integrate environmental factors into ergonomic risk evaluation. To address this need, this study develops a Contextual Ergonomic Risk Amplification (C-ERA) framework as the theoretical foundation for the ECERI model, as described in the next section.

3. Theoretical Framework: Contextual Ergonomic Risk Amplification (C-ERA)

C-ERA provides a principled basis for integrating environmental context into ergonomic risk assessment for elevated construction work. This framework provides the theoretical foundation for ECERI and conceptualizes ergonomic risk in elevated environments as a baseline postural demand that is amplified by the surrounding environmental context. Rather than treating contextual factors as separate, additive risk components, C-ERA uses a multiplicative, interaction-aware structure that integrates environmental state into the risk assessment. This framework draws on three complementary theoretical perspectives:

3.1. Systems Thinking and Work System Interaction

(derived from sociotechnical systems theory, macroergonomics, SEIPS): These perspectives emphasize that safety and risk are emergent properties of the entire work system, arising from interactions between people, tasks, tools, environment, and organization (Carayon et al., 2014; Imanghaliyeva et al., 2020; Murphy et al., 2014). In C-ERA, contextual variables such as height

and surface are treated as integral system components that modulate task demands. This viewpoint supports ECERI's multiplicative formulation, which captures how system interactions amplify baseline risk, analogous to coupling terms in the RNLE (Waters et al., 1994), rather than adding isolated scores.

3.2. Adaptive Behavior and Synergistic Effects

(derived from Safety-II, Resilience Engineering, Mesoergonomics): Safety-II highlights that worker adaptations (e.g., stiffer postures on slopes) are necessary for safety but may have unintended consequences like increased biomechanical load (Martins et al., 2022; Vanderhaegen, 2015). Mesoergonomics emphasizes that cross-level interactions (e.g., environment × task) are critical risk drivers (Karsh et al., 2014). C-ERA incorporates these principles by explicitly modeling synergistic amplification, where co-occurring stressors elevate risk beyond their additive effects. This theoretical grounding mandated the inclusion of second-order interaction terms in ECERI (e.g., Height × Slope, Height × Surface, Surface × Edge), reflecting empirically observed compounded effects (Simeonov, 2003) and ensuring the model captures these critical non-linearities.

3.3. System Constraints and Boundaries

(derived from STAMP): In STAMP, accidents arise from inadequate control of constraints(Leveson, 2012). Within C-ERA, steep slopes and proximity to edges act as constraints that tighten the safe operating envelope. Combined with psychophysical evidence on perception at height(Hsiao and Simeonov, 2001), this motivates non-linear factor functions for height, slope, and edge distance. A representative parameterization (height exponent $\alpha = 0.8$, slope $\beta = 1.2$, edge $\gamma = 0.7$), captures accelerating or decelerating amplification as workers approach environmental or perceptual limits.

Guided by these principles, C-ERA organizes contextual influences into four domains relevant to elevated work: Spatial (e.g., height, edge proximity), Environmental (e.g., surface, slope, weather), Temporal (e.g., duration, pace), and Organizational (e.g., supervision, policies, training) as shown in Figure 1. This structure provides a systematic basis for identifying and classifying potential amplifiers

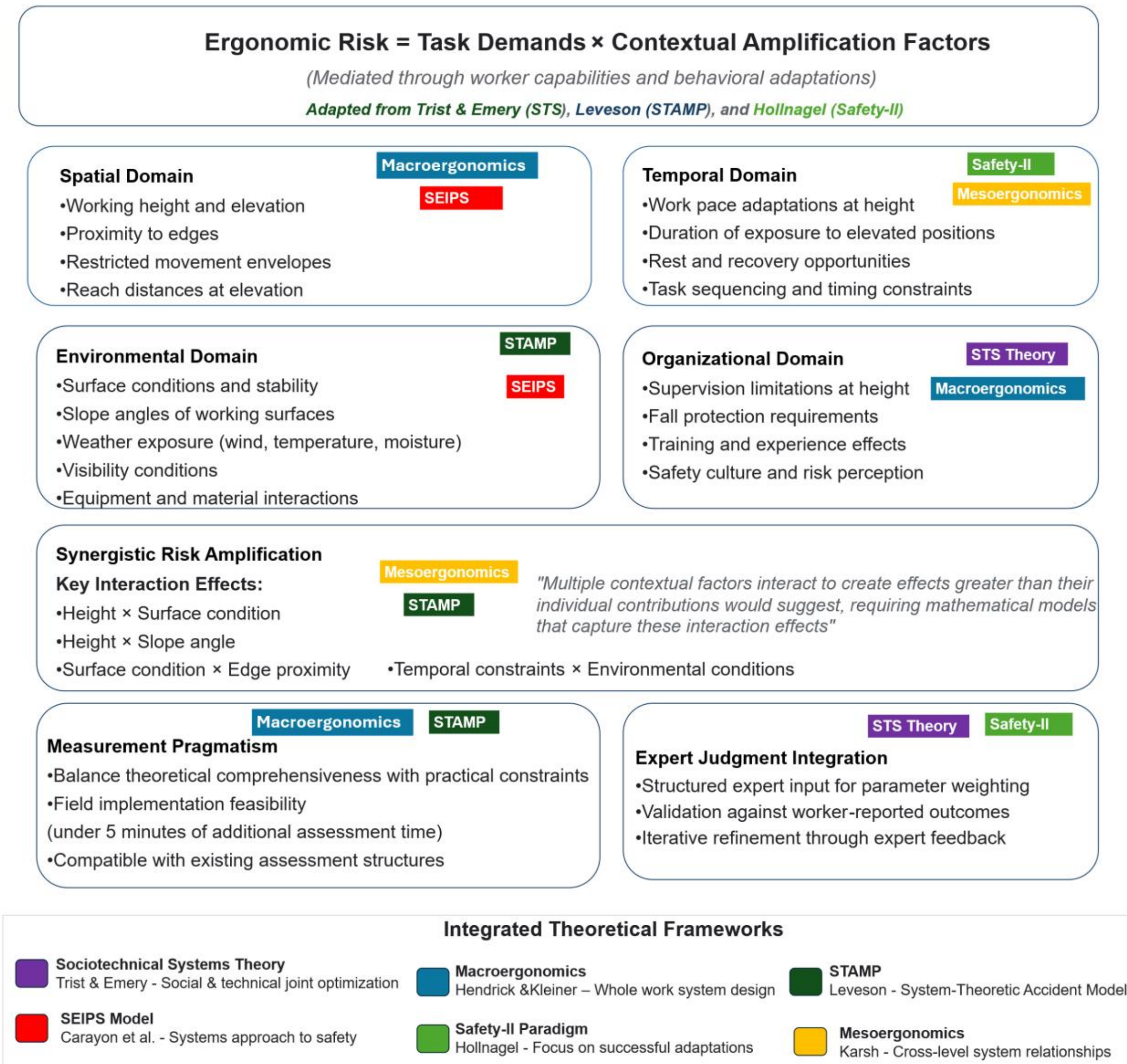

Fig 1. Contextual Ergonomic Risk Amplification (CERA) framework with theoretical foundations. (Colored tags indicate connections to established ergonomics and safety science frameworks).

Two pragmatic principles directed translation from framework to model. Measurement pragmatism ensured that selected factors are field-measurable in standard units (meters, degrees, ordinal scales). Expert-judgment integration prioritized factors and derived weights where empirical data are limited (Leontaris et al., 2019). Through literature review, C-ERA–guided factor analysis, and structured expert input, four high-priority amplifiers were selected for initial ECERI implementation: Height (HF), Surface Condition (SF), Slope Angle (SLF), and Edge Proximity (EPF), representing key spatial and environmental influences.

In sum, C-ERA justifies ECERI's core design: a multiplicative structure with non-linear main effects and theory-driven interactions. The framework bridges traditional posture scoring and the interactive realities of elevated work and anchors the model development presented in the next section.

4. Methodology

4.1. ECERI Model Development

Model development progressed from the conceptual framework and factor identification to mathematical formulation and parameterization.

4.1.1. Framework Integration

ECERI operationalizes C-ERA by modeling ergonomic risk in elevated work as baseline postural demand (REBA) that is amplified by environmental context. Rather than adding independent penalties, the REBA score serves as a foundational risk kernel that is scaled by a bounded, multiplicative, interaction-aware amplifier reflecting working height, surface condition, slope, and edge proximity.

This structure follows established precedents in occupational ergonomics that use multiplier-based models to capture co-occurring stressors. The Revised NIOSH Lifting Equation (Waters et al., 1994) demonstrates how task-specific multipliers interact with baseline load requirements, using the formula *Weight Limit* = *Reference Weight* × *hm* × *vm* × *dm* × *am* × *fm* × *cm*, where environmental and task factors multiplicatively modify lifting capacity rather than providing additive adjustments. Similarly, the Strain Index model (Moore & Garg, 1995) employs six multiplicative factors; *Strain Index = Intensity* × *Duration* × *Efforts/min* × *Hand/Wrist Posture* × *Speed* × *Duration per Day*; explicitly recognizing that co-occurring stressors produce synergistic rather than linear cumulative effects. The OCRA Index (Occhipinti, 1998) further exemplifies this paradigm, deriving exposure limits as the product of posture, force, recovery, and duration multipliers, thereby formalizing context-driven amplification in repetitive task assessment. These established precedents suggest that complex occupational risk scenarios are more appropriately represented using multiplicative modeling, as this approach better captures the synergistic interactions between environmental constraints and baseline biomechanical demands.

Empirical ergonomic studies further confirm nonlinear synergistic effects between environmental constraints and biomechanical load, particularly in elevated work contexts (Simeonov, 2003; Bhattacharya et al., 2003). These precedents support ECERI's core premise that environmental factors at height do not simply add to baseline risk; they fundamentally alter the risk relationship through amplification mechanisms that compound rather than summate individual stressor contributions.

The C-ERA framework's systems thinking perspective directly informed this multiplicative approach, where environmental factors like height, slope, and surface conditions act as system-level constraints that modify worker adaptation strategies, creating emergent risk properties beyond simple postural assessment. This aligns with mesoergonomic principles demonstrating that cross-level interactions between macro-environmental factors and micro-level outcomes produce synergistic effects (Karsh et al., 2014).

By embedding contextual amplification within a mathematically coherent structure, ECERI advances beyond context-agnostic assessment toward systematic integration of environmental risk drivers. This approach recognizes that workers at height operate within constrained systems where environmental factors fundamentally alter the biomechanical and cognitive demands of task execution, necessitating assessment tools that capture these interaction effects rather than treating context retroactively.

4.1.2. Height-Related Risk Factor Taxonomy and Selection

To translate C-ERA into a tractable model, we developed a structured taxonomy of height-relevant contextual factors through literature synthesis and expert consensus. A modified Delphi with eleven domain experts (eight safety professionals, three ergonomists) identified and grouped potential amplifiers across the four C-ERA domains: Spatial, Environmental, Temporal, and Organizational. The resulting taxonomy is presented in Table 1, it catalogs 23 factors, spanning working elevation and surface stability to production pressures and supervision limitations.

Each factor was screened against three criteria:

- Risk significance based on expert consensus;
- Field measurability using standard units and tools; and
- Alignment with C-ERA amplification principles.

Model parsimony guided final selection to balance explanatory power and site usability.

Four high-priority amplifiers were retained for the initial ECERI implementation:

- Working height (HF, Spatial): Vertical distance from ground or stable reference. Height is the primary spatial constraint influencing stability and perceived fall risk; it alters muscle activation and movement strategies (see Section 2.1). Measurement: meters.

- Surface condition (SF, Environmental): Stability, friction, and uniformity of the working surface. Rated on a 0–3 ordinal scale (0 = optimal/dry/uniform; 3 = hazardous/irregular or slippery). Surface quality affects balance control and movement confidence (Bhattacharya et al., 2003).
- Slope angle (SLF, Environmental): Inclination from horizontal. Sloped planes create asymmetric loading and require specialized postural adaptations that amplify strain (Gates and Dingwell, 2011). Measurement: degrees.
- Edge proximity (EPF, Spatial): Horizontal distance from the worker's center of gravity to the nearest unprotected edge. Proximity increases postural conservatism and restricts movement, particularly with limited visual references (Hsiao and Simeonov, 2001). Measurement: meters.

These factors capture the most measurable, high-impact spatial and environmental amplifiers and can be assessed with common site tools (tape measures, inclinometers, standardized surface ratings). Additional factors from the temporal and organizational domains may be incorporated in future iterations as empirical data accumulate, following the same selection procedure.

Table 1.

Taxonomy of height-related ergonomic risk factors

Domain	Factor	Definition	Measurement & Examples
Spatial Domain	• Working Height/Elevation	• Vertical distance from ground level or stable reference platform	• Distance measured in meters from standing surface to ground level • Range: 0-30m (model upper bound) • Examples: Roof work (5-10m), High-rise construction (10-30m+)
	• Proximity to Edges	• Horizontal distance from unprotected or protected edges with fall potential	• Distance measured in meters from worker's center of gravity to nearest edge • Range: 0.1-3.0m (closer than 0.1m generally prohibited) • Examples: Roof perimeter work (0.5m), Structural beam placement (0.2m)
	• Restricted Movement Envelopes	• Limitations on normal movement patterns due to physical constraints	• Qualitative assessment of movement restrictions in 3D space • Examples: Narrow scaffold platforms, Confined spaces in steel structures
	• Reach Distances	• Extended reaching requirements beyond normal work envelope	• Measured as percentage increase over standard reach envelope • Examples: Reaching across parapet walls, Extension work over edges
	• Access Constraints	• Restricted pathways and positioning options for optimal work posture	• Qualitative assessment of access limitations and body positioning constraints • Examples: Limited ladder access points, Obstructed pathways on structures
Environmental Domain	Surface Conditions	• Stability, friction, and uniformity of working surfaces	• Rated on a 0-3 scale: • 0: Optimal (dry, uniform, high friction) • 1: Moderate (minor irregularities or slightly reduced friction) • 2: Challenging (uneven or potentially slippery) • 3: Hazardous (highly irregular and/or slippery) • Examples: Metal decking (1), Wet concrete (2), Icy surfaces (3)
	• Slope Angles	• Inclination of working surfaces from horizontal	• Measured in degrees from horizontal • Range: 0-45° (model upper bound) • Examples: Flat roof (0-3°), Standard residential pitch (20-30°), Steep roof (40-45°)
	• Weather Exposure	• Wind, precipitation, and temperature effects on stability and function	• Qualitative assessment of weather conditions affecting work • Examples: High wind conditions, Rain exposure, Extreme temperatures

	• Visibility Conditions	• Visual clarity and perceptual challenges at height	• Qualitative assessment of visual conditions affecting task performance • Examples: Low light conditions, Glare from reflective surfaces, Visual distractions
	• Equipment Interactions	• Interface with tools and materials at height	• Qualitative assessment of equipment-related constraints • Examples: Material handling at edges, Tool use on sloped surfaces
	• Work Pace Adaptations	• Changes in task execution speed at elevation	• Measured as percentage change from normal ground-level pace • Examples: Slowed movements near edges, Cautious material handling at height
Temporal Domain	• Duration of Exposure	• Time spent at elevation without ground-level breaks	• Measured in continuous minutes/hours at elevation • Examples: Extended roofing shifts, Prolonged aerial lift operations
	• Rest Opportunities	• Frequency and quality of break periods during elevated work	• Measured as number and duration of rest breaks per work period • Examples: Limited break options on scaffolding, No seated rest areas on roofs
	• Task Sequencing	• Order and flow of activities at height	• Qualitative assessment of task organization and transitions • Examples: Multiple transitions between positions, Repeated position changes
	• Production Pressures	• Time constraints and productivity demands affecting pace	• Qualitative assessment of schedule and production expectations • Examples: Accelerated schedule due to weather concerns, Incentivized production
Organizational Domain	• Supervision Limitations	• Reduced oversight effectiveness at height	• Qualitative assessment of supervision quality and accessibility • Examples: Limited visual monitoring of high-rise work, Communication challenges
	• Fall Protection Requirements	• Constraints from safety equipment on movement and posture	• Qualitative assessment of PPE effects on ergonomics • Examples: Full-body harness restrictions, Lanyard positioning limitations
	• Training Effects	• Skill levels for elevated work and height-specific techniques	• Measured as hours of specific training for elevated work tasks • Examples: Experience with height-exposed work, Task-specific training
	• Work Planning	• Organization of height-exposed tasks and resource allocation	• Qualitative assessment of work organization effectiveness • Examples: Pre-task planning for elevated work, Resource allocation for height tasks

• Safety Culture	• Risk perception and safety prioritization in elevated work	• Qualitative assessment of organizational safety emphasis for elevated work • Examples: Management support for safer practices, Peer safety enforcement

4.1.3. Mathematical Formulation

4.1.3.1. Core Equation. ECERI modifies baseline REBA scores by treating environmental context as a multiplicative amplifier of baseline postural risk rather than a simple additive factor. This choice follows the same logic used in the Revised NIOSH Lifting Equation (RNLE), where task multipliers (e.g., asymmetric, coupling) scale a core biomechanical term to capture synergistic stressors (Waters et al., 1994). Let R_0 denote the REBA score obtained from joint-angle observation. Empirical studies of work at height (Bhattacharya et al., 2002; Simeonov et al., 2005) show that increased elevation and slope do not add a fixed risk increment; instead, they magnify spinal load, trunk sway, and cognitive demand in a nonlinear manner. Therefore, we model total risk as in Equation (1):

$$R_{\text{ECERI}} = R_0 \left(1 + \Phi(x)\right), \tag{1}$$

where $x = \{\text{height, surface, slope, edge}\}$ and $\Phi(x) \in [0,0.40]$ is an amplification factor, bounded by design so that REBA's five-level ordinal structure is preserved.

Structure of $\Phi(x)$.

(i) Main effects. Each contextual variable is first converted to a bounded risk multiplier $f_i(x_i) \in [0,1]$ capturing its marginal impact. We adopt monotonic functions validated in gait-stability and slope-load studies: sub-linear for height ($\alpha = 0.8$), super-linear for slope ($\beta = 1.2$), linear for surface, and an inverse exponential for edge proximity ($\gamma = 0.7$).

(ii) Interaction effects. Biomechanical evidence shows height × slope produces an off-axis moment that exceeds the sum of individual loads; similar rationale applies to height × surface and surface × edge. Hence second-order cross-terms are retained.

(iii) Weighting. Expert judgements (n = 11) were synthesized via Analytic Hierarchy Process (CR = 0.037) to yield weights $w_1 \ldots w_4$ and w_{12}, w_{13}, w_{24}, normalized so $\sum w = 1.20$.

(iv) Normalization constant. Dividing the weighted sum by 3.0 forces $\Phi \leq 0.40$, making the maximum possible score increase one risk category for extreme but credible field conditions, thus ECERI remains interpretable within REBA's original 1-11+ range.

The resulting formulation is shown in Equation (2)

$$\Phi(x) = \frac{1}{3}(w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 + w_{12} f_1 f_2 + w_{13} f_1 f_3 + w_{24} f_2 f_4) \tag{2}$$

Where w_1–w_4 represent the main effect weights, and w_{12}, w_{13}, and w_{24} represent the interaction weights, the denominator (3.0) serves as a normalization constant that regulates the amplification magnitude. Given that the total sum of all weights (main effects and interactions) equals 1.20, dividing by 3.0 sets a theoretical maximum Amplification Factor of 0.40 (or 40%). This 40% cap was set a priori to (i) limit the maximum increase to roughly one REBA risk band under extreme but credible contexts, (ii) maintain neutral-context recovery ($\Phi = 0$) and prevent scale drift, and (iii) align category shifts with realistic decision thresholds. Monte-Carlo analysis (n = 5 000) confirmed that 99% of credible scenarios yield $\Phi \leq 0.35$, while expert review (Section 4.3) showed ECERI explains an additional 11.5 % of variance in perceived risk over baseline REBA, demonstrating both theoretical soundness and empirical utility

4.1.3.2. Component Factor Definitions. The component factor definitions are as follows.

- *Height Factor (HF)*: The height factor quantifies risk amplification due to working elevation and it was calculated using the following Equation (3).

$$HF = min\left(1, \left(\frac{height}{h_{max}}\right)^{\alpha}\right) \tag{3}$$

height = working height in meters, h_{max}= 30 (reference maximum in meters), α = 0.8 is s scaling parameter. This sublinear growth (α < 1) captures psychophysical principles showing that perceived instability increases rapidly at lower heights but plateaus at extreme elevations

(Cleworth et al., 2018; Simeonov, 2003). It produces a non-linear response curve that increases rapidly at lower heights and gradually approaches 1 as height approaches h_{max}.

- *Surface Factor (SF)*: The Surface Factor quantifies risk amplification due to surface conditions was calculated using the following Equation (4).

$$SF = \frac{Surface}{s_{max}} \tag{4}$$

where *surface* $\in \{0,1,2,3\}$, s_{max} = *3.* represents discrete hazard levels (0=optimal, 3=hazardous) and S_{max}= 3: Modeled as a discrete ordinal scale representing slip/trip hazard levels, assumed linear for field usability, shown in the Taxonomy presented in Table 1.

- *Slope Factor (SLF)*: Quantifies surface-condition risk through a linear ordinal scale it was calculated using the following Equation (5).

$$SLF = min(\,1, \left(\frac{Slope}{\theta}\right)^{\beta}\,) \tag{5}$$

where slope = surface angle (degrees), $\theta_{\max} = 45°$ (reference maximum) and β = *1.2*, The superlinear exponent (β > 1) reflects disproportionate biomechanical loading increases on inclined surfaces, consistent with postural sway research showing exponential stability degradation above 20-30° (Bhattacharya et al., 2003).

- Edge Proximity Factor (EPF): models distance-dependent risk through rapid decay, and it was calculated using the following Equation (6).

$$EPF = \max\left(0,1\, - \left(\frac{edge_{dist}}{d_{max}}\right)^{\gamma}\right) \tag{6}$$

where $edge_{dist}$ is distance from unprotected edges (meters), d_{max} = *3m* (reference distance*).* γ = *0.7* The sublinear decay (γ < 1) captures rapid risk reduction with increased edge distance, reflecting improved postural stability when visual references are available (Luo et al., 2017)

4.1.3.3. Parameter Validation. All exponent parameters (α, β, γ) were derived from empirical literature and validated through sensitivity analysis across reasonable ranges (α=0.7-0.9, β=1.1-1.3, γ=0.6-0.8). Risk classification outcomes showed minimal variation (<5%) across these ranges, confirming parameter stability and supporting theoretical rather than fitting-based derivation.

Each contextual factor utilizes bounded functions normalized to [0,1], ensuring mathematical consistency and interpretable scaling. The non-linear formulations reflect C-ERA's emphasis on constraint-based amplification, where risk increases non-uniformly as workers approach environmental or perceptual boundaries. Figure 2 illustrates these behavioral patterns, confirming intended mathematical properties across operational ranges.

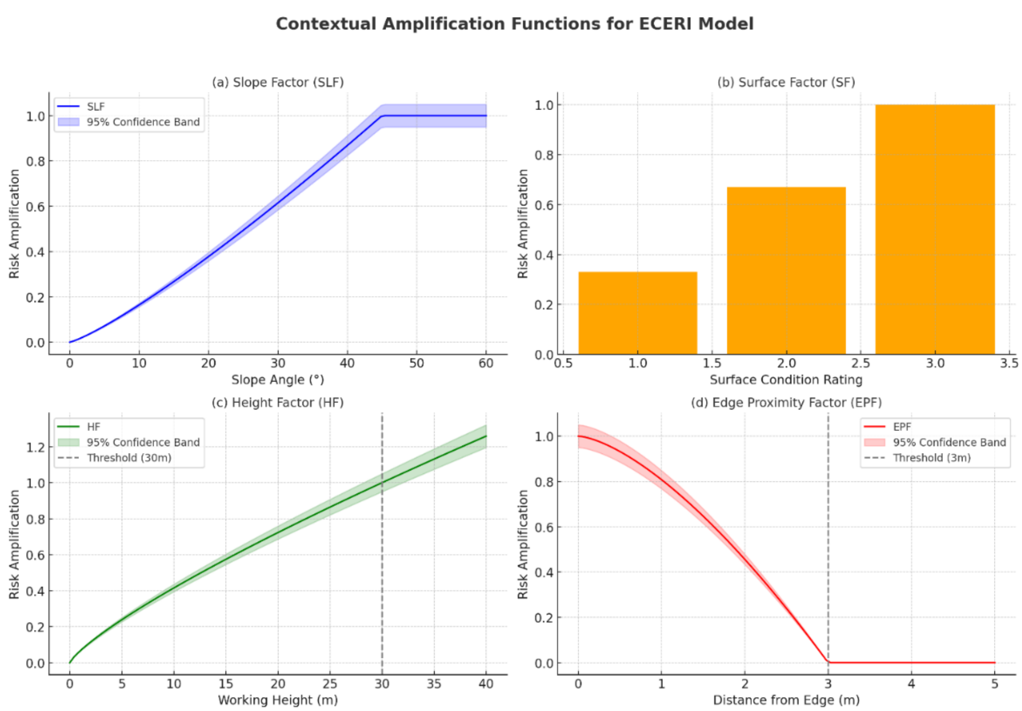

Fig 2. Behavior of contextual amplification functions used in the ECERI model.

4.1.3.4. Weight Derivation and Interaction Terms. Main Effect Weights: Weights for the four contextual amplifiers Height, Surface, Slope, and Edge Proximity, were derived using structured Analytic Hierarchy Process (AHP) consistent with Saaty's protocol (Koulinas et al., 2023). Eleven domain experts (eight construction safety professionals and three ergonomists) participated in three iterative rounds of pairwise comparisons using a standardized 1–9 importance scale (Lin et al., 2008). Individual matrices with Consistency Ratios > 0.10 were revised through expert feedback. The final aggregated matrix achieved CR=0.037, indicating internal consistency.

Table 2:

The aggregated pairwise comparison matrix from expert judgments

Factor	Height (HF)	Surface (SF)	Slope (SLF)	Edge (EPF)
Height (HF)	1.00	1.50	1.00	1.50
Surface (SF)	0.67	1.00	0.67	1.00
Slope (SLF)	1.00	1.50	1.00	1.50
Edge (EPF)	0.67	1.00	0.67	1.00

Final Weights: Height (w_1=0.30), Surface (w_2=0.20), Slope (w_3=0.30), Edge Proximity (w_4=0.20). Expert consensus reflected height and slope as dominant risk drivers, constraining the "safe operating envelope" through systemic postural control demands, while surface and edge conditions act as localized amplifiers affecting task-specific balance and movement quality.

4.1.3.5. Interaction Terms. To account for non-linear amplification mechanisms, three theoretically-justified second-order interactions capture synergistic amplification beyond additive effects:

- Height × Slope ($w_{13} = 0.10$): Represents a dominant synergy where elevated incline conditions exponentially increase postural instability. This reflects mesoergonomic principles of cross-domain coupling, in which vertical and angular stressors interact to exceed the sum of their parts (Simeonov, 2003).

- Height × Surface (w_{12} = 0.05) and Surface × Edge (w_{24} = 0.05): Capture risk scenarios where unstable footing coincides with edge exposure or vertical elevation, impairing balance control and reducing movement adaptability (Bhattacharya et al., 2002)

These interactions operationalize C-ERA's amplified constraint concept, where co-occurring stressors reduce adaptive capacity and produce elevated ergonomic loads beyond individual factor contributions. Post-hoc validation confirmed statistical significance (Height × Slope: η^2=0.317, $p<0.01$; others: $\eta^2>0.08$, $p<0.05$), substantiating their inclusion within the multiplicative framework. Table 3 summarizes the final weights assigned to each contextual factor and interaction term used in the ECERI model.

Table 3.

Assigned weights and interaction terms

Parameter	**Symbol**	**Weight**	**Description**
Height Factor	w_1	0.30	Contribution from vertical elevation
Surface Factor	w_2	0.20	Contribution from surface friction/stability
Slope Factor	w_3	0.30	Contribution from inclined working surface
Edge Proximity	w_4	0.20	Contribution from proximity to fall hazard
Interactions			
Height-Surface interaction	w_{12}	0.05	Risk due to elevation on unstable footing
Height-Slope interaction	w_{13}	0.10	Compounded destabilization from height and incline
Surface-Edge interaction	w_{24}	0.05	Gait and balance disruption near edge on poor surface

Total Weight Sum = 1.20, yielding maximum theoretical amplification of 40% when divided by the normalization constant (3.0), as detailed in Section 3.1.3.3.

4.1.3.6. Risk Categorization Scheme. ECERI adopts the standard five-level REBA classification applied directly to the calculated ECERI score: Negligible (1), Low (2–3), Medium (4–7), High (8–10), and Very High (≥11). Preserving these thresholds ensures seamless integration with established safety management systems and allows direct comparison between context-aware and conventional posture-based assessments. Maintaining familiar cut-points also reduces the need for additional training, enabling safety professionals to interpret results without modifying existing practices.

4.2. Validation Methodology

A multi-tier validation framework, shown in Figure 3, was adopted to evaluate the ECERI model's integrity across three domains: mathematical formulation, behavioral response under varied scenarios, and alignment with professional judgment.

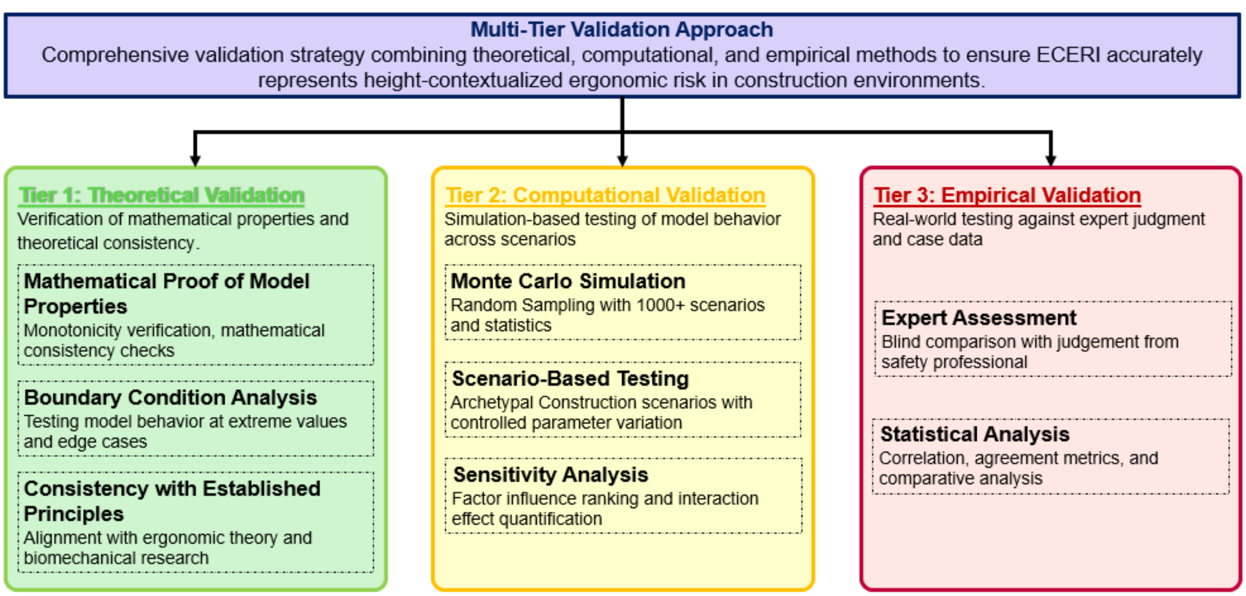

Fig. 3. Multi-Tier Validation Methodology.

The framework consists of:

- Tier 1 – Theoretical Validation: Analytical testing of core model properties, including monotonicity, boundary behavior, interaction effects, and normalization stability.
- Tier 2 – Simulation or Computational Validation: Simulation-based analysis using Monte Carlo sampling and scenario-based testing to evaluate ECERI behavior across field-relevant configurations.
- Tier 3 – Empirical Validation: Comparison of ECERI scores to expert assessments using photographic scenarios to assess alignment with professional ergonomic judgment.

This structure reflects the C-ERA model's emphasis on systems-level coherence: validation proceeds from structural soundness (Tier 1), through dynamic behavior analysis (Tier 2), to external ecological credibility (Tier 3). Together, these tiers form a triangulated assessment of the models' reliability, robustness, and practical relevance.

4.2.1. Tier 1: Theoretical Validation

Theoretical validation assessed ECERI's adherence to fundamental ergonomic modeling axioms, ensuring mathematical consistency and biomechanical plausibility across the operational domain.

- *Axiom 1 (Monotonic Dose-Response):*

Verification that increasing contextual severity produces non-decreasing risk. For any contextual factor X with a corresponding positive weight w > 0 the model ensures monotonicity by construction. A function *f*(x)is said to be monotonic as shown in Equation (7):

$$x_1 < x_2 = f(x_1) \leq f(x_2) \tag{7}$$

This involved examining the partial derivatives of the ECERI score with respect to height, surface rating, and slope (expecting positive values) and edge distance (expecting negative values). as expressed in Equation (8):

$$\frac{\partial ECERI}{\partial height} > 0 \quad \frac{\partial ECERI}{\partial surface} > 0 \quad \frac{\partial ECERI}{\partial slope} > 0 \quad \frac{\partial ECERI}{\partial edge\_dist} < 0 \tag{8}$$

- *Axiom 2 (Consistent Boundary Behavior):*

Model behavior was analyzed under best-case and worst-case input values. When all contextual risks were minimized, the ECERI score had to converge to the baseline REBA score. Under maximal risk exposure (e.g., 30 m height, 45° slope, hazardous surface, 0.1 m edge distance), the model needed to maintain a bounded response, avoiding unreasonably inflated scores.

For minimum conditions (no amplification expected):

$$If\ Height = 0,\ Surface = 0,\ Slope = 0,\ EdgeDist = dmax\ \Rightarrow ECERI = REBA$$

For extreme conditions (maximum amplification):

$$IF\ Height\ =\ h_{max}, Surface\ =\ s_{max},, Slope\ =\ \theta_{max}, EdgeDist\ \rightarrow\ 0\ \Rightarrow\ ECERI$$
$$\rightarrow\ REBA\ +\ MaxAmplification$$

- *Axiom 3 (Synergistic Interaction Effects)*

Validation that interaction terms capture compounding risk beyond linear summation. Interaction terms were assessed to verify whether ECERI captures compounding risk effects, as theorized by the C-ERA framework.

A hypothetical linear model would assume the Equation (9):

$$ECERI_{linear} = \sum wi \cdot xi \tag{9}$$

But the ECERI model introduces interaction terms as shown in Equation (10):

$$ECERI_{actual} = \sum wi \cdot xi + \sum wij \cdot xi \cdot xj \tag{10}$$

Where: w_i = weight for individual factor, w_{ij} = weight for interaction between $factors\ i\ and\ j$

This allows the model to express synergistic amplification, a key principle in mesoergonomics. particularly for theoretically justified combinations like Height-Slope.

- Axiom 4 (Normalization Consistency):

Assessment of amplification stability across the REBA spectrum. This involved calculating the amplification ratio described in Equation. (11) across the full range of baseline REBA scores to check for stability (i.e., proportional amplification) and examining the consistency and logic of risk category transitions resulting from amplification.

$$Amplification\ Ratio = \frac{ECERI - REBA}{REBA} \tag{11}$$

Theoretical validation summarizes analytical testing of mathematical properties including monotonicity verification through partial derivative analysis, boundary condition assessment at extreme parameter values, interaction effect confirmation through second-order partial derivatives, and normalization stability evaluation across the full REBA range (1-15). This comprehensive mathematical validation is aimed at establishing ECERI's theoretical soundness before empirical testing.

4.2.2. Tier 2: Computational Validation

Computational validation examined ECERI's behavioral characteristics, robustness, and responsiveness through systematic variation of input parameters across realistic construction scenarios.

4.2.2.1. Monte Carlo Simulation Design. A large-scale probabilistic simulation (n = 5,000) was conducted to evaluate ECERI behavior across realistic parameter distributions. Each contextual factor was modeled using a probability distribution chosen to reflect field-observed patterns and ergonomic risk variability:

- Height (m) was modeled using a lognormal distribution as shown in Equation (12), reflecting the right-skewed elevation exposure where most tasks occur at low-to-moderate heights, with fewer at extreme elevations:

$$f(x;\mu,\sigma) = \frac{1}{x \cdot \sigma \cdot \sqrt{2\pi}} \cdot \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right) \tag{12}$$

Parameters μ = 1.8 and σ = 0.7, yielding a median simulated height of approximately 6.0 m with an interquartile range of 3.2–10.8 m. This distribution aligns with observed patterns where routine tasks (scaffolding assembly, façade work) cluster between 3–8 m, while specialized high-rise activities extend the upper tail. Sensitivity analysis confirmed distribution stasbility: alternative parameterizations (μ = 1.6–2.0, σ = 0.6–0.8) produced minimal variance in risk classification outcomes (<3% change in category transitions).

- Slope Distribution (Gamma): followed a gamma distribution, appropriate for modeling continuous, positive values with skew, such as incline angles observed in roofing and ramped surfaces, shown in Equation (13):

$$f(x;\alpha,\beta) = \frac{x^{\alpha-1} \cdot e^{-x/\beta}}{\beta^{\alpha} \cdot \Gamma(\alpha)} \tag{13}$$

Parameters α = 2.0 and β = 7.0 were calibrated against residential roof pitch data from the National Association of Home Builders and commercial building slope specifications from OSHA fall protection standards (OSHA, 2019). This yields a mean slope of ~14° with most surfaces in the mild-to-moderate range (5–25°) and occasional steep applications up to ~35°, consistent with standard residential pitches (4/12 to 8/12) and commercial low-slope requirements. The gamma formulation captures the natural lower bound (slopes ≥ 0°) while accommodating the positive skew toward steeper pitches in specialized applications.

- Edge Proximity Distribution (Exponential): Distance from unprotected edges was simulated using an exponential distribution, reflecting the empirical observation that workers maintain greater distances from fall hazards when operationally feasible. This is represented using Equation (14):

$$f(x;\lambda) = \lambda \cdot e^{-\lambda x} \tag{14}$$

Parameter $\lambda = 1.0$ corresponds to an average working position of 1.0 m from an unprotected edge, with fewer instances at critical close distances.

- Surface condition Distribution: Surface hazard levels were modeled as discrete uniform variables sampled from ordinal values {0, 1, 2, 3}, representing the taxonomic surface classification developed in Section 3.2.2. This uniform sampling reflects the exploratory nature of the analysis, where equal representation of surface conditions enables a comprehensive assessment of their relative impacts without a priori assumptions about field prevalence. Post-hoc analysis confirmed that alternative weightings (e.g., higher prevalence of optimal conditions) did not materially alter domain rankings or interaction patterns.

4.2.2.2. Sample Bounds and Validation. All continuous samples were truncated to physically realistic bounds aligned with regulatory limits and equipment specifications:

- Height: 0.5–30 m (lower bound excludes ground-level work; upper bound reflects standard aerial platform limits)
- Slope: 0–45° (upper bound aligned with OSHA walking/working surface definitions)

- Edge distance: 0.1–3.0 m (lower bound reflects minimum approach distances; upper bound represents typical work zone depths)

Boundary violations occurred in <2% of samples and were resampled to maintain distribution properties.

4.2.2.3 Scenario-Based Simulation Approach and Domain Parameterization. To test domain-specific behavior in decision zones, five archetypes were parameterized using mid-to-upper-quartile anchors derived from regulatory thresholds, manufacturer specifications, and observed practice: roofing, structural steel erection, façade scaffolding, aerial lift, and a ground-level control. Parameters were selected to stress the Medium–High transition, where contextual amplification is most consequential. Example anchors are Roofing (H = 8 m, S = 2, SLP = 30°, ED = 1.0 m) and Structural Steel (H = 25 m, S = 1, SLP = 5°, ED = 1.5 m). To ensure results were not dependent on single anchor points, each domain was perturbed ±25% for each parameter individually, and Monte Carlo sweeps were run around these nominal settings. While absolute ECERI values shifted, the relative domain ordering and qualitative amplification patterns were preserved.

4.2.2.4 Domain prioritization mapping. For each simulated scenario i in domain d, an amplification factor was computed as in Equation (15):

$$a_i = \frac{ECERI_i - REBA_i}{REBA_i} \times 100\%. \tag{15}$$

A category-change indicator captured whether context moved the task to a higher risk band,

$$c_i = 1\{cat(ECERI_i) > cat(REBA_i)\}.$$

Domain summaries were then defined as (i) average amplification

$$A_d = \frac{1}{N_d} \sum_{i \in d} a_i,$$

and (ii) category change rate

$$C_d = 100\% \times \frac{1}{N_d} \sum_{i \in d} c_i.$$

Domains were plotted on the A_d–C_d plane with a priori cutpoints at 15% on each axis, chosen near the global mean amplification from the simulations (≈14%) and a practically meaningful migration rate of about one in six scenarios. Nonparametric bootstrap intervals (1,000 resamples) were computed for A_d and C_d for transparency. Sensitivity checks showed that shifting the cutpoints by ±2 percentage points did not change quadrant assignments

Sensitivity Analysis: A targeted sensitivity analysis was conducted to evaluate the relative influence of each contextual factor on the ECERI score and to validate the coherence of the model's weighting logic. This assessment serves two purposes: (1) to confirm that model behavior aligns with AHP-derived priority weights, and (2) to detect non-obvious non-linearities or interaction effects that may influence risk classification

- *Baseline Scenario*

All analyses were anchored to a mid-risk baseline scenario defined as: REBA score = 7; Height = 10 m; Surface Condition = 1; Slope = 15°; Edge Distance = 1.5 m. The scenario balances biomechanical load and contextual exposure, avoiding extremes while capturing field-relevant condition, serving as a stable reference point to isolate the marginal influence of each parameter.

- *One-at-a-Time (OAT) Sensitivity Index*

To isolate the contribution of each individual parameter, a one-at-a-time (OAT) sensitivity approach was used. For each parameter X_i the ECERI score was computed across its full operational range while holding all other inputs at their baseline values. The absolute sensitivity index S_i was calculated using Equation (15):

$$S_i = max(ECERI_i) - min(ECERI_i) \quad (15)$$

Where S_i measures the total ECERI change from varying X_i alone.

- *Normalized Sensitivity Index*

To facilitate comparison across parameters with differing units and scales, a normalized sensitivity index NS_i was computed using Equation (16)

$$NS_i = \frac{Si}{max(X_i) - min(X_i)} \quad (16)$$

Here, NS_i represents the rate of change in ECERI per unit change in parameter X_i enabling relative influence comparison across all factors.

- *Interaction Effect Testing*

To assess non-linear relationships between parameter pairs, interaction effects were evaluated using a second-order response surface method. For each factor pair (Xi, Xj), the interaction effect index $IEij$ was computed using Equation (17):

$$IEij = ECERI(Xi = max, Xj = max) - ECERI(Xi = max, Xj = min) - ECERI(Xi = min, Xj = max) + ECERI(Xi = min, Xj = min) \quad (17)$$

A positive value of $IEij$ indicates synergistic amplification, i.e., the combined influence of the two parameters exceeds the additive effect of each individually. This analysis validated the theoretical justification for the included interaction terms while screening for unmodeled non-linearities requiring future consideration.

4.2.3. Tier 3: ECERI Expert Validation Methodology

To complement the theoretical and simulation-based validation tiers, an expert assessment was conducted to evaluate how well ECERI scores align with professional judgment in elevated construction contexts. While the models' core strength lies in its mathematical formulation and behavioral coherence under varied input conditions, expert validation provides external grounding, ensuring that model outputs are not only theoretically robust but also perceptually credible to domain professionals.

4.2.3.1. Expert Panel and Assessment Instrument Design. A focused panel of seven domain experts was assembled, prioritizing depth of expertise over sample size. The panel comprised four certified safety professionals (mean construction experience = 14.2 years) and three ergonomists with knowledge in elevated-work evaluation. All participants were familiar with the REBA method and held above-basic knowledge in construction safety or occupational ergonomics. This composition emphasizes expertise quality over quantity and is consistent with focused validation approaches used in the ergonomic model (Hignett & Mcatamney, 2000)

To support structured assessment, 25 photographic scenarios were developed using a stratified sampling approach to span ergonomic risk levels and contextual combinations. Scenarios reflected five task archetypes consistent with the Tier 2 simulation task type: roofing, structural steel erection, façade scaffolding, aerial-lift operations, and ground-level work. The set included five ground-level control scenarios (working height = 0 m; IDs S-05, S-10, S-15, S-20, S-25) and twenty elevated-task scenarios across the remaining archetypes.

Each scenario featured:

- A high-resolution image of a real or staged elevated task
- Metadata for height, surface condition, slope, and edge proximity

- A brief, standardized description of the activity and work environment

Figure 4 presents representative examples of the photographic scenarios included in the assessment. Prior to deployment, the instrument was piloted with two independent experts to confirm clarity, interpretability, and usability.

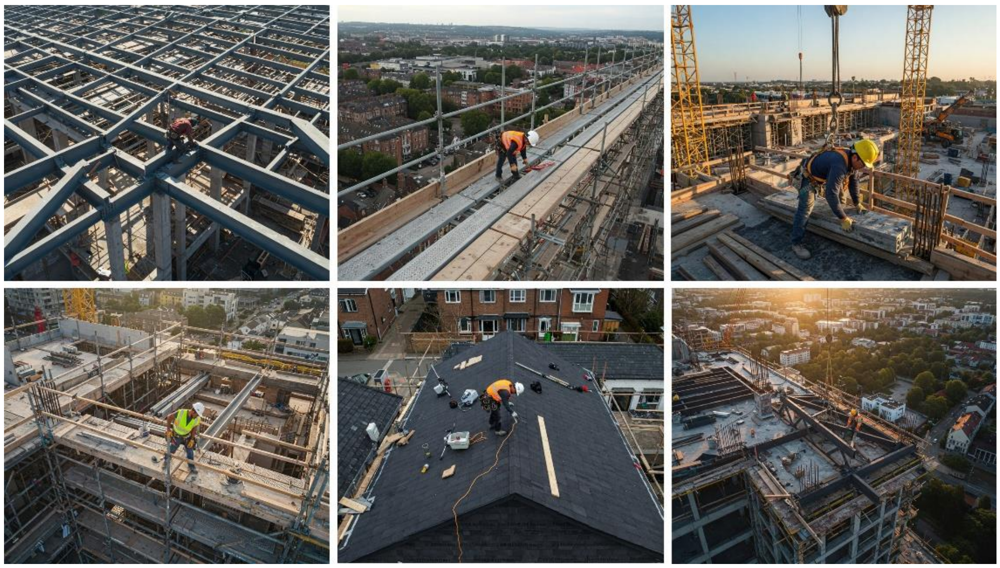

Fig. 4 Sample photographic scenarios

4.2.3.2. Expert Rating Protocol and Statistical Framework. Experts independently rated each scenario on a continuous 1–10 ergonomic risk scale, where 1 = negligible and 10 = very high. To ensure rating reliability and minimize bias, some procedural safeguards were implemented including withholding REBA and ECERI First, REBA and ECERI scores from the panel to eliminate anchoring effects. Also, ensuring all assessments were conducted independently was important.

4.2.3.2.1. Analytical Framework. A multi-method statistical framework was applied to compare expert scores with ECERI and REBA outputs:

- Inter-rater Reliability: Measured using Intraclass Correlation Coefficient (ICC) and Cronbach's alpha to assess consistency within the panel

- Correlation analysis: Pearson correlations (r) with Steiger's Z-test for dependent correlations
- Categorical agreement analysis: Cohen's Kappa (κ), weighted Kappa (κw), and adjacent agreement percentages assessed ordinal match rates.
- Classification Performance: Sensitivity, specificity, and ROC area were calculated using an expert score threshold (≥ 8) to classify high-risk cases.
- Hierarchical Regression: Nested models sequentially introduced REBA, contextual amplifiers, and interaction terms to assess their incremental predictive power. Partial η^2 was used to quantify effect size contributions.

While limited in scale, this tier introduces a structured point of comparison between the model's outputs and expert judgment. It is intended as an exploratory step, complementing the preceding tiers and informing future validation with broader samples and task diversity.

5. Result

This section presents the findings from the multi-tier validation of the ECERI model, covering theoretical properties, computational simulations, and empirical comparisons against expert judgment.

5.1 Tier 1: Theoretical Validation

Tier 1 establishes that ECERI behaves sensibly as a context-aware extension of REBA. Figure 5 reports the partial derivatives with respect to each contextual factor. The score increases with height, surface condition, and slope, and decreases as edge distance grows, confirming directional correctness. The height derivative is positive but gradually smaller at higher elevations, indicating a tapering marginal effect at the upper range. The slope derivative steepens with angle, which matches the growing balance demand on inclined planes. The surface derivative is approximately constant across its 0–3 range, while the edge-distance derivative is most negative very close to the edge and attenuates with clearance. These profiles show monotonic responses with logical curvature and no irregularities.

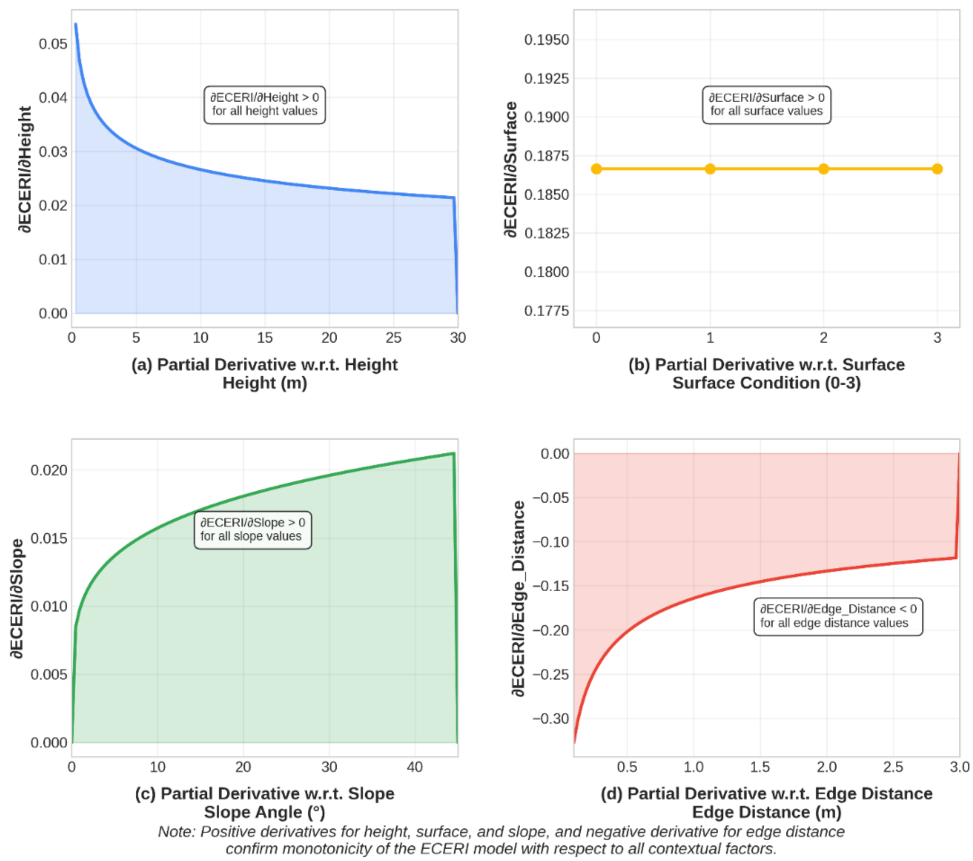

Fig 5. Partial derivatives of the contextual factors

Figure 6 examines how factors combine at a representative baseline of REBA = 7. Surfaces that include interactions sit above the additive wireframes, so the gap between them is the non-additive amplification. Height with slope is the dominant pairing: the heat map highlights a ridge where moderate to steep slopes at higher elevations yield the largest departures from additivity, approaching about 0.25 ECERI units. Height with surface shows a smaller band of amplification, and surface with edge is present but modest. The contribution panel summarizes this hierarchy under the displayed weights: roughly 4.1 percent for height × slope, 3.2 percent for height ×

surface, and 2.6 percent for surface × edge. While exact values reflect the illustrated weights, the ordering is stable across reasonable settings and aligns with field mechanics in elevated work

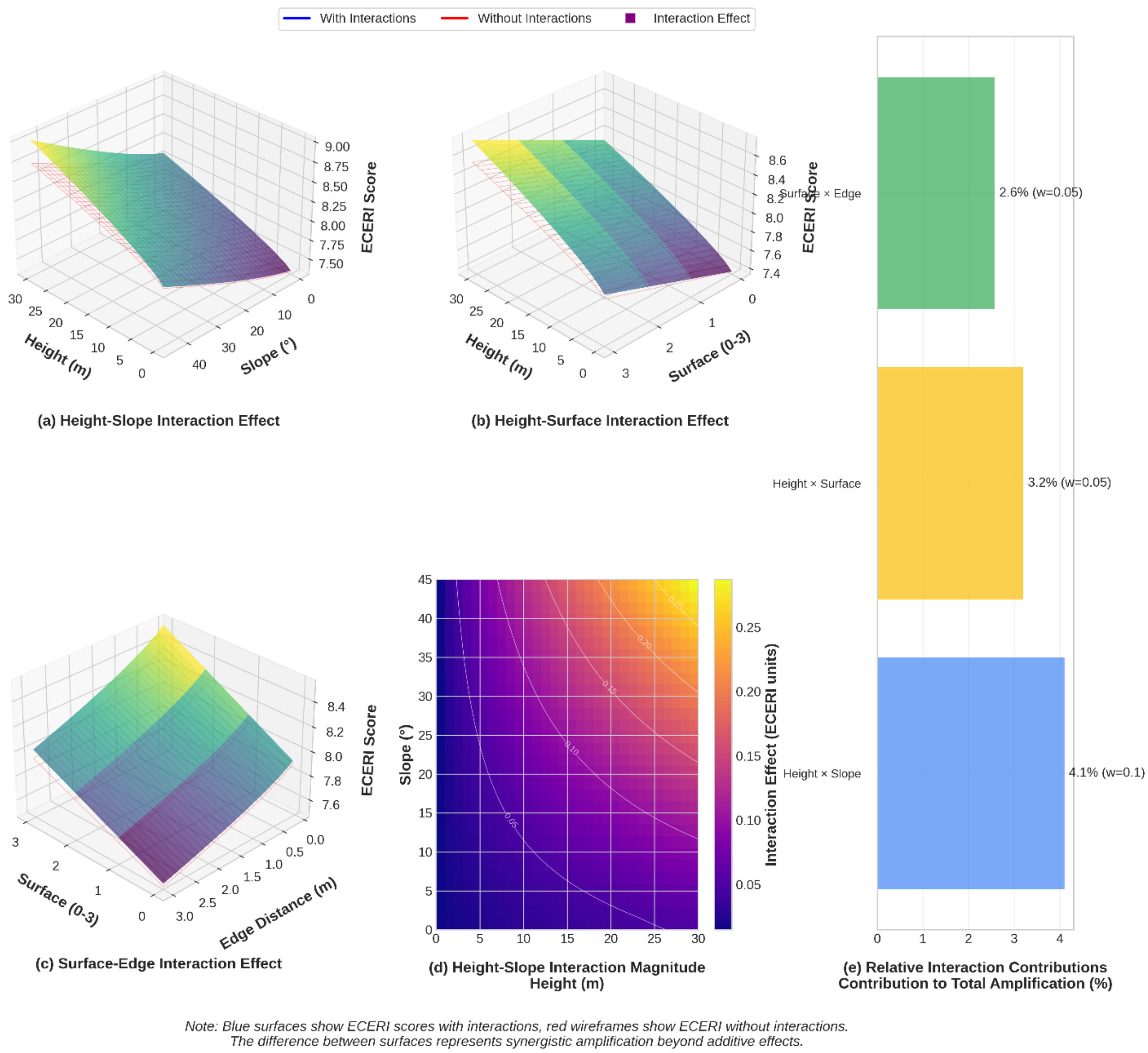

Fig. 6. ECERI synergistic effects visualization (REBA=7)

Normalization preserves scale and comparability. Under a neutral context, ECERI equals the baseline REBA. With uniformly increasing contextual demand, ECERI rises while preserving task rank and producing predictable category shifts. Additional analyses and results verify these properties and show orderly category migration without scale drift.

Together, these results verify directional response, an interpretable interaction structure dominated by height × slope, and scale integrity relative to REBA. Tier 2 tests how these properties play out at scale through simulation, focusing on sensitivity ranking, threshold behavior, and domain patterns.

5.2. Tier 2: Simulation results

Tier 2 evaluates ECERI at scale using simulation, focusing on how context shifts scores relative to REBA and how those shifts differ by domain. The simulation produces a distribution of contextual amplification centered near routine elevated conditions. Figure 12 shows a mean amplification of 14.1% with a standard deviation of 4.7%. The interquartile range spans 10.8% to 17.1%, with a lower bound of 1.7% and an upper tail reaching 35.7%. This indicates that most elevated scenarios add roughly 11–17 percent to baseline REBA, with a smaller set of demanding cases producing substantially higher increases. These values provide a reference point for interpreting later domain patterns.

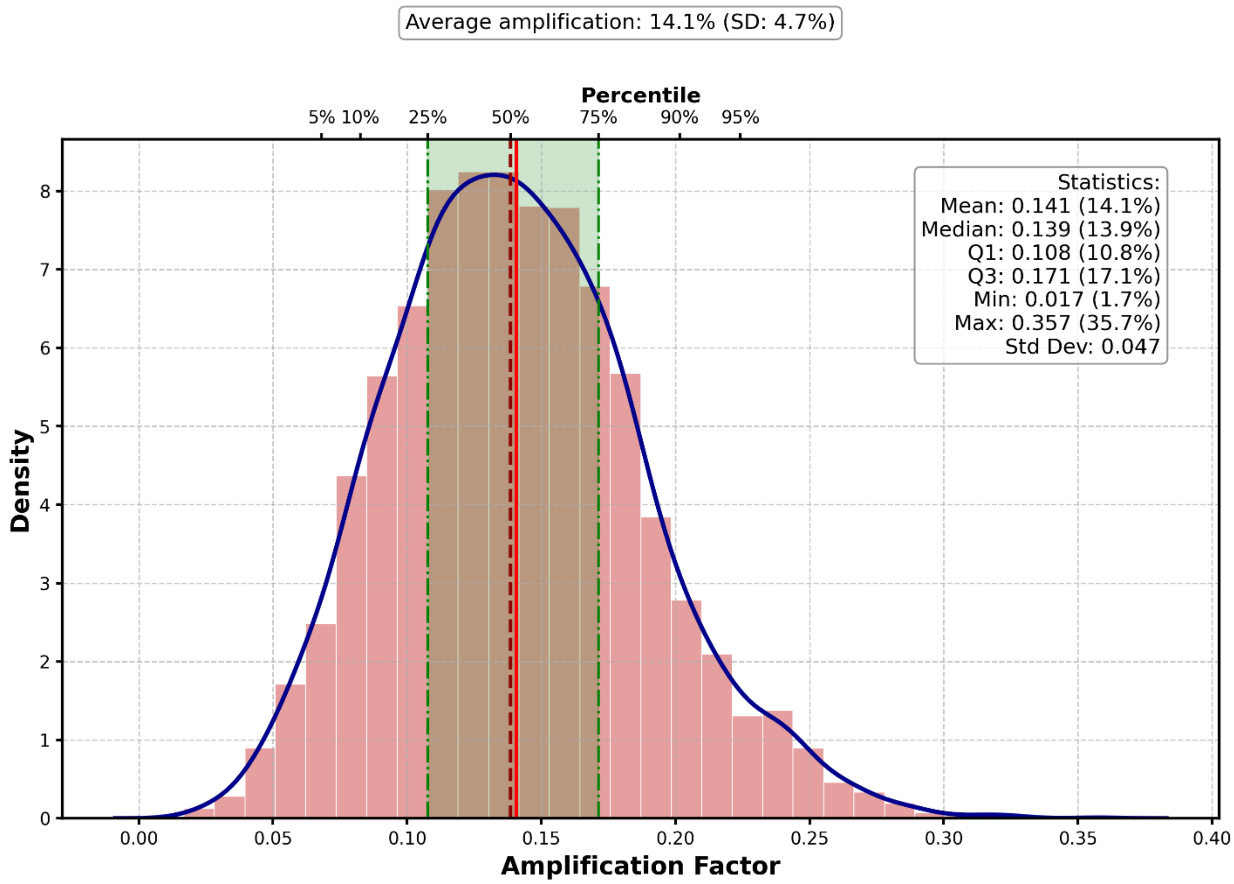

Fig. 7. Distribution of Amplification Factors from Monte Carlo Simulation (n = 5,000)

The joint behavior of ECERI and REBA across all scenarios is summarized in Figure 8. Points lie close to the ECERI = REBA diagonal, and the linear association is strong (r = 0.994), confirming that ECERI preserves the ordinal structure of REBA. The meaningful differences appear as category migrations: 25.1 percent of scenarios move upward in risk classification once context is considered. Upward shifts concentrate in the critical decision zone where Medium REBA baselines rise to High or Very High under elevated height, steeper slope, or adverse surface conditions. Marker size and color indicate that larger heights and higher amplification factors are most associated with these migrations, while low-baseline, low-context scenes cluster near the diagonal.

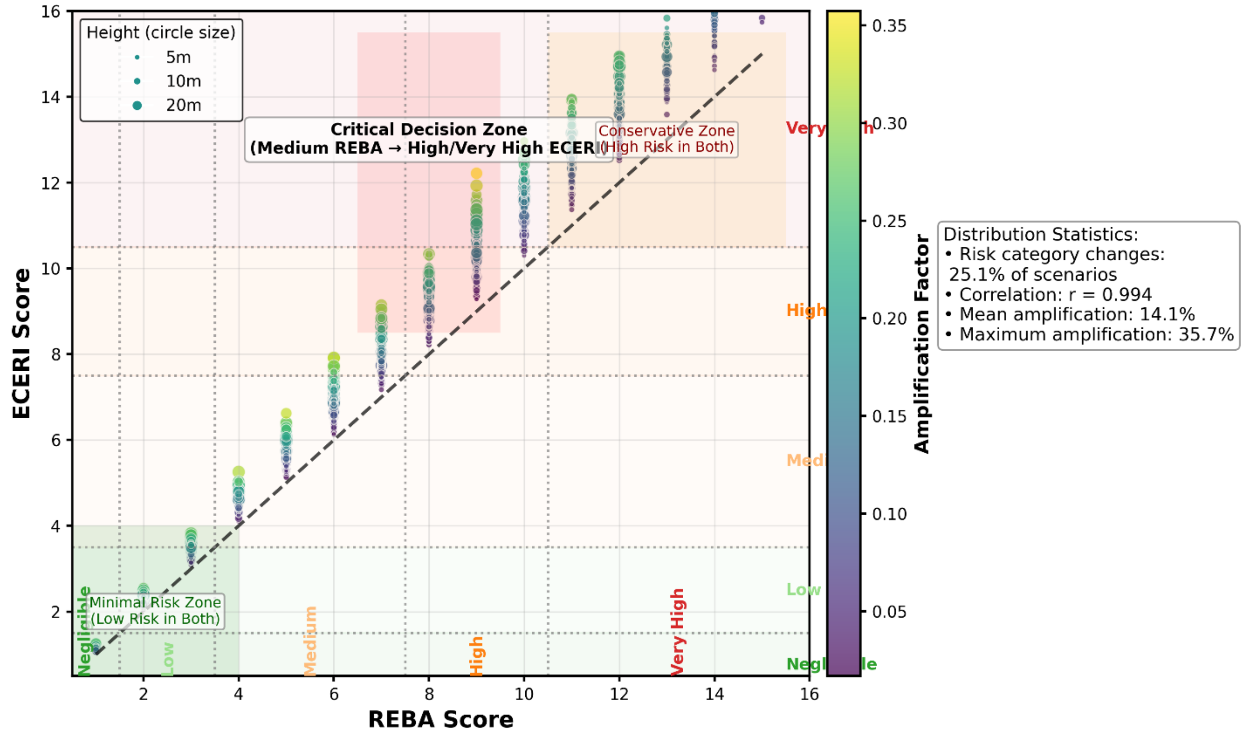

Fig. 8. ECERI vs REBA across simulated scenarios.

Domain behavior is examined in Figure 9, which overlays domain-specific response curves. All domains sit above the ECERI = REBA reference, but with different offsets that track their contextual profiles. Average amplification is highest for roofing at 19.3 percent, followed by structural steel at 15.0 percent, scaffolding at 14.5 percent, and aerial lift at 10.5 percent. The ordering matches expected mechanics: roofing pairs elevation with slope exposure; structural steel emphasizes sustained elevation; scaffolding presents balanced surface and edge conditions; aerial lift is comparatively controlled in slope with more stable platforms.

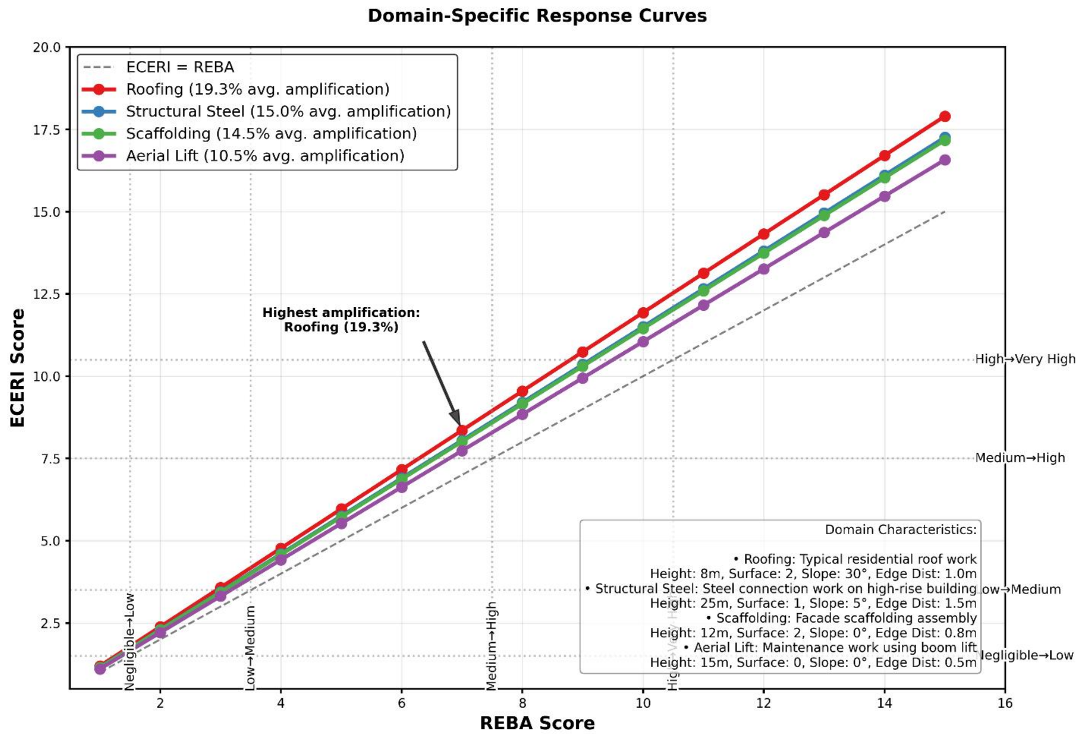

Fig. 9. Domain-specific ECERI Response Curves

Table 5 provides complementary diagnostics that explain these separations. Roofing shows the highest mean amplification and the largest category transition rate (26.7%), driven primarily by slope with a Height × Slope interaction. Structural steel, scaffolding, and aerial lift each show transition rates near 13.3% but differ in dominant contributors: height in structural steel with a Height × Surface interaction, a balanced profile with Surface × Edge effects in scaffolding, and combined height and edge distance with minimal interaction in aerial lift

Table 5

Domain summaries from simulation.

Domain	Mean Amplification (%)	Risk Transition Rate (%)	Dominant Contextual Factor	Dominant Interaction	Risk Classification
Roofing	19.3	26.7	Slope	Height × Slope	Critical Priority
Structural Steel	15.0	13.3	Height	Height × Surface	Engineering Priority

Scaffolding	14.5	13.3	Balanced	Surface × Edge	Standard Priority
Aerial Lift	10.5	13.3	Height + Edge	Minimal interaction	Standard Priority

To translate these domain differences into intervention priorities, Figure 10 maps each domain using two metrics defined in Methods: average amplification A_d on the x-axis and category change rate C_d on the y-axis. Reference lines partition the space into operational regions labeled Standard, Process, Engineering, and Critical. These labels are study-specific, aligned with the hierarchy of controls. Standard denotes routine baselines with monitoring. Process points to administrative or procedural measures when migration is driven by decision-zone effects. Engineering highlights the need for engineered or design controls when exposure magnitude is high. Critical indicates both high exposure and high migration and calls for near-term engineered controls with possible pause until risks are reduced. Roofing falls in the Critical region, structural steel in Engineering, scaffolding in Process, and aerial lift in Standard.

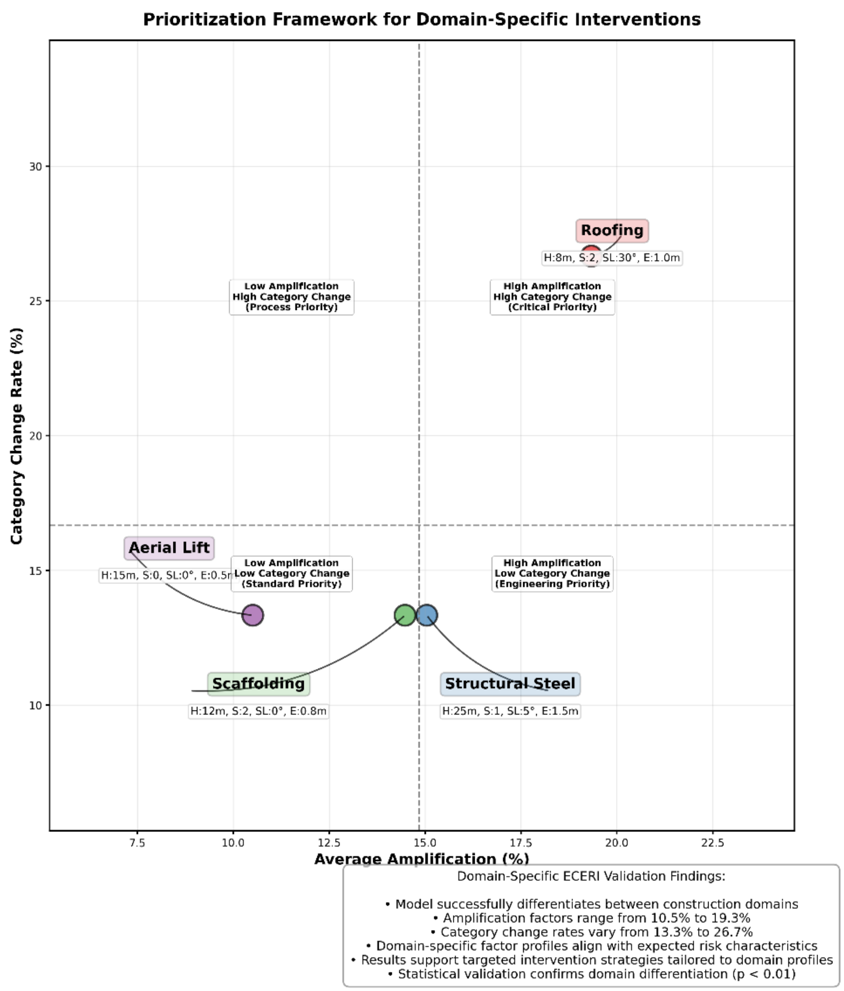

Fig. 10. Domain prioritization map derived from Tier-2 simulations.

Taken together, Tier 2 shows that ECERI retains the rank ordering of tasks while revealing where context materially changes classification. The domain analysis connects these shifts to concrete control priorities. Tier 3 assesses whether these patterns align with independent expert judgment.

5.3. Tier 3: Empirical Validation

Tier 3 tests whether ECERI aligns with independent expert judgment. Figure 23 summarizes the distribution of ratings across scenarios from seven experts and the scenario-wise mean. The panel shows wide coverage of the 1–10 scale with most scenes clustered in the mid-to-upper range and a few low-risk scenes anchoring the lower tail. Variation across scenarios is visible but the mean series is stable enough to support correlation and classification analyses.

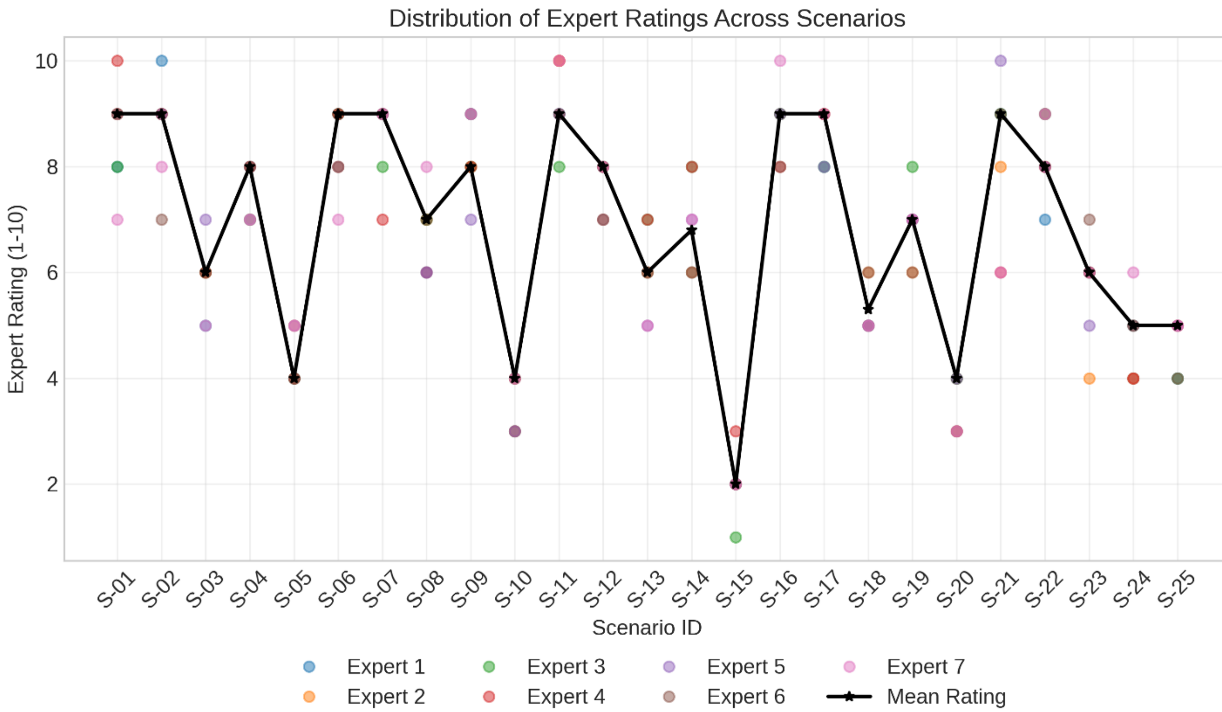

Fig. 11. Distribution of expert ratings across scenarios.

Figure 12 compares model scores with mean expert ratings. ECERI explains more variance in expert judgment than REBA ($R^2 = 0.852$ vs 0.737; $r = 0.923$ vs 0.859). The LOWESS curves track the 1:1 trend closely for ECERI, while REBA underestimates at higher expert ratings, consistent with contextual amplification not captured by the baseline score.

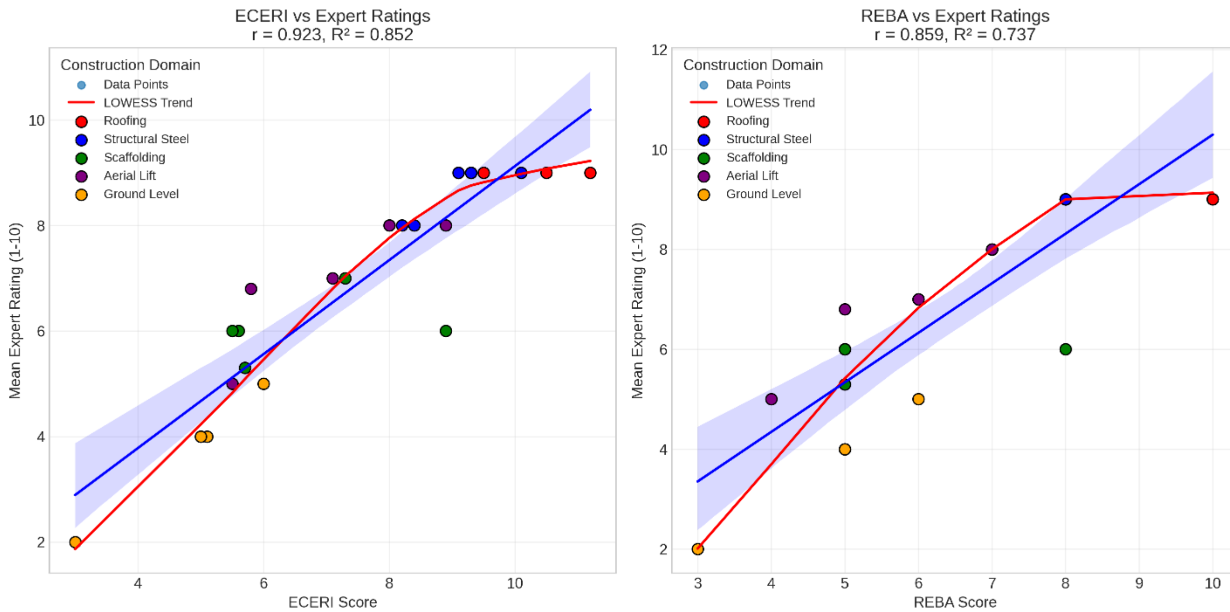

Fig. 12. Model scores vs mean expert ratings.

High-risk classification performance is summarized in Figure 26 and Table 6. ROC curves show an AUC of 0.920 for ECERI and 0.766 for REBA. Agreement metrics with the expert benchmark favor ECERI: Cohen's kappa 0.483 vs 0.155 (+212.3%), weighted kappa 0.737 vs 0.602 (+22.3%), overall agreement 64.0% vs 44.0% (+45.5%), and accuracy 0.920 vs 0.760 (+21.1%). Sensitivity for identifying high-risk scenes improves from 0.615 to 0.923 (+50%) without loss of specificity (0.917 for both). Positive and negative predictive values also increase (0.923 vs 0.889 and 0.917 vs 0.688), yielding a higher F1 score (0.923 vs 0.727).

Table 6

Agreement statistics between assessment methods and expert judgment

Agreement Metric	ECERI-Expert	REBA-Expert	Improvement
Cohen's Kappa	0.483	0.155	+212.3%
Weighted Kappa	0.737	0.602	+22.3%
Overall Agreement (%)	64.0%	44.0%	+45.5%
Adjacent Agreement (%)	100.0%	100.0%	+0.0%
Sensitivity (High Risk)	0.923	0.615	+50.0%
Specificity (High Risk)	0.917	0.917	+0.0%
PPV (High Risk)	0.923	0.889	+3.8%

NPV (High Risk)	0.917	0.688	+33.3%
Accuracy	0.920	0.760	+21.1%
F1 Score	0.923	0.727	+26.9%

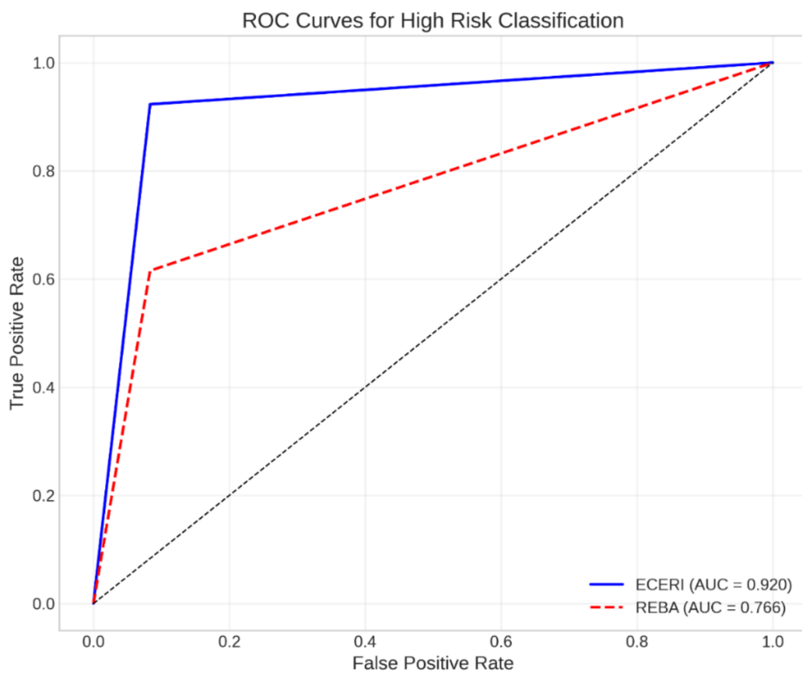

Fig 13. ROC curves for high-risk classification.

Table 7 examines which contextual terms contribute to expert perception after accounting for the REBA baseline. The REBA term remains a strong predictor ($\beta = 0.859$, $p < 0.001$), but height adds a significant main effect ($\beta = 0.440$, $p = 0.021$, partial $\eta^2 = 0.250$). The Height × Slope interaction is also significant ($\beta = 1.672$, $p = 0.015$, partial $\eta^2 = 0.317$). Other main effects and interactions are not statistically significant in this sample. These results mirror the Tier 1 and Tier 2 findings that height and slope jointly create the most consequential departures from additivity

Table 7.

Regression on expert ratings.

Factor	**Standardized Coefficient (β)**	**p-value**	**Partial η²**	**ECERI Weight**

REBA Score	0.859	0.000	0.563	1.00
HF	0.440	0.021	0.250	0.30
SF	0.176	0.150	0.106	0.20
SLF	0.097	0.493	0.025	0.30
EPF	0.030	0.851	0.002	0.20
HF_SF	-0.320	0.237	0.086	0.05
HF_SLF	1.672	0.015	0.317	0.10
SF_EPF	0.209	0.531	0.025	0.05

Together, Tier 3 shows that ECERI aligns more closely with expert judgment than REBA on both correlation and classification, and that the interaction structure highlighted earlier is statistically evident in expert-rated scenes. This convergence across tiers supports ECERI as a context-sensitive extension of REBA for elevated construction tasks.

6. Discussion

6.1. Interpretation of Key Findings

Environmental context substantially amplifies baseline postural risk in a non-linear manner. ECERI accounted for a larger share of variance in expert judgment than REBA ($R^2 = 0.852$ vs. REBA's 0.737), indicating that the model formalizes the contextual cues practitioners implicitly use in the field. Classification performance improved accordingly: sensitivity for identifying high-risk scenes increased without loss of specificity.

Monte Carlo analysis showed that 25.1% of scenarios migrate to a higher risk category once context is considered, with transitions concentrated near the medium-to-high decision boundary where control choices are most consequential. These results suggest that posture-only tools systematically understate risk in elevated conditions and that incorporating environmental context yields a more faithful representation of operational hazard.

6.2. Practical Application and Implementation Protocol

Inputs are few and measurable with tools already common on construction sites. Height can be drawn from BIM attributes or range measurements. Slope and surface condition can be inferred from computer vision models. Edge proximity can be estimated from plan overlays or scene segmentation. A key consideration for any ergonomic tool in construction is its utility within a dynamic work environment. The proposed model is not intended for continuous monitoring, but as a "snapshot" assessment tool. The following protocol outlines how it can be deployed in three primary use cases:

6.2.1. Proactive Risk Assessment (Pre-Task Planning):

During the Job Hazard Analysis (JHA) meeting, a safety professional identifies a high-risk elevated task. Using project plans, they input the known parameters (Height, Surface, Slope, Edge Proximity) and a representative REBA score into the ECERI calculator. The resulting score provides a quantitative basis to mandate specific controls before the task begins.

6.2.2. Representative Sampling for Dynamic Tasks:

An ergonomist observing a dynamic task identifies the most frequent or awkward postures. They score one or two of these key "snapshot" postures using the model calculator. A high score indicates that this representative posture is hazardous, and the intervention would then focus on controls to eliminate or modify that specific harmful component of the task.

6.2.3. Post-Incident Analysis:

Following an incident, an investigator reconstructs the event by measuring the environmental conditions and posture to derive an ECERI score. This score provides objective, quantifiable data for the incident report, justifying recommendations for corrective actions to prevent recurrence.

Developing this model into a risk calculator gives access to almost instant risk score side by side with the REBA score, and highlights the biggest score contributors based on the modeling for transparency. A user interface can be seen in Figure 14.

6.3 Linking ECERI Scores to Actionable Controls

A crucial question for any risk assessment tool is how it guides action, especially when environmental hazards like architectural slopes are unchangeable. ECERI addresses this by linking the quantitative risk score to the required level of intervention based on the hierarchy of controls. A high ECERI score, even if driven by a "fixed" hazard, serves as a clear signal that lower-level administrative controls are insufficient and that more robust engineering or substitution solutions are required.

The Action Matrix presented in Table 8 provides a framework for this decision-making process. It translates the ECERI risk levels into a response priority, a recommended control emphasis, and illustrative actions. For example, a medium score (4-7) on a fixed slope might require administrative controls like task rotation. However, if other factors amplify the risk to a Very High score (11+), the framework mandates a shift to elimination or substitution, such as using an aerial lift to avoid having workers on the slope altogether. This structure ensures that the tool's output is directly linked to actionable, preventative strategies that are proportional to the quantified risk.

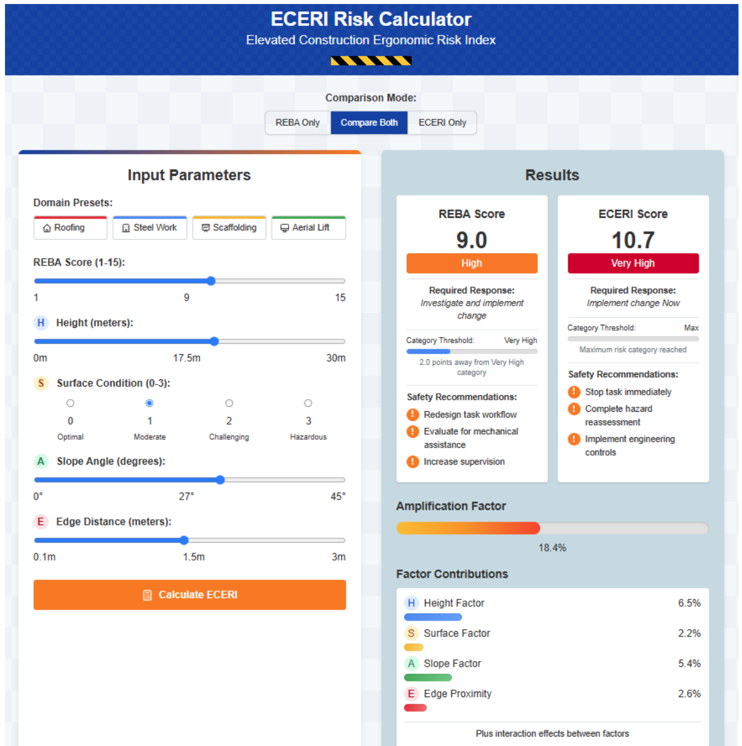

Fig 14. ECERI risk calculator web interface

Table 8.

Interpreting ECERI categories and indicative controls (examples are illustrative; site-specific assessment governs)

ECERI Score	Risk Level	Response Priority	Control Emphasis	Illustrative Actions
1	Negligible	Routine Monitoring	Maintain Current Controls	**Heigh**t: Verify tie-off policy coverage; **Slope**: Confirm designated access paths; **Surface**: Enforce housekeeping; **Edge**: Confirm guardrail integrity.
2–3	Low	Procedural Review	Administrative & Process Controls	**Height**: Schedule shorter exposure durations; **Slope**: Mandate high-traction footwear; **Surface**: Pre-treat surfaces for moisture; **Edge**: Mark clear travel lanes and no-go zones.
4–7	Medium	Intervention Planning Required	Enhanced Administrative & Simple Engineering	**Height**: Implement formal work/rest cycles; **Slope**: Use mechanical assistance for load carrying (e.g., material hoist); **Surface**: Deploy anti-slip mats or grating; **Edge**: Relocate materials staging further from edges.
8–10	High	Immediate Intervention Required	Primary Engineering Controls	**Height**: Install temporary work platforms or scissor lifts; **Slope**: Add temporary stairways or staging planks; **Surface**: Install temporary flooring system over irregular surfaces; **Edge**: Add toe boards and debris netting to guardrails.
11+	Very High	Stop Work; Re-engineer Task	Elimination & Substitution	**Height**: Shift work to an aerial lift or perform pre-fabrication at ground level; **Slope**: Use remotely operated tools to avoid on-slope tasks; **Surface**: Postpone work until surface conditions are optimal; **Edge**: Redesign the task to be performed away from the edge entirely.

6.4 Theoretical Implications

This study provides empirical support for the proposed C-ERA framework, which theorizes that environmental factors act as multiplicative amplifiers of baseline task demands. The validation of significant, non-linear interaction effects, particularly the Height × Slope synergy, offers quantitative evidence for mesoergonomic principles in a field setting, demonstrating that the combined effect of environmental factors on postural risk is not merely additive. This work provides a practical methodology for incorporating these theoretically important, but often overlooked, interaction effects into risk assessment.

6.5 Limitations and Future Research

Simulation anchors were selected from mid-to-upper quartile field values and then perturbed. Alternative anchors could shift absolute levels even if relative ordering remains stable. The expert panel was focused and small by design, which favors depth of judgement over breadth of representation. The regression results reflect the contextual range represented in the rated scenes and may change with a wider variety. Analyses used scenario snapshots rather than time-resolved exposure, so duration effects and within-task variability were not modeled. These limitations define the current scope and motivate further study.

Future efforts should expand empirical validation with larger and more diverse datasets, incorporate time at risk by modeling sequences rather than snapshots, and return calibrated uncertainty alongside point scores to support triage of supervisory attention. Another priority is automation of contextual inputs from imagery and plans while preserving the transparency that makes the model usable in the field. Domain extensions such as bridge maintenance and tower crane assembly would broaden external validity.

7. Conclusion

This study introduced ECERI as a context-aware extension of a standard posture score that makes the effects of height, slope, surface, and edge proximity explicit while preserving scale and interpretability. Across theoretical, simulation, and empirical tiers, the model showed directional correctness, a stable interaction hierarchy dominated by height with slope, a centered amplification distribution with meaningful category migration, and stronger alignment with expert judgment than the baseline score.

The proposed model is grounded in the C-ERA (Contextual Ergonomic Risk Assessment) framework, which formalizes how context enters ergonomic scoring. C-ERA sets the principles that context should be represented by measurable state variables, responses should be monotonic and normalized to the baseline score under neutral conditions, interactions should be modeled when they are mechanistically justified, and outputs should map to clear decision cues. ECERI instantiates these principles for elevated construction tasks and demonstrates that a context-aware model can remain transparent and usable.

The findings translate directly into practice. A priority schema ties scores to Standard, Process, Engineering, and Critical responses, and a web-based calculator supports consistent snapshot assessments during planning, observation, and post-incident review. Future work will expand empirical datasets, incorporate time at risk and calibrated uncertainty, and streamline automated extraction of contextual inputs from BIM and computer vision. Overall, ECERI validates the C-ERA framework and proposes a defensible way to integrate contextual exposure into ergonomic risk decisions for elevated work.

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Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: