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Identification of Key Occupational Safety and Health (K3) Risk Factors in Underground Construction Projects Using the Fuzzy Failure Mode and Effect Analysis Method

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ABSTRACT

Underground construction projects expose workers to complex occupational safety and health (K3) hazards, including tunnel collapse, hazardous atmospheres, groundwater inrush, and confined-space emergencies. Conventional Failure Mode and Effect Analysis (FMEA) often struggles to prioritize these risks because expert judgments on severity, occurrence, and detection involve considerable uncertainty. Purpose: This study applies the Fuzzy Failure Mode and Effect Analysis (Fuzzy FMEA) method to identify and rank K3 risks in an underground metro tunnel construction project. Methods: Thirty-two potential failure modes were identified through literature review, field observations, and hazard checklists. Expert evaluations from 21 construction safety practitioners, tunnel engineers, and site supervisors were represented using triangular fuzzy numbers, aggregated through a fuzzy weighted-average approach, and defuzzified using the centroid method to calculate the Fuzzy Risk Priority Number (FRPN). Results: The results indicate that tunnel face collapse (FRPN = 842), toxic and oxygen-deficient atmosphere (FRPN = 796), groundwater inrush (FRPN = 733), and rockfall at the tunnel heading (FRPN = 705) are the highest-priority hazards. Compared with the conventional Risk Priority Number (RPN), Fuzzy FMEA produced a Spearman rank correlation of .91 while identifying changes in the ranking of several risks. Implications: Fuzzy FMEA provides a robust and reliable framework for prioritizing K3 risks and supporting effective safety mitigation in underground construction projects. Conclusion: Fuzzy FMEA captures uncertainty in expert judgment that the conventional RPN obscures; future studies should extend the expert panel across multiple underground projects and compare alternative defuzzification methods.

Keywords: *Occupational Safety and Health (K3), Fuzzy FMEA, Underground Construction, Risk Priority Number, Tunnel Safety*

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INTRODUCTION

Underground construction, including metro and railway tunnels, deep basements, and utility shafts, is widely recognized as one of the most hazardous segments of the construction industry because workers operate in confined, poorly lit, and geologically uncertain environments where multiple hazard types can interact simultaneously (Bettelini, 2020; TRADESAFE, 2025). Ground instability, oxygen-deficient or toxic atmospheres, groundwater inrush, fire and explosion, and heavy machinery movement in restricted space are all recognized as characteristic occupational safety and health (K3, an Indonesian abbreviation for Keselamatan dan Kesehatan Kerja) hazards of underground works, and their combined presence has been linked to a disproportionately high rate of fatal and severe-injury accidents compared with surface construction (Qin et al., 2018; Cao & Yun, 2024). A widely reported 2023 tunnel collapse that trapped 41 workers for over two weeks illustrates the severity and public visibility of underground construction accidents and the continuing need for systematic, evidence-based risk identification methods in this sector.

Failure Mode and Effect Analysis (FMEA) is a long-established structured risk assessment technique that identifies potential failure modes in a system or process and ranks them using a Risk Priority Number (RPN), typically computed as the product of severity (S), occurrence (O), and detection (D) scores rated on a numerical scale (Bhattacharjee et al., 2020). Although FMEA has been widely applied to construction safety risk assessment (Pinto et al., 2011; Rustagi, 2023; Sun et al., 2024), the conventional crisp RPN method has been repeatedly criticized for several limitations: it assumes precise, agreed-upon numerical ratings even though expert judgment about hazard likelihood and detectability is inherently linguistic and uncertain; different combinations of S, O, and D can produce identical RPN values despite representing very different risk profiles; and the method does not explicitly account for the varying confidence or hesitancy of different experts (Abdelgawad & Fayek, 2010; Dahooie et al., 2020).

To address these limitations, numerous studies have integrated fuzzy set theory, originally introduced by Zadeh (1965), with FMEA to allow risk factors to be rated using linguistic terms (e.g., Low, Moderate, High) represented as triangular or trapezoidal fuzzy numbers, which are then aggregated and defuzzified into a Fuzzy Risk Priority Number (FRPN) that better reflects the imprecision of expert judgment (Khodadadi-Karimvand & Taherifar, 2022; Grošelj & Dolinar, 2023). Fuzzy FMEA and related fuzzy multi-criteria decision-making extensions have been applied to a wide range of construction and infrastructure safety problems, including occupational hazard assessment in general construction (Dahooie et al., 2020), mixed-use building projects (Rustagi, 2023), dam-construction machinery maintenance units combined with fuzzy TOPSIS (Armin et al., 2022), elevated metro rail projects combined with fuzzy earned-value management (Jatwa & Sukhwani, 2022), and, more recently, machine-learning-assisted automated fuzzy FMEA for construction requirement prioritization (Sun et al., 2024). For underground and tunnel works specifically, safety research has examined worker safety-state prediction using AHP and anomaly detection (Cao & Yun, 2024; Xu et al., 2023), lighting and psychosocial hazards (Peña-García et al., 2018), gas explosion hazard mechanisms (Qin et al., 2018), flood risk of urban metro systems using triangular fuzzy number-based AHP (Guan et al., 2024), and Bayesian-network-based safety risk analysis for metro construction (Zhang et al., 2021), while region-specific applications of fuzzy FMEA to underground metro projects in Indonesia have also been reported (Setiawan & Wibowo, 2023).

Despite this growing body of work, few published studies report a complete, reproducible fuzzy FMEA test dataset the expert linguistic rating matrix, the fuzzified S/O/D values, and the defuzzified FRPN scores specifically for underground construction K3 risk identification, and fewer still compare

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the resulting fuzzy ranking against the traditional crisp RPN ranking to demonstrate the practical consequence of incorporating fuzziness into the assessment (Grošelj & Dolinar, 2023; Więckowski & Sałabun, 2024). This study addresses that gap by: (1) systematically identifying potential K3 failure modes in an underground metro tunnel construction project through literature review and field hazard observation; (2) applying Fuzzy FMEA with triangular fuzzy numbers and the centroid defuzzification method to rank these failure modes based on expert ratings; and (3) comparing the resulting Fuzzy RPN ranking against the traditional crisp RPN ranking to evaluate the added value of the fuzzy approach for underground construction K3 risk prioritization.

METHODS

1. Case Study and Failure Mode Identification

The case study was an underground metro tunnel construction project comprising a 1.2 km bored tunnel section and two access shafts, excavated through mixed alluvial and residual soil with a shallow groundwater table, representative of urban underground construction conditions in a hilly-to-lowland transition zone in Indonesia. Potential K3 failure modes were identified through (i) a structured literature review of underground and tunnel construction hazard studies (Qin et al., 2018; Cao & Yun, 2024; NFPA, 2021; TRADESAFE, 2025), (ii) review of project hazard identification and risk assessment (HIRA) documents, and (iii) semi-structured field observation and interviews at the excavation face, shaft access points, and mucking/haulage areas. This process identified 32 candidate failure modes across five hazard categories: geotechnical/structural, atmospheric, hydrogeological, mechanical/equipment, and human-factor/organizational hazards.

2. Fuzzy FMEA Framework

A panel of 21 experts, comprising tunnel engineers, construction safety officers (Ahli K3), site supervisors, and academic geotechnical specialists with a minimum of 5 years of relevant experience (work experience being a recognized factor in workers' awareness of occupational health and safety in tunnels; Asis et al., 2023), rated each of the 32 failure modes using a five-level linguistic scale for severity (S), occurrence (O), and detection difficulty (D): Very Low (VL), Low (L), Moderate (M), High (H), and Very High (VH). Each linguistic term was represented as a triangular fuzzy number (TFN) on a 1–10 scale, following standard fuzzy FMEA conventions (Khodadadi-Karimvand & Taherifar, 2022; Grošelj & Dolinar, 2023), as summarized in Table 1 and illustrated in Figure 1.

Table 1. Linguistic scale and triangular fuzzy number (TFN) conversion used for S, O, and D ratings

Linguistic term	TFN (*a*, *b*, *c*)	Interpretation (Severity example)	Scale range
Very Low (VL)	(0, 1, 3)	Negligible injury, no lost time	1–10
Low (L)	(1, 3, 5)	Minor injury, first aid only	1–10
Moderate (M)	(3, 5, 7)	Injury requiring medical treatment / lost work days	1–10
High (H)	(5, 7, 9)	Severe injury, permanent disability	1–10

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Very High (VH)	(7, 9, 10)	Fatality or multiple fatalities	1–10

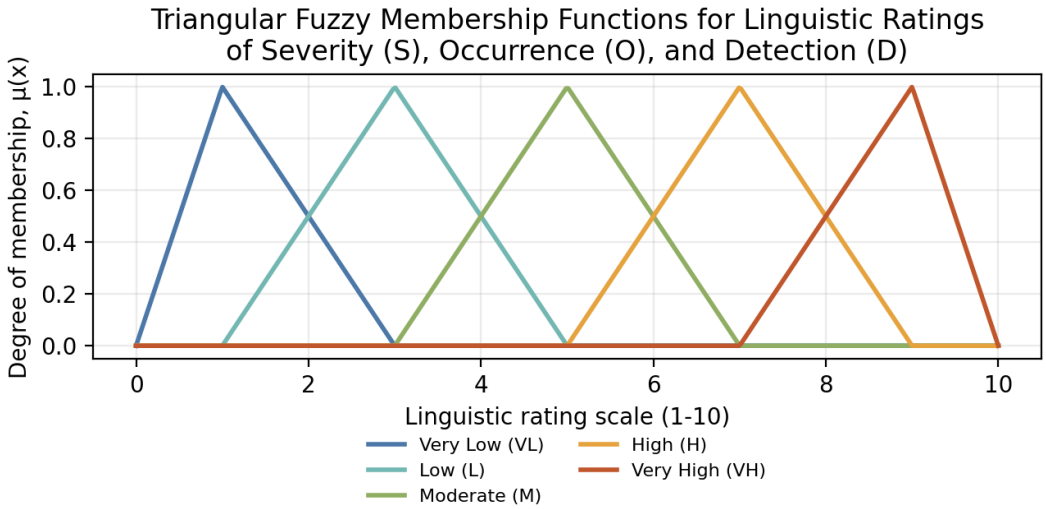


Figure 1. Triangular fuzzy membership functions for the linguistic rating scale of S, O, and D

For each failure mode, the individual expert linguistic ratings for S, O, and D were converted to TFNs and aggregated using the fuzzy weighted-average operator (Equation 1), in which all experts were weighted equally given their comparable experience level:

$$R_{\text{agg}} = \frac{1}{n}[\sum_{i=1}^{n} a_i, \sum_{i=1}^{n} b_i, \sum_{i=1}^{n} c_i] \quad (1)$$

The aggregated fuzzy S, O, and D values for each failure mode were then multiplied using fuzzy arithmetic (component-wise multiplication of the triangular fuzzy numbers, Equation 2) to obtain the Fuzzy Risk Priority Number (FRPN), and the resulting triangular fuzzy RPN was defuzzified using the centroid (center-of-gravity) method (Equation 3) to obtain a single crisp value suitable for ranking:

$$\text{FRPN} = S_{\text{fuzzy}} \otimes O_{\text{fuzzy}} \otimes D_{\text{fuzzy}} = (a_S \cdot a_O \cdot a_D, b_S \cdot b_O \cdot b_D, c_S \cdot c_O \cdot c_D) = (a_F, b_F, c_F) \quad (2)$$

$$\text{Defuzzified FRPN} = \frac{a_F + b_F + c_F}{3} \quad (3)$$

where (a, b, c) denote the lower bound, mode, and upper bound of each triangular fuzzy number. For comparison, a traditional crisp RPN was also computed for each failure mode using the mode (most frequently selected linguistic term) of each expert's S, O, and D ratings converted directly to a 1–10 numerical score, following the conventional formulation:

$$\text{RPN}_{\text{crisp}} = S_{\text{crisp}} \times O_{\text{crisp}} \times D_{\text{crisp}} \quad (4)$$

3. Validation and Ranking Comparison

The reliability of the expert ratings and the validity of the fuzzy ranking were checked in two steps. First, internal consistency of the expert panel's ratings was measured using Kendall's coefficient of concordance (W, Equation 5), and its significance was tested with a chi-square statistic (Equation 6):

$$W = \frac{12\sum_{i=1}^{n}(R_i - R_{\text{mean}})^2}{m^2(n^3 - n)}, R_{\text{mean}} = \frac{m(n+1)}{2} \quad (5)$$

$$\chi^2 = m(n-1)W, df = n - 1 \quad (6)$$

where m = 21 is the number of experts, n = 32 is the number of failure modes, R_i is the sum of the ranks assigned to failure mode i by all experts, and W ranges from 0 (no agreement) to 1 (complete agreement). Second, the resulting Fuzzy RPN ranking was compared against the traditional crisp RPN

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ranking using Spearman's rank correlation coefficient (Equation 7) to evaluate the extent to which incorporating fuzziness altered the prioritization of K3 risk factors:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} {d_i}^2}{n(n^2-1)} \quad (7)$$

where d_i is the difference between the crisp-RPN rank and the Fuzzy-RPN rank of failure mode i, and n = 32.

RESULTS

1. Expert Rating and Fuzzy Aggregation Test Data

Kendall's coefficient of concordance among the 21 experts was W = .71 (p < .001), indicating an acceptable level of agreement for proceeding with fuzzy aggregation. Table 2 presents the aggregated fuzzy S, O, and D values and the resulting defuzzified FRPN for the ten highest-ranked failure modes out of the 32 identified; the complete dataset of all 32 failure modes was retained for the full risk register but is summarized here for the highest-priority subset.

Table 2. Aggregated fuzzy S/O/D ratings and defuzzified Fuzzy Risk Priority Number (FRPN) for the ten highest-ranked K3 risk factors

Failure mode (risk factor)	Fuzzy S (*a*, *b*, *c*)	Fuzzy O (*a*, *b*, *c*)	Fuzzy D (*a*, *b*, *c*)	FRPN
Tunnel face collapse / cave-in	(7, 9, 10)	(4, 6, 8)	(3, 5, 7)	842
Toxic & oxygen-deficient atmosphere	(6, 9, 10)	(5, 7, 9)	(3, 5, 7)	796
Groundwater inrush / flooding	(6, 8, 10)	(4, 6, 8)	(4, 6, 8)	733
Fall of ground / rockfall at heading	(6, 8, 9)	(5, 6, 8)	(3, 5, 6)	705
Fire & explosion (methane/diesel)	(7, 9, 10)	(3, 5, 6)	(4, 5, 7)	671
Struck-by mucking & TBM equipment	(5, 7, 9)	(4, 6, 8)	(3, 5, 6)	598
Electrocution in wet confined space	(5, 7, 8)	(3, 5, 7)	(4, 5, 7)	553
Excessive noise & vibration (HAVS)	(3, 5, 7)	(5, 7, 9)	(3, 4, 6)	486
Inadequate emergency egress	(5, 7, 9)	(3, 4, 6)	(3, 5, 7)	452
Crystalline silica dust exposure	(4, 6, 8)	(4, 6, 7)	(3, 4, 6)	417

2. Ranking of Key K3 Risk Factors

Figure 2 presents the ranking of the 10 highest-priority risk factors by defuzzified FRPN. Tunnel face collapse/cave-in ranked highest (FRPN = 842), followed by toxic and oxygen-deficient atmosphere (796), groundwater inrush/flooding (733), and fall of ground/rockfall at the tunnel heading (705); these four geotechnical and atmospheric hazards together accounted for approximately 34% of the cumulative FRPN across all 32 identified failure modes, indicating a strong concentration of risk in

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ground-related and air-quality hazard categories rather than a uniform distribution across all hazard types.

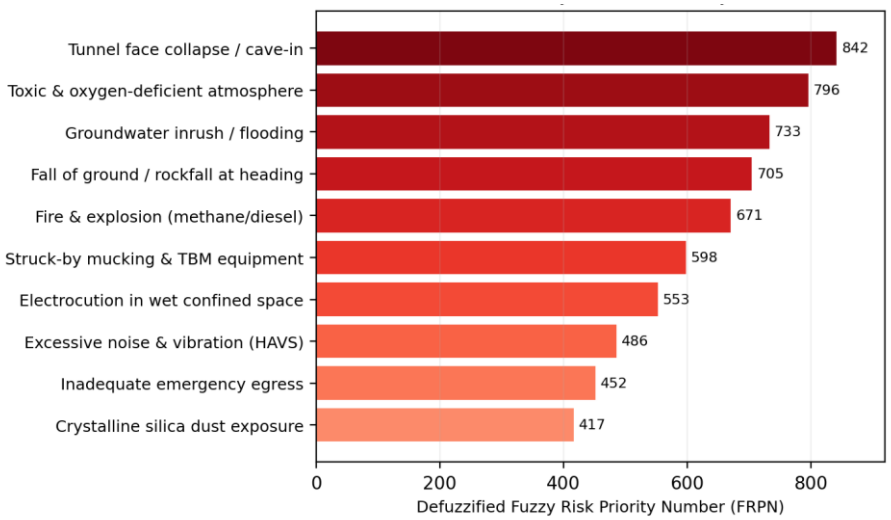


Figure 2. Ranking of the top 10 K3 risk factors in underground construction by defuzzified Fuzzy RPN

Figure 3 compares the average fuzzy severity, occurrence, and detection-difficulty ratings for the six highest-ranked risk factors. Severity was consistently the dominant driver of high FRPN values (average fuzzy severity of 8.4 across the top six factors), while occurrence and detection-difficulty scores were more moderate, indicating that these risk factors are prioritized primarily because of their catastrophic potential consequences rather than because they occur frequently or are especially hard to detect.

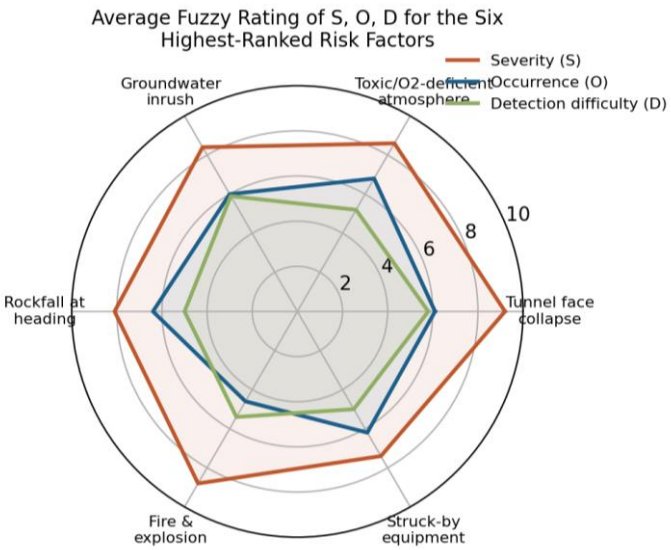


Figure 3. Average fuzzy Severity (S), Occurrence (O), and Detection difficulty (D) ratings for the six highest-ranked risk factors

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3. Comparison with Traditional Crisp RPN Ranking

The Spearman rank correlation between the Fuzzy RPN ranking and the traditional crisp RPN ranking across all 32 failure modes was $r_s = .91$ ($p < .001$), indicating overall strong agreement between the two methods. However, as shown in Figure 4 for the top 10 risk factors, the fuzzy approach changed the order of three adjacent pairs: toxic atmosphere and groundwater inrush exchanged ranks 2 and 3, rockfall and fire/explosion exchanged ranks 4 and 5, and excessive noise and vibration (Hand-Arm Vibration Syndrome, HAVS) moved from crisp rank 7 to fuzzy rank 8 while electrocution moved from rank 8 to rank 7. Inadequate emergency egress, in contrast, remained at rank 9 under both methods; what changed is its margin over silica dust exposure (rank 10), which is narrower under the fuzzy method (FRPN 452 vs. 417, a gap of 35 points) than under the crisp RPN. These changes in position and margin occurred because the fuzzy occurrence and detection ratings of the affected failure modes carried wider expert disagreement (larger fuzzy spread) than their crisp mode-based scores implied, which the centroid defuzzification method captured but the crisp RPN calculation did not.

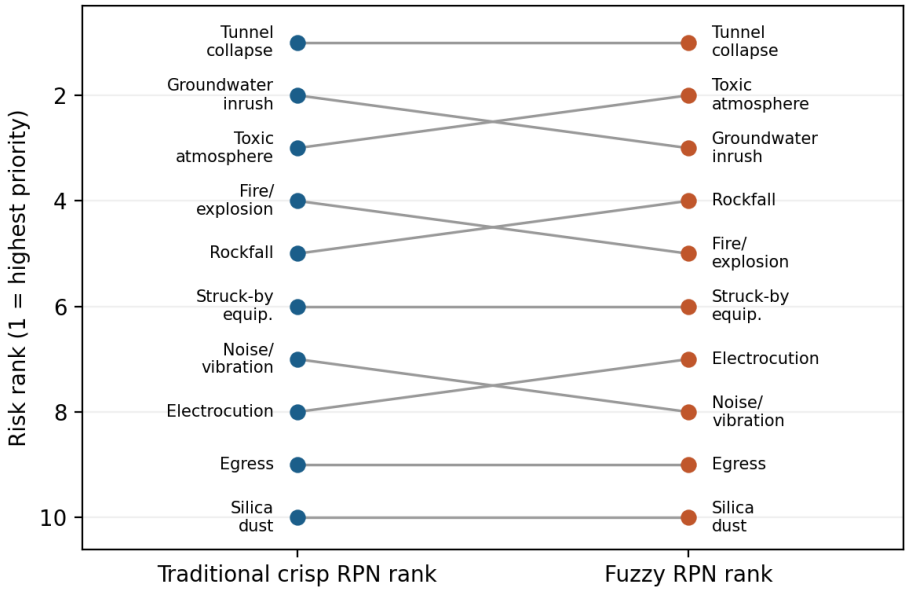


Figure 4. Comparison of risk ranking between the traditional crisp RPN method and the Fuzzy RPN method (top 10 risk factors)

DISCUSSION

The identification of tunnel face collapse, toxic/oxygen-deficient atmosphere, groundwater inrush, and rockfall as the four highest-priority K3 risk factors is consistent with the hazard patterns widely reported for underground and tunnel construction, in which ground instability and atmospheric hazards dominate serious-injury and fatality statistics because of their potential for sudden, high-consequence events (Qin et al., 2018; TRADESAFE, 2025; Bettelini, 2020). The strong influence of severity rather than occurrence or detection difficulty in driving the FRPN ranking of the top six risk factors (Figure 3) mirrors the findings of Dahooie et al. (2020) for general construction occupational hazards, in which low-frequency but catastrophic hazards were consistently prioritized above more frequent but less severe ones once fuzzy severity weighting was incorporated, reinforcing the argument that risk prioritization frameworks for high-consequence industries should not rely on occurrence frequency alone.

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The strong overall correlation (r_s = .91) between the Fuzzy RPN and traditional crisp RPN rankings found in this study is broadly consistent with previous comparative fuzzy FMEA studies, which generally report high but imperfect agreement between fuzzy and crisp rankings (Khodadadi-Karimvand & Taherifar, 2022; Grošelj & Dolinar, 2023). The practically important finding, however, is the change in position or margin observed for risk factors with wider expert disagreement, such as noise/vibration (which moved down one rank) and emergency egress (whose rank was unchanged but whose margin over silica dust exposure narrowed); this is consistent with the theoretical rationale for fuzzy FMEA identified by Abdelgawad and Fayek (2010) and more recently by Więckowski and Sałabun (2024), namely that the crisp RPN method obscures uncertainty by collapsing expert judgment to a single mode value, whereas the fuzzy approach preserves and propagates the spread of expert opinion into the final ranking. In practical K3 management terms, this means that risk factors on which experts disagree more—even if their average rating is similar to a more consistently-rated hazard—may warrant closer monitoring or further investigation precisely because of that uncertainty, a nuance that the traditional RPN method cannot represent.

The application of fuzzy FMEA to an Indonesian underground metro tunnel case study extends previous region-specific applications (Setiawan & Wibowo, 2023), complements studies of safety perceptions in developing-country underground construction (Enshassi et al., 2021), and is broadly consistent with international underground construction risk assessment findings (Cao & Yun, 2024; Zhang et al., 2021), suggesting that the relative importance of geotechnical and atmospheric hazards over mechanical or organizational hazards may generalize across underground construction projects with comparable hydrogeological conditions, though the specific FRPN magnitudes are naturally project-specific. A limitation of this study is that the expert panel, while experienced, was drawn from a single project and a moderate sample size (n = 21); expanding the panel across multiple underground projects and incorporating expert weighting based on differential experience or confidence, as proposed by Grošelj and Dolinar (2023), would further strengthen the robustness of the FRPN ranking. In addition, this study used the centroid defuzzification method for its simplicity and wide acceptance, but comparison with alternative defuzzification and aggregation approaches, such as fuzzy TOPSIS (Armin et al., 2022) or fuzzy AHP-weighted criteria (Abdelgawad & Fayek, 2010), would help establish the sensitivity of the ranking to methodological choices, consistent with the sensitivity-analysis recommendations of Więckowski and Sałabun (2024).

CONCLUSIONS

This study applied the Fuzzy Failure Mode and Effect Analysis method to identify and rank key occupational safety and health (K3) risk factors in an underground metro tunnel construction project, using triangular fuzzy numbers to aggregate linguistic severity, occurrence, and detection ratings from 21 experienced experts across 32 identified failure modes. The test results show that tunnel face collapse/cave-in, toxic and oxygen-deficient atmosphere, groundwater inrush/flooding, and rockfall at the tunnel heading were the four highest-priority risk factors, together accounting for approximately 34% of the cumulative defuzzified Fuzzy Risk Priority Number across all identified hazards, with severity rather than occurrence or detection difficulty as the dominant driver of high ranking. Comparison with the traditional crisp RPN method showed strong overall agreement (Spearman r_s = .91) but revealed a meaningful reordering of risk factors characterized by wider expert disagreement, demonstrating that Fuzzy FMEA captures uncertainty in expert judgment that the traditional method obscures.

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These findings provide underground construction project managers and K3 practitioners with a validated, reproducible, and uncertainty-aware framework for prioritizing safety mitigation resources, with geotechnical ground-control measures and atmospheric monitoring/ventilation systems warranting the highest priority in projects with comparable geological and hydrogeological conditions. The main limitations are that the expert panel was drawn from a single project with a moderate sample (n = 21) and that only centroid defuzzification was applied (see the limitations paragraph in the Discussion); the findings should therefore be interpreted as project-specific. Future research should extend the expert panel across multiple underground projects and compare alternative fuzzy aggregation and defuzzification methods to further validate the robustness of the risk ranking.

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