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An Integrated Modified Failure Mode Effects Analysis Shannon Entropy Combined Compromise Solution Approach to Safety Risk Assessment in Stone Crusher Unit of Ceramic Sector

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A B S T R A C T

Identifying and assessing the most critical work-related hazards is essential for implementing effective corrective actions through Occupational Health and Safety Risk Assessment (OHSRA). Due to the inherent ambiguity of human judgment, it is often difficult to evaluate occupational risks using precise numerical values during the OHSRA process. To address this challenge, various mathematical techniques have been developed to support risk-based decision-making by managing uncertainty, identifying optimal solutions, and ranking alternatives. This study introduces a novel OHSRA model for assessing and prioritizing occupational hazards, integrating Modified Failure Mode and Effects Analysis (MFMEA), Shannon entropy, and the Combined Compromise Solution (CoCoSo) method. Specifically, the risk assessment is based on five criteria: severity (S), occurrence (O), detectability (D), prevention (P), and cost (C). To manage the complexity and vagueness of expert evaluations, Shannon entropy is used to determine the weights of the criteria, while the CoCoSo method ranks the identified hazards. The robustness of the proposed framework is evaluated through a one-at-a-time (OAT) sensitivity analysis by varying each criterion weight by ±0.05, ±0.10, and ±0.20. A case study of the stone crusher unit in the ceramic industry showcases the practical applicability of the proposed methodology. The key advantages of the proposed approach include its flexibility in handling complex expert data and its effectiveness in delivering reliable and discriminative risk evaluations of occupational hazards.

Graphical Abstract
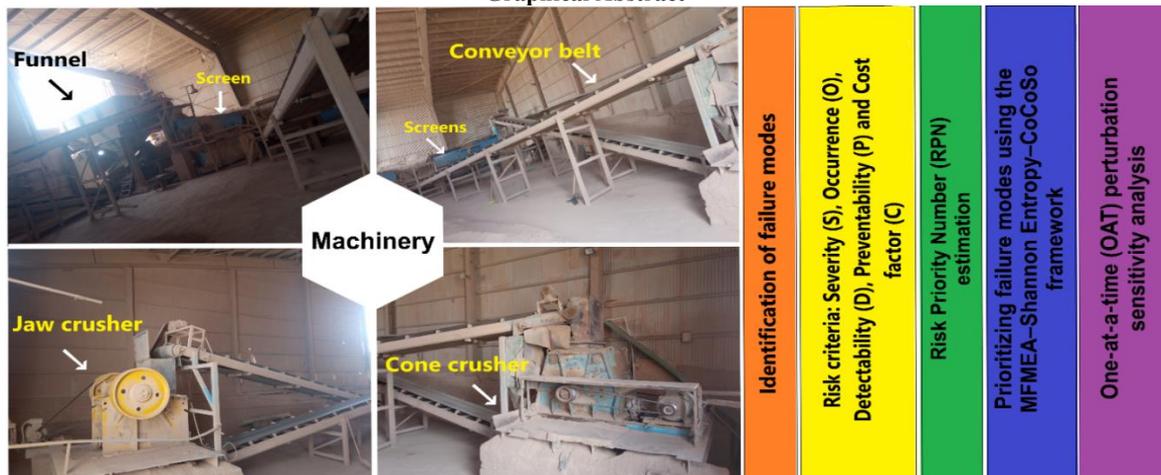
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1. INTRODUCTION

The prosperity of a country's is strongly influenced by the performance of its industrial sector, with manufacturing serving as one of the most vital and adaptable components of economic development (1-3). However, the growth of manufacturing and service industries is accompanied by inherent occupational risks that affect both workers and organizations (4-6).

In many developing economies, the increasing frequency of workplace accidents and occupational illnesses has elevated occupational health and safety (OHS) to a critical area of concern for policymakers, researchers, and industry practitioners (7-9). Recognizing these challenges, industries worldwide have begun to acknowledge the importance of OHS management systems and their role in safeguarding employees, improving productivity, and ensuring sustainable growth (10, 11).

The World Health Organization defines OHS as a multidisciplinary field concerned with the promotion and maintenance of the highest degree of physical, mental, and social well-being of workers across all occupations (12). Its core objectives include: (i) the prevention of work-related injuries and diseases; (ii) the creation of safe and health-promoting work environments; (iii) the enhancement of workers' well-being; and (iv) the facilitation of socially and economically productive lives (13, 14).

Despite global awareness of these objectives, the practical implementation of OHS systems varies widely across industries, particularly in sectors characterized by labor-intensive processes and high-risk operations. The ceramics industry represents a particularly relevant case in this regard. Owing to rising global demand for housing and infrastructure, the industry has expanded significantly and now constitutes an important contributor to national economies (15, 16). Nevertheless, the sector continues to experience disproportionately high rates of occupational injuries and illnesses. These challenges are largely attributable to the use of heavy machinery, exposure to harmful factors, and the physically demanding nature of production processes. While technological advancements have improved certain aspects of production, the persistence of hazardous working conditions highlights the urgent need for effective risk management strategies within the ceramics sector (17).

Risk assessment constitutes the foundation of OHS management, as it enables the systematic identification, evaluation, and mitigation of workplace hazards. Traditional techniques, such as risk matrices and Failure Mode and Effect Analysis (FMEA), remain widely adopted; however, their effectiveness is often constrained by subjectivity, oversimplification of risk factors, and difficulties in handling uncertainty (18). To overcome these limitations, recent research has emphasized the integration of advanced weighting mechanisms and multi-criteria decision-making (MCDM) approaches (19). Among these, the Combined Compromise Solution (CoCoSo) method has emerged as a particularly robust tool due to its capacity for high-ranking precision, computational efficiency, and adaptability to both quantitative and qualitative data. Its hybrid structure, which balances compensatory and non-compensatory effects, makes it especially well-suited for complex occupational risk assessment contexts such as ceramics manufacturing (20).

Despite such methodological advancements, two critical gaps remain evident in the literature (21-23). First, there is insufficient consideration of the imprecision and uncertainty inherent in expert-based evaluations of occupational risks. Second, there is a lack of consensus regarding the development of reliable and rational approaches for ranking identified hazards in a way that reflects their true significance (18). Addressing these gaps is crucial for improving the effectiveness of OHS risk management systems, particularly in ceramic sectors. Accordingly, the objective of this research is to enhance the assessment and prioritization of occupational hazards by integrating a modified FMEA (MFMEA), Shannon entropy, and the CoCoSo method into a unified framework. This study makes the following contributions: (i) it proposes an framework designed to capture the ambiguity and uncertainty inherent in experts' evaluations of occupational hazards; (ii) it develops an extended approach capable of producing more accurate and consistent rankings of occupational risks; (iii) it demonstrates the applicability and effectiveness of the proposed framework through an empirical case study of a stone crusher unit within the ceramic industry; and (iv) it evaluates the validity and robustness of the proposed risk assessment framework through comprehensive sensitivity analysis.

2. MATERIALS AND METHOD

2. 1. Definitions   The *risk source* is the equipment, operation, or system component where the failure physically or functionally originates (24-26).

A *failure mode (FM)* is a specific manner in which a product, process, or system fails to perform its intended function. It typically involves potential defects, errors, breakdowns, malfunctions, or deviations from expected performance (27).

Failure mechanisms include things like fatigue (28), collapse (29), loss of performance (30), deformation (31), corrosion (32), binding (24), seizure, buckling, looseness, misalignment (33), leakage (2), vibrations (34), burning (35), and so on.

A *defect* or *error* refers to a condition in which a component, process, or system fails to operate correctly or does not perform as intended (18).

Failure effect refers to the consequences or impacts that a failure mode has on people, the environment, or operations (e.g., injury, financial loss, system downtime) (36).

Failure cause refers to the underlying reason or root cause that leads to the occurrence of a failure mode, often stemming from design flaws, material defects, human error, or process deficiencies (37).

2. 2. Description of the Raw Material Crushing Process in the Crusher Unit
The raw material crushing process prepares materials for ceramic production by reducing their size to around 2 cm before further processing. The raw material crushing process in the crusher unit are shown in Figure 1. Various natural raw materials, such as quartz, flint, silicates, aluminosilicates (such as clays and feldspar), silica, and sand, are fed into the crushing unit via a hopper and conveyor system (16, 38). Jw crushers are used for primary crushing, applying compressive force between fixed and moving jaws to handle large feed sizes efficiently (17). Cone crushers handle secondary and tertiary crushing, using a gyratory motion between a moving mantle and stationary concave to achieve finer, more uniform particles (39). After crushing, materials are transported via conveyor belts to vibrating screens, which classify particles by size (40). Fine particles are collected, while oversized material is sent back for re-crushing (24). This system ensures efficient flow, quality control, and optimized preparation of materials for subsequent ceramic production processes (41).

2. 3. Identification of Failure Modes
The first stage of the stone crusher unit's risk assessment involves identifying potential failure modes, ranging from minor irregularities to major breakdowns impacting performance, quality, safety, or compliance. Using a structured multi-source approach, the study combined brainstorming sessions, historical data analysis, and expert consultation from a multidisciplinary team with over ten years of experience each (25, 42). This method resulted in the identification of sixteen failure modes, along with their corresponding causes and effects, as detailed in Table 1.

2. 4. Risk Assessment
Traditional FMEA, created by the U.S. military in the 1950s and later used in industries like aerospace and automotive, systematically identifies and prevents equipment failures (18, 36). The traditional FMEA approach assesses risk using Risk Priority Number (RPN) through three key criteria: Severity (S), Occurrence (O), and Detection (D) (43). The RPN helps identify the most critical failure modes by highlighting those with high severity, frequent occurrence, and low detectability (37).

The modified FMEA (MFMEA) extends this framework by incorporating additional factors—cost (C) and prevention potential (P)—thereby providing a more comprehensive assessment of failure modes (44, 45). The modified RPN formula applied in this study is presented in Equation 1:

$$RPN = \frac{S \times O \times D \times P}{C} \tag{1}$$

A more detailed description of all the criteria is provided below:

S: Assesses the seriousness of potential injuries or fatalities, rated on a 1–10 scale from minor incidents to catastrophic events affecting multiple individuals (46).

O: Measures the probability of a failure occurring during system operation, with higher values indicating more frequent failures (43).

D: Evaluates how effectively current controls can detect or prevent a failure, with 1 representing high detectability and 10 indicating low detectability (47).

P: Reflects the strength of preventive measures in reducing failure likelihood and detectability, scored 1–10 to prioritize proactive controls (44).

C: Represents the financial burden of implementing corrective or preventive actions, expressed as a percentage of the total safety budget and incorporated in the denominator of the modified RPN formula (33).

The scale of the criteria is shown in Figure 2.

2. 5. Weighting the Criteria
In this study, the Shannon Entropy Theory approach was used to weight the criteria. The concept of entropy was introduced by Claude Shannon in 1948 as part of information theory, with further developments contributed by Dwivedi and Sharma (48). The entropy method objectively determines criterion weights by quantifying data uncertainty, avoiding subjective judgment. A lower entropy value indicates less disorder and, consequently, greater importance of the corresponding criterion (19). The entropy process generally involves the following steps:

Figure 1. Schematic of machinery and equipment in a stone crushing unit

TABLE 1. Identified Failure Modes (FMs) in the stone crusher unit

FM Code	Operational Activity	Failure Mode	Effect of Failure	Source of Failure	Cause of Failure
FM1	Screen operation	Screen mesh rupture or tearing	Flying fragments, risk of eye or facial injury, unfiltered oversized material	Vibrating screen deck	Metal fatigue, wear, improper material loading
FM2	Screen mesh change	Lifting heavy screen panels	Back injuries or muscle strain	Manual handling of mesh	Lack of lifting aids; improper ergonomics
FM3	Feeding the crusher	Oversized feed causing blockage	Sudden release may cause trauma or impact injuries to nearby workers	Feed hopper	Lack of screening; improper sizing of feed
FM4	Feeding zone	Bridging of feed material	Sudden collapse may injure workers clearing the jam	Crusher feed opening	Irregular loading; oversized or moist material
FM5	Material loading	Overloading the screen deck	Risk of collapse, excessive dust release	Loading equipment	Operator error, poor feed control
FM6	Screen operation	Body part caught in screen	Amputation	Screen	Lack of protective guarding, unsafe maintenance practices
FM7	Discharge zone	Blocked discharge chute	Workers at risk during manual removal—entrapment or crush injury	Conveyor or chute	Sticky material; inadequate flow design
FM8	Crushing operation	Exposure to excessive dust	Respiratory disorders	Stone crusher	Absence of dust control
FM9	Manual handling	Prolonged poor posture	Musculoskeletal disorders	Workstation	Non-ergonomic design, repetitive motion
FM10	Crushing operation (cone)	Excessive vibration	neurological effects, ergonomic stress	Crusher body and motor	Lack of damping; poor isolation; prolonged exposure
FM11	Electrical panel access	Electric shock	Death	Electrical panel	Inadequate insulation, failed grounding system
FM12	Crushing operation	Exposure to excessive noise	Hearing damage	Stone crusher	Absence of noise control
FM13	Hand tool use	Tool slips during operation	Trauma, amputation, fracture	Work tools	Poor grip, worn handles, unsuitable personal protective equipment
FM14	Equipment handling	Equipment falls on personnel	Head injury, bone fracture	Crusher equipment	Improperly secured or positioned equipment
FM15	Hydraulic adjustment (cone)	Hydraulic hose burst	High-pressure fluid injection injury; risk of slips or burns	Cone crusher hydraulic system	Worn components; lack of maintenance
FM16	Crushing process (jaw crusher)	Eccentric shaft failure	Machine failure can cause falling debris or sudden shutdown-related injuries	Jaw crusher drive mechanism	Fatigue, insufficient lubrication, wear

Constructing the decision matrix (DM): The first step is to create a DM with choices and criteria. In Equation 2, the initial decision matrix is displayed:

$$DM = [x_{ij}]_{m \times n} =$$
$$\begin{bmatrix} x_{11} & x_{12} & x_{13} & ... & x_{1n} \\ x_{21} & x_{22} & x_{23} & ... & x_{2n} \\ ... & ... & ... & ... & ... \\ x_{m1} & x_{m2} & x_{m3} & ... & x_{mn} \end{bmatrix}; i = 1, 2, 3 \, ... \, m; j = \quad (2)$$
$$1, 2, 3 \, ... \, n.$$

In this equation, the symbol *xij* represents the performance value of alternative *i* with respect to criterion *j*. The decision matrix thus evaluates *m* alternatives across *n* criteria, which may include both quantitative (numerical) data and qualitative (linguistic) assessments.

Normalizing the decision matrix: To ensure comparability across different criteria, the values in the decision matrix are normalized. This is done by extracting each element from the original decision matrix and applying a normalization process, as state in Equation 3:

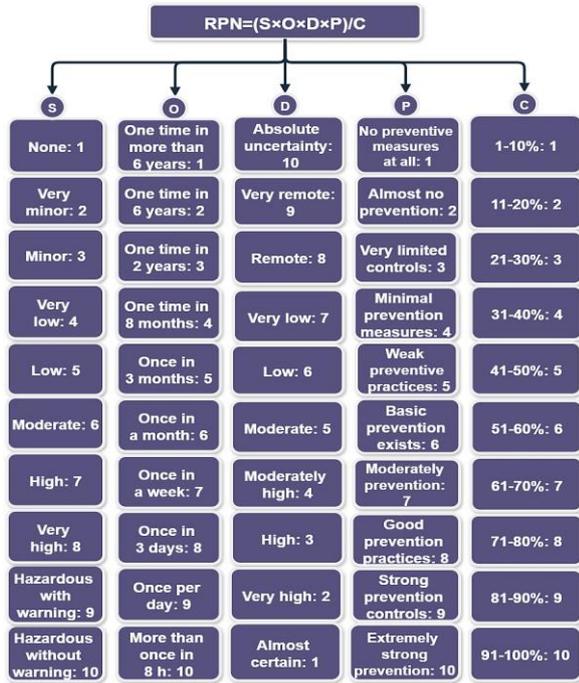$$n_{ij} = \frac{x_{ij}}{\sum x_{ij}} \qquad (3)$$

Figure 2. Criteria and their scale in modified RPN. Note: S – Severity; O – Occurrence; D – Detection; P – Preventiveness; C – Cost factor.

Calculating the entropy values: Following normalization, the entropy value Ej for each criterion is calculated using the formula below. The constant k ensures that Ej remains within the range of 0 to 1 (Equations 4 and 5).

$$k = \frac{1}{Ln\,(a)} \tag{4}$$

$$E_j = -k \sum [n_{ij} LN(n_{ij})] \tag{5}$$

Determining the degree of divergence: The degree of deviation, denoted as dj, is calculated to quantify the amount of useful information contributed by each criterion. When the values of competing alternatives for a given criterion are similar, the criterion provides less discriminatory power (Equation 6).

$$d_j = 1 - E_j \tag{6}$$

Computing the objective weights: At this stage, the weights of the criteria are calculated using Equation 7, which determines the relative importance of each criterion based on the degree of deviation.

$$W_j = \frac{d_j}{\sum d_j} \tag{7}$$

The entropy method ultimately derives the weights for each criterion, with the sum of all weight coefficients always equal to 1. In Equation 7, Wj represents the weight assigned to criterion j.

2. 6. Ranking the Criteria The CoCoSo method combines elements of the weighted sum model (WSM) and the weighted product model (WPM) through three distinct compromise-based aggregation procedures (20, 49). By integrating these methods, CoCoSo enhances both the robustness and flexibility of the decision-making process, ultimately yielding more reliable and discriminative ranking results.

Once the alternatives, evaluation criteria, and their corresponding weights have been determined, the CoCoSo decision-making procedure proceeds through a structured sequence of steps to derive the final ranking of alternatives. The methodological steps are outlined as follows:

Normalization of the Decision Matrix: The decision matrix is normalized to transform the original values into a comparable scale between 0 and 1. The normalization depends on whether a criterion is positive (beneficial) or negative (non-beneficial):

For Positive criteria—where higher values indicate better performance—normalization is performed using Equation 8:

$$r_{ij} = \frac{x_{ij} - \min\limits_{i} x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}} \tag{8}$$

For Negative criteria—where lower values are preferred—normalization is performed using Equation 9:

$$r_{ij} = \frac{\max\limits_{i} x_{ij} - x_{ij}}{\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij}} \tag{9}$$

Calculation of the Weighted Sum (S_i) and Weighted Power (P_i): In this step, the S_i and P_i values are computed for each alternative (Equations 10 and 11). These are fundamental components of the CoCoSo method, combining the effects of all criteria using their respective weights.

$$S_i = \sum_{j=1}^{n} W_j r_{ij} \tag{10}$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \tag{11}$$

The weights Wj for each criterion were previously determined using Shannon Entropy.

Aggregation of scores to determine final ranking: The relative weights of the alternatives are determined using the following aggregation approaches (Equations 12, 13, and 14).

$$K_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}(P_i + S_i)}, \tag{12}$$

$$K_{ib} = \frac{S_i}{\min\limits_{i} S_i} + \frac{P}{\min\limits_{i} P_i}, \tag{13}$$

$$K_{ic} = \frac{\lambda(S_i) + (1-\lambda)(P_i)}{\lambda \max\limits_{i}(S_i) + (1-\lambda)\max\limits_{i}(P_i)}; 0 \leq \lambda \leq 1 \tag{14}$$

Equation 11 reflects the total of the relative scores derived from the Weighted Sum Model (WSM) and the Weighted Product Model (WPM), normalized with respect to the best-performing alternative. Equation 12 represents the arithmetic mean of the normalized WSM and WPM scores, providing a balanced measure of performance. Equation 13 introduces a compromise formulation in which the scores of WSM and WPM are proportionally balanced through the parameter λ. Decision-makers choose λ in Equation 13, which is typically λ = 0.5.

Determining final score and ranking alternatives: In this final phase, the overall performance score K_i for each alternative is calculated to determine the final ranking. This is done by combining the results from three aggregation strategies—K_{ia}, K_{ib}, and K_{ic}—according to Equation 15:

$$K_i = (K_{ia}K_{ib}K_{ic})^{\frac{1}{3}} + \frac{1}{3}(K_{ia}+K_{ib}+K_{ic}) \tag{15}$$

The alternatives are then ranked in descending order of their corresponding K_i values, with higher scores indicating superior overall performance. This final step ensures that the ranking reflects not only the relative importance of the evaluation criteria but also the balance between different aggregation perspectives, thereby supporting more reliable decision-making outcomes.

2. 7. One-at-a-time (OAT) Perturbation Sensitivity Analysis

In this study, the OAT method was employed to examine the stability of the proposed MFMEA–Shannon Entropy–CoCoSo framework. The analysis was performed using the normalized decision matrix along with criterion weights obtained through the Shannon Entropy method. Perturbations were applied systematically to each criterion weight individually, while the remaining weights were held constant, followed by renormalization to maintain the total weight sum (50).

For each criterion j, the original baseline weight W_j, was perturbed by a relative factor $(1 + \delta)$, where the perturbation levels were set as:

$$\delta \in \begin{Bmatrix} -0.20, -0.10, -0.05, +0.05, \\ +0.10, +0.20 \end{Bmatrix}$$

The perturbed weight for criterion j was calculated according to Equation 16:

$$W_j' = W_j \times (1 + \delta) \tag{16}$$

After perturbing W_j, the entire weight vector was renormalized to ensure that (Equation 17):

$$\sum_{j=1}^{n} W_j' = 1 \tag{17}$$

The renormalization was performed according to Equations 18 and 19:

$$W_j' = \frac{W_j \times (1+\delta)}{\sum_{k=1}^{n} W_k^*} \tag{18}$$

$$W_k^* = \begin{cases} W_k, & \text{if } k \neq j \\ W_k \times (1 + \delta), & \text{if } k = j \end{cases} \tag{19}$$

Following renormalization, the subsequent steps of the risk assessment process were re-executed for each perturbed scenario. For each perturbation scenario, the change in rank (ΔRank i) relative to the baseline was recorded for each entity i. Additionally, the Spearman rank correlation coefficient (ρ) between the baseline ranking and each perturbed scenario was computed as a compact metric of rank stability (Equation 20):

$$\rho = 1 - \frac{6\sum_{i=1}^{m}(R_i - R_i')^2}{m(m^2-1)} \tag{20}$$

where R_i is the baseline rank of entity i; R_i' is theperturbed rank of entity i, and m is the total number of ranked entities. By analyzing ρ across all perturbation levels, the resilience of the model rankings to weight variations was quantitatively assessed, enabling the identification of criteria with the most substantial influence on the final prioritization outcomes.

3. RESULTS

3. 1. Initial Decision Matrix of Risks

The results of the initial matrix formation by the decision-making team are presented in Table 2.

TABLE 2. Initial Decision matrix of FMs

FM	Criterion				
	S	O	P	C	D
FM1	6	6	4	4	6
FM2	5	5	3	3	7
FM3	7	7	3	5	6
FM4	8	6	2	5	7
FM5	6	5	3	4	6
FM6	9	5	2	6	8
FM7	8	6	3	5	6
FM8	10	10	10	4	2
FM9	4	6	5	8	1
FM10	10	6	4	4	6
FM11	10	2	5	9	2
FM12	6	10	6	4	4
FM13	7	4	2	8	3
FM14	7	2	2	8	3
FM15	9	4	4	6	7
FM16	8	4	4	5	7

Note: FM – Failure Mode.

3. 2. Weights of the Criteria Table 3 presents the entropy values and the corresponding weights for each MFMEA criterion. In this analysis, the priority ranking of the criteria follows the standard order: P > D > O > C > S.

Based on this ranking and entropy analysis, the weights for the MFMEA variables are derived and used in subsequent risk assessment calculations.

3. 3. CoCoSo Approach
3. 3. 1. Normalized Decision Matrix In this study, Min–Max normalization was adopted for its simplicity and clarity in application to occupational risk assessment. The resulting normalized decision matrix, derived using the Min-Max method, is presented in Table 4.

3. 3. 2. Relative Weighting of the Alternatives In the CoCoSo method, the coefficients Kia, Kib, and Kic are key parameters that integrate multiple aggregation strategies into a single decision-making framework. They control the contribution of different score functions, such as Si and Pi, to each alternative's overall score. By adjusting these coefficients, the method ensures a balanced and customized evaluation that reflects both the criteria's importance and the decision-maker's preferences. The resulting relative weights of the alternatives are shown in Table 5.

3. 3. 3. Ranking FMs based on Traditional FMEA, MFMEA, and MFMEA–Shannon Entropy–CoCoSo Models Figure 3 illustrates the outcomes of risk prioritization using three methods: the traditional FMEA, MFMEA, and MFMEA–Shannon Entropy–CoCoSo approach.

The descending order of risk prioritization according to the traditional FMEA method is as follows:
FM10 = FM6 > FM4 > FM3 > FM7 > FM15 > FM12 > FM16 > FM1 > FM8 > FM5 > FM2 > FM13 > FM14 > FM11 > FM9.

The descending order of risk prioritization according to the MFMEA method is as follows:
FM8 > R10 = R12 > FM1 > FM16 > FM3 > FM2 > FM7 > FM15 > FM5 > FM4 > FM6 > FM11 > FM13 > FM9 > FM14.

TABLE 3. Weighting parameters for criteria by Shannon entropy

Criteria/Parameter	S	O	P	C	D
k	0.360	0.360	0.360	0.360	0.360
Ej	0.989	0.971	0.961	0.983	0.962
Dj	0.010	0.028	0.038	0.016	0.037
Wj	0.079	0.218	0.290	0.125	0.285

TABLE 4. Normalized input decision matrix

FM	Criteria				
	Non-beneficial			Non-beneficial	
	S	O	P	C	D
FM1	0.333	0.500	0.250	0.833	0.285
FM2	0.166	0.375	0.125	1.000	0.142
FM3	0.500	0.625	0.125	0.666	0.285
FM4	0.660	0.500	0.000	0.666	0.142
FM5	0.333	0.375	0.125	0.833	0.285
FM6	0.833	0.375	0.000	0.500	0.000
FM7	0.666	0.500	0.125	0.666	0.285
FM8	1.000	1.000	1.000	0.833	0.857
FM9	0.000	0.500	0.375	0.166	1.000
FM10	1.000	0.500	0.250	0.833	0.285
FM11	1.000	0.000	0.375	0.000	0.857
FM12	0.333	1.000	0.500	0.833	0.571
FM13	0.500	0.250	0.000	0.166	0.714
FM14	0.500	0.000	0.000	0.166	0.714
FM15	0.833	0.250	0.250	0.500	0.142
FM16	0.666	0.250	0.250	0.666	0.142

TABLE 5. Relative weighting of the alternatives and determining final score

FM	Si	Pi	Kia	Kib	Kic	Ki
FM1	0.394	4.123	0.068	3.427	0.770	1.987
FM2	0.298	3.798	0.062	2.847	0.698	1.700
FM3	0.377	4.047	0.067	3.318	0.754	1.931
FM4	0.286	3.353	0.055	2.624	0.620	1.547
FM5	0.330	3.949	0.065	3.060	0.729	1.809
FM6	0.210	2.710	0.044	2.022	0.498	1.209
FM7	0.363	4.026	0.066	3.244	0.748	1.897
FM8	0.935	4.934	0.089	6.309	1.000	3.290
FM9	0.523	3.411	0.060	3.775	0.670	2.034
FM10	0.446	4.206	0.070	3.709	0.793	2.116
FM11	0.432	2.710	0.048	3.077	0.535	1.648
FM12	0.656	4.565	0.079	4.842	0.890	2.635
FM13	0.318	3.393	0.056	2.793	0.632	1.624
FM14	0.264	2.653	0.044	2.256	0.497	1.300
FM15	0.296	3.886	0.063	2.874	0.713	1.723
FM16	0.304	3.902	0.064	2.918	0.717	1.743

Note: Si – Weighted sum of normalized comparability matrix; Pi – Weighted power of normalized comparability matrix; Kia – Summation-based Aggregation; Kib – Relative Minimum-based Aggregation; Kic – Weighted Max-normalized Aggregation; Ki – Overall Performance Score.

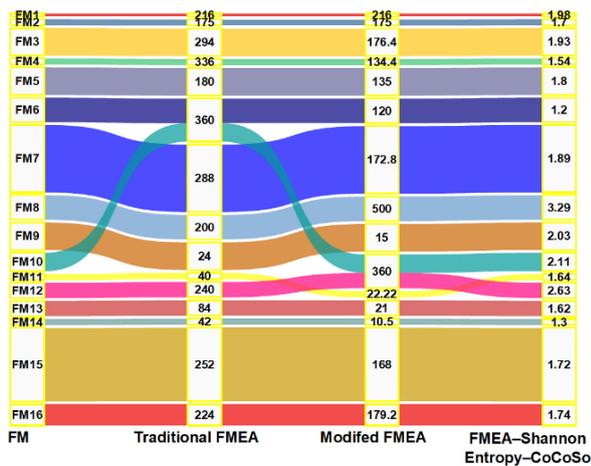**Figure 3.** FMs prioritization based on traditional FMEA, MFMEA, and MFMEA–Shannon Entropy–CoCoSo approaches

Figure 4. Stability of failure mode rankings under OAT weight perturbations

Figure 5. Most influential criteria and perturbation levels for each failure mode

In comparison, the MFMEA–Shannon Entropy–CoCoSo-based ranking sequence is:
FM8 > FM12 > FM10 > FM9 > FM1 > FM3 > FM7 > FM5 > FM16 > FM15 > FM2 > FM11 > FM13 > FM4 > FM14 > FM6.

3. 3. 4. OAT Perturbation Sensitivity Analysis   A sensitivity analysis involving 480 scenarios was conducted for the MFMEA–Shannon Entropy–CoCoSo model, with results shown in Figures 4-7. Figure 4 illustrates the OAT perturbation sensitivity for all FMs, comparing baseline ranks with their minimum, maximum, and maximum absolute rank changes across scenarios. The analysis indicates that most failure modes are highly stable, with rank changes ≤ 1, while FM11 shows a moderate sensitivity with a shift of up to two positions. Several FMs (FM12, FM14, FM16, FM3, FM5, FM6, FM7, and FM8) retain identical rankings under all perturbations, reflecting strong robustness to single-criterion weight variations.

Figure 5 highlights, for each failure mode (FM), the criterion and perturbation level that caused the greatest rank deviation during the OAT sensitivity analysis. The analysis shows that significant rank changes generally result from large positive or negative weight perturbations (±0.20) applied to specific criteria. FM11 exhibits the highest sensitivity, shifting two positions under a +20% increase in the D criterion weight. In contrast, multiple failure modes (FM3, FM5, FM6, FM7, FM8, FM12, FM14, and FM16) display no ranking changes across all tested perturbations, confirming their high stability and robustness.

Figure 6 presents criterion sensitivity based on the maximum absolute rank change and the number of affected failure modes under weighted perturbations.
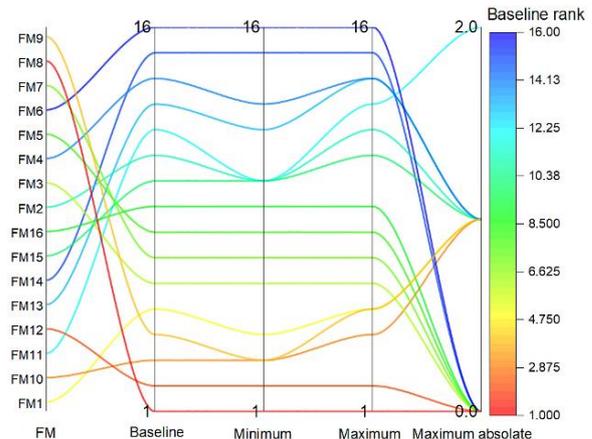
Criterion D had the greatest impact, influencing five failure modes with a maximum rank shift of two positions. Criteria C, D, O, and S showed minor sensitivity under −0.20 perturbations, limited to one rank position, while criterion P remained completely insensitive to all tested perturbations.

Figure 7 shows Spearman's ρ between the baseline failure mode rankings and rankings after proportional weight perturbations (−0.2 to +0.2) of each criterion. A ρ of 1 indicates perfect agreement. The analysis reveals that perturbations up to ±0.1 maintain perfect correlation (ρ = 1), confirming full rank stability under moderate changes. Slight deviations occur at ±0.2, with criterion D (+0.2) showing the lowest correlation (ρ = 0.98) and criterion C (+0.2) yielding ρ = 0.99. These results demonstrate that the ranking method is highly robust, with minimal reordering even under relatively large perturbations.
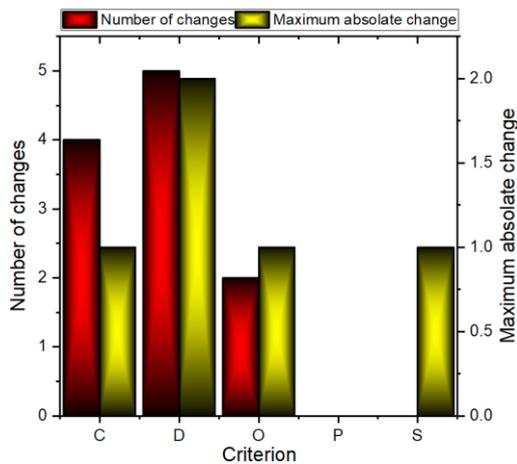
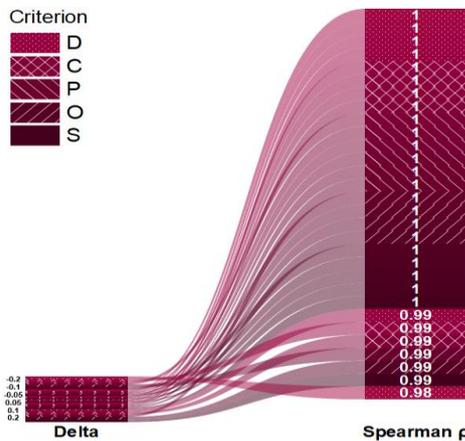**Figure 6.** Sensitivity of failure mode rankings to criterion weight perturbations

Figure 7. Spearman rank correlation coefficients (ρ) for perturbed criterion weights

4. DISCUSSION

4. 1. FMEA-Shannon Entropy-CoCoSo Approach Versus Traditional FMEA and MFMEA
Traditional FMEA is limited by its reliance on RPN, which assumes linearity, equal weighting of S, O, and D, and can assign identical scores to different risk profiles. It also lacks uncertainty handling, economic considerations, and preventive factors. MFMEA improves on this by including C and P factors, enabling a more balanced, proactive, and economically informed risk assessment.

Integrating Shannon Entropy with CoCoSo allows objective weighting of criteria and more accurate ranking of failure modes. The resulting priority order—P > D > O > C > S—highlights the significance of preventiveness and detectability, while severity has the least influence due to low variability.

The MFMEA–Shannon Entropy–CoCoSo framework provides superior risk discrimination over conventional MFMEA. Both methods identified FM8 and FM12 as critical hazards, but the integrated model prioritized FM8 higher due to its lower detectability, emphasizing early detection. Sensitivity analysis confirmed the model's robustness, with minimal rank shifts under extreme weight changes, demonstrating resilience to expert judgment variability and enhancing reliability for complex industrial decision-making.

4. 2. Risk Treatment
Crusher unit in the ceramic industry pose major health risks, and effective safety management requires systematic hazard identification, risk evaluation, control measures, and continuous monitoring (17, 51). The integrated MFMEA–Shannon Entropy–CoCoSo analysis identified excessive dust (FM8), noise (FM12) and vibration (FM10) as the highest-risk hazards in ceramic crusher unit.

In crusher unit, dust arises mainly from material tipping, mineral comminution, and handling, with dry feedstock and poor ventilation intensifying emissions. Resuspension from accumulated dust further elevates exposure. Mitigation measures include equipment enclosure, misting or spray systems, and pre-wetting of feedstock to reduce particle release.

In crusher unit, noise originates from particle impacts, mechanical components, feeders, chutes, and structural vibrations, often exceeding the 85 dB(A) limit. Contributing factors include misalignments and worn parts. Mitigation strategies involve engineering and operational controls, such as soundproof enclosures, optimized feed rates, low-noise equipment, vibration isolators, and noise monitoring.

Key sources of vibration include mass imbalances in rotating components, shaft misalignments, uneven feed material, wear of crushing surfaces, and inadequate lubrication. Mitigation requires a multi-faceted strategy involving real-time condition monitoring, predictive diagnostics, preventive maintenance, feed regulation, foundation reinforcement, vibration isolation, and automated lubrication systems.

4. 3. Proposed Further Research
Future research should focus on enhancing the MFMEA–Shannon Entropy–CoCoSo framework by integrating dynamic, adaptive, and data-driven approaches. Key directions include developing real-time weighting mechanisms to reflect evolving operational contexts, comparing entropy-based methods with advanced computational models such as neural networks and machine learning, and exploring alternative MCDM techniques (e.g., MARCOS, EDAS, WASPAS) combined with uncertainty modeling tools like gray relational analysis or cloud theory. Expanding the framework to multiple

industrial sectors will allow broader validation of its generalizability, robustness, and practical applicability.

5. CONCLUSION

The application of the MFMEA–Shannon Entropy–CoCoSo framework in a case study of a ceramic industry crusher unit demonstrated its practical effectiveness, with results identifying dust, noise, and vibration as the most critical hazards requiring immediate and targeted control measures. Moreover, the inclusion of Shannon Entropy provided objective weighting of criteria, reducing subjective bias in expert evaluations, while the CoCoSo method ensured robust and discriminative ranking performance. Sensitivity analysis further validated the reliability and stability of the framework, with Spearman correlation coefficients exceeding 0.98 under multiple weight perturbation scenarios. This high level of consistency underscores the model's robustness, even in conditions of uncertainty. Overall, the MFMEA–Shannon Entropy–CoCoSo framework represents a significant advancement in occupational risk assessment methodologies, offering a systematic, adaptable, and evidence-based approach that can be scaled to diverse industrial contexts for improving workplace safety and operational efficiency.

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Persian Abstract

چکیده

شناسایی و ارزیابی خطرناک‌ترین عوامل زیان‌آور شغلی برای اجرای اقدامات اصلاحی از طریق ارزیابی ریسک بهداشت و ایمنی شغلی (OHSRA) امری حیاتی است. با توجه به ماهیت مبهم درک انسانی، اغلب ارزیابی دقیق ریسک خطرات شغلی در فرآیند OHSRA دشوار است. برای مقابله با این چالش، تکنیک‌های ریاضی متعددی جهت تصمیم‌گیری مبتنی بر ریسک، مدیریت عدم قطعیت، یافتن راه‌حل‌های بهینه و رتبه‌بندی گزینه‌های مختلف توسعه یافته‌اند. این پژوهش، یک مدل نوین OHSRA را برای ارزیابی و اولویت‌بندی خطرات شغلی پیشنهاد می‌دهد که از ترکیب روش تحلیل حالات و آثار خرابی (FMEA)، آنتروپی شانون و روش راه‌حل سازشی ترکیبی (CoCoSo) بهره می‌برد. در این مدل، ارزیابی ریسک بر اساس پنج معیار شامل شدت (S)، احتمال وقوع (O)، قابلیت تشخیص (D)، میزان پیشگیری (P) و عامل هزینه (C) انجام می‌شود. برای مقابله با پیچیدگی و ابهام در ارزیابی‌های کارشناسی، وزن‌دهی معیارها با استفاده از آنتروپی شانون صورت می‌گیرد و رتبه‌بندی خطرات شناسایی‌شده از طریق روش CoCoSo انجام می‌شود. استحکام چارچوب پیشنهادی از طریق تحلیل حساسیت یک به یک (OAT) با تغییر وزن هر معیار به میزان ۰.۰۵±، ۰.۱۰± و ۰.۲۰± ارزیابی می‌شود. کارایی و کاربردی بودن این روش با استفاده از یک مطالعه موردی در واحد سنگ‌شکن صنعت سرامیک به نمایش گذاشته شده است. از جمله مزایای اصلی این رویکرد، انعطاف‌پذیری بالا در مدیریت داده‌های پیچیده کارشناسی و توانایی آن در ارائه ارزیابی‌های دقیق و قابل اعتماد از خطرات شغلی است.