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An Integrated Grey System Theory Approach for Operational Risk Assessment and Interdependency Analysis in Mineral Processing Plants: A Case of Gohar Zamin Iron Ore Complex (Sirjan, Iran)

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Abstract

Operational risk assessment in complex industrial systems like mineral processing plants is hindered by inherent uncertainty and incomplete information. This study presents an integrated grey system theory-based framework to address this challenge. Combining Grey Multi-Criteria Decision-Making (GST-MCDM) and Grey Relational Analysis (GRA), the methodology enables a systemic analysis that prioritizes risks, quantifies interdependencies, and measures cumulative burden across four key objectives: time, cost, quality, and safety. Applied to a case study at the Gohar Zamin iron ore processing plant (Iran), the model analyzed 26 operational risks, classifying them into Critical (8 risks), Significant (9), and Controllable (9) tiers. Electrical power shortage (RPS: 0.19) and raw material supply delay (RPS: 0.21) were identified as the most critical risks. The analysis quantified that the safety objective bears the highest cumulative risk burden at 32%, primarily due to human factor vulnerabilities, while cyber-physical threats ranked among the top 8 critical risks. Strong interdependencies were revealed, notably a quality cascade (relational grade: 0.84) between poor consumable materials and final product failure. Sensitivity analysis confirmed high model robustness (Spearman's $p = 0.91$). The framework provides managers with an actionable tool for strategic, cluster-based mitigation and evidence-based resource allocation, emphasizing investment in human capital as a core risk reduction strategy. This research contributes a replicable, quantitative methodology for enhancing operational resilience under uncertainty in capital-intensive industries.

Keywords: operational risk assessment; mineral processing; multi-criteria decision making (MCDM); grey relational analysis (GRA); risk prioritization; Gohar Zamin Iron Ore Complex

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1. Introduction

Mineral processing plants constitute complex, tightly coupled socio-technical systems in which physical transformation processes, energy infrastructures, automation platforms, maintenance regimes, supply networks, and human operators interact continuously under uncertain conditions. The increasing scale, capital intensity, and digitalization of contemporary mineral processing facilities have amplified systemic vulnerability, such that localized disturbances—energy shortages, raw material variability, equipment degradation, cyber intrusion, or human error—may propagate nonlinearly across subsystems and escalate into multidimensional operational failures affecting production continuity, cost efficiency, product quality, and workforce safety [1–4]. In capital-intensive continuous-process industries, operational risk management is therefore a strategic resilience mechanism rather than a purely compliance-driven function [5,6].

The mineral processing domain presents a particularly relevant setting for advancing operational risk modelling. Continuous production systems are sensitive to energy instability and upstream supply disruptions [2,7]. Simultaneously, increasing automation and industrial control system connectivity expose plants to cyber-physical vulnerabilities that may interact with traditional operational hazards [8]. Human factors, i.e., competence, training, and safety culture, remain critical determinants of system reliability, particularly under disturbance conditions [6,9]. However, existing studies in this sector largely focus on isolated reliability metrics, safety compliance indicators, or equipment-level analyses, with insufficient attention to systemic interdependencies and cross-objective risk aggregation [10,11]. The challenge of operational risk assessment in such environments is compounded by inherent uncertainty and incomplete information. Expert judgments are typically linguistic and subjective, data are often scarce or unavailable, and causal relationships among risks are poorly understood. These conditions render conventional deterministic or probabilistic approaches inadequate for capturing the full complexity of industrial risk landscapes. Consequently, there is a pressing need for analytical frameworks that can systematically handle uncertainty, prioritize risks under multiple criteria, quantify interdependencies, and translate analytical outputs into actionable managerial strategies.

2. Literature Review

2.1. Conventional Risk Assessment Approaches

Conventional risk assessment techniques, including Failure Mode and Effects Analysis (FMEA), Hazard and Operability Study (HAZOP), Fault Tree Analysis (FTA), and Bow-Tie analysis, remain widely applied in process industries due to their structured identification and causal decomposition capabilities [12,13]. However, their methodological foundations are predominantly deterministic or semi-quantitative, presupposing precise input information despite the epistemic ambiguity inherent in operational environments [1,14]. Moreover, these approaches typically assess hazards independently and provide limited capability for modelling cross-risk interactions, cascade propagation, and performance trade-offs across strategic objectives such as time, cost, quality, and safety [15]. In highly integrated processing plants, where energy supply, material logistics, maintenance planning, and operator competence are interdependent, linear risk taxonomies may underrepresent systemic exposure [4,16].

2.2. Multi-Criteria Decision-Making in Risk Prioritization

To overcome multidimensionality, Multi-Criteria Decision-Making (MCDM) methods have been extensively adopted in industrial risk prioritization. Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Vise Kriterijumska Optimizacija i Kompromisno Resenje (VIKOR),

and hybrid approaches allow structured evaluation under competing criteria and have been applied in maintenance planning, supply chain vulnerability assessment, and safety management [17–19]. Recent comprehensive reviews confirm the centrality of MCDM in sustainable and resilient industrial decision-making contexts [20].

Nevertheless, classical MCDM techniques rely on crisp numerical judgements and exact preference structures, assumptions that are rarely satisfied in operational risk environments characterized by linguistic assessments, limited data, and expert subjectivity [21–25]. Fuzzy-based extensions have been widely introduced to address uncertainty, giving rise to fuzzy-AHP, fuzzy-TOPSIS, and integrated fuzzy-MCDM frameworks [26–28]. Although these approaches improve uncertainty representation relative to crisp models, they frequently require defuzzification procedures that collapse interval information into single-point estimates, potentially reducing epistemic transparency and distorting ambiguity embedded in expert judgment [26]. In addition, many fuzzy risk models emphasize ranking outputs without systematically integrating structural interdependency analysis and aggregate burden quantification [27,28].

2.3. Grey System Theory and Its Applications

Grey System Theory (GST), originally formulated to model systems characterized by partially known information, offers a mathematically robust alternative for decision-making in small-sample and incomplete-data environments [29,30]. Unlike probabilistic or fuzzy paradigms, grey theory preserves uncertainty explicitly through interval grey numbers ($\otimes$) and supports algebraic operations without forced crispification [30]. Over the past decade—and particularly since 2020—grey-based methods have gained renewed attention in resilience analytics, supply chain risk modelling, infrastructure vulnerability assessment, and engineering decision-making under uncertainty [31–34]. Grey entropy weighting has been shown to reduce subjective bias in criteria evaluation [35], while Grey Relational Analysis (GRA) provides a robust mechanism for quantifying relational strength among system elements and detecting structural coupling [32,36]. Recent integrated grey-DEMATEL and grey-MCDM architectures further demonstrate the capacity of grey systems to model influence pathways and interdependencies in complex industrial contexts [33,37].

2.4. Identified Research Gaps

Despite these methodological advances, three substantive gaps remain in the literature:

1. Integration Gap: Most grey-based risk studies treat prioritization and interdependency analysis as sequential or independent analytical tasks, rather than embedding them within a unified systemic architecture that simultaneously captures ranking, coupling, and aggregate exposure [33,37].
2. Cumulative Impact Gap: Existing models rarely quantify the cumulative burden of operational risks across strategic performance objectives, thereby limiting managerial interpretability and resource allocation guidance [5,20].
3. Sector-Specific Gap: Empirical applications of integrated grey-system frameworks in mineral processing plants—characterized by continuous flows, energy dependency, raw material heterogeneity, maintenance complexity, and cyber-physical integration—remain limited [3,16,38].

To explicitly position the proposed framework within the existing body of operational risk assessment research, Table 1 presents a systematic comparison of representative conventional and grey-based approaches. Rather than comparing mathematical formulations alone, the comparison focuses on analytical capabilities, uncertainty representation, treatment of interdependencies, computational characteristics, and decision-support outputs in order to clarify the methodological contribution of the proposed integrated framework.

Table 1. Systematic comparison of representative operational risk assessment approaches and the proposed integrated GST framework.

Study/Approach	Uncertainty Representation	Objective Weighting	Risk Prioritization	Interdependency Analysis	Cumulative Impact Assessment	Decision-Support Outputs	Main Limitation
Conventional MCDM	Deterministic	Subjective	✓	✗	✗	Risk ranking	Requires precise data
Fuzzy MCDM	Fuzzy numbers	Hybrid	✓	Limited	✗	Risk ranking	Membership-function dependency
Rajesh & Ravi [32]	Grey intervals	Not used	✓	✗	✗	Supplier ranking	No interaction analysis
Li et al. [33]	Grey intervals	Grey Entropy	✓	Partial (DEMATEL)	✓	Structural relationships	No integrated prioritization
Rehman & Al Faify [34]	Grey intervals	Grey Entropy	✓	✗	✗	Configuration ranking	Standalone ranking
Hashemi et al. [39]	Grey intervals	Partial	✓	✗	✗	Alternative evaluation	No cumulative assessment
Proposed Framework	Grey intervals	Grey Entropy	✓	✓	✓(CIS)	Risk prioritization + interdependency mapping + cumulative objective analysis + managerial clustering	Integrated analytical architecture

where: ✓- yes; ✗ - no.

As demonstrated in Table 1, existing operational risk assessment approaches generally emphasize a single analytical function, such as risk ranking, uncertainty representation, or structural relationship analysis. Even recent grey-based studies typically employ individual grey techniques to address specific decision-making problems without integrating complementary analytical modules into a unified framework. In contrast, the proposed framework combines Grey Entropy weighting, Grey Multi-Criteria Decision-Making, Grey Relational Analysis, and Cumulative Impact Score evaluation within a single uncertainty-preserving analytical architecture. This integration enables simultaneous prioritization of operational risks, identification of interdependencies, quantification of cumulative impacts across strategic objectives, and generation of cluster-oriented managerial recommendations.

3. Aim and Scope of the Work

In response to the identified research gaps, this study develops an integrated Grey System Theory–based operational risk assessment framework that unifies prioritization, interdependency modelling, and cumulative burden evaluation within a single analytical architecture. By combining Grey Multi-Criteria Decision-Making with Grey Relational Analysis, the proposed framework preserves interval uncertainty while constructing a systemic representation of operational risk structure. In addition to generating a stratified priority ranking, the model quantifies relational coupling among risks and introduces a Cumulative Impact Score (CIS) to measure total risk load distribution across four strategic performance objectives: Time, Cost, Quality, and Safety.

Accordingly, the methodological contributions of this study are summarized as:

1. Development of an integrated uncertainty-preserving analytical framework that combines Grey Entropy weighting, Grey MCDM, Grey Relational Analysis, and Cumulative Impact Score evaluation;
2. Simultaneous assessment of operational risk priority, interdependency structures, and cumulative impacts on strategic operational objectives within a unified analytical workflow;
3. Translation of multiple analytical outputs into cluster-oriented managerial decision support for strategic resource allocation under uncertainty; and
4. Demonstration of the applicability and reproducibility of the proposed framework through a large-scale mineral processing plant case study.

The scope of this work is limited to the operational risk assessment of the Gohar Zamin iron ore processing plant in Sirjan, Iran. The study focuses on 26 operational risks identified and validated through a systematic Delphi process involving domain experts. The framework evaluates these risks against four performance criteria (Time, Cost, Quality, and Safety) and analyzes their interdependencies using Grey Relational Analysis. While the case study provides a robust empirical demonstration, the framework is designed to be replicable and adaptable to other continuous-process industries. The remainder of this paper is organized as follows: Section 4 presents the methodology, including research design, case study context, data collection, and the integrated grey-based analytical framework. Section 5 presents the results, including risk prioritization, cumulative impact analysis, interdependency mapping, and model validation. Section 5 discusses the findings, managerial implications, and study limitations. Finally, Section 6 concludes the paper and outlines directions for future research.

4. Methodology

4.1. Research Design and Philosophical Underpinning

This study adopts a pragmatic research philosophy, employing a sequential mixed-methods design structured around an in-depth, single-case study framework. The research is explicitly exploratory-descriptive, aiming to both map the complex risk landscape and establish a quantifiable prioritization mechanism for the operational environment of the Gohar Zamin iron ore processing plant. The methodological framework is anchored in Grey System Theory (GST), which is positioned to handle the inherent uncertainty, incomplete information, and subjective judgments characteristic of operational risk assessment in complex industrial systems. The design unfolds in two integrated phases: a qualitative phase for systematic risk identification and validation, followed by a quantitative phase for measurement, modelling, and prioritization using a GST-MCDM model. This approach ensures that the derived model is both grounded in expert reality and analytically robust. The study pathway and details are provided in Figure 1 and Table 2. For clarity, a simplified computational workflow, together with a summary of each analytical stage is presented in Supplementary Materials S1 of the Supplementary Materials. The methodological components of the proposed framework were selected according to three complementary criteria: (i) preservation of uncertainty throughout the analytical process, (ii) objective and reproducible decision-making with minimal expert-induced bias, and (iii) capability to simultaneously evaluate risk importance, operational interdependencies, and cumulative impacts. Accordingly, each analytical module was chosen based on its methodological suitability rather than its individual novelty, enabling the construction of a coherent decision-support architecture for complex mineral processing systems operating under incomplete information.

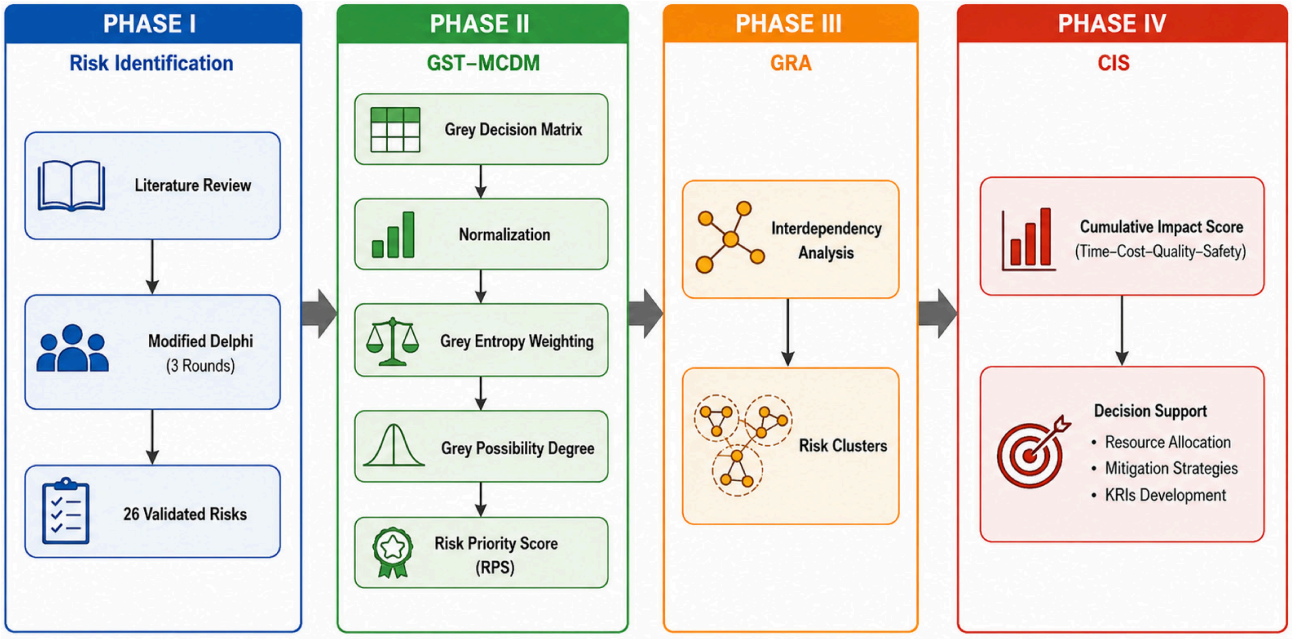


Figure 1. Integrated grey system theory framework developed for operational risk assessment.

Table 2. Sequential mixed-methods research design overview.

Phase	Primary Objective	Methods and Techniques	Output
Phase 1: Qualitative Exploration	To identify, define, and validate context-specific operational risks.	1. Systematic Literature Review (SLR) 2. Three-Round Modified Delphi Technique with Expert Panel 3. Semi-structured Interviews	A finalized, consensus-based list of 26 critical operational risks.
Phase 2: Quantitative Modeling and Analysis	To measure, prioritize, and analyze the interrelationships between identified risks.	1. Grey-Based Survey Instrument (Linguistic Scales) 2. Grey Multi-Criteria Decision-Making (GST-MCDM) Model 3. Grey Relational Analysis (GRA) for Interdependency 4. Sensitivity and Validation Analysis	A stratified risk priority ranking, criterion-wise impact scores, interdependency maps, and validated model outputs.

4.2. Case Study Context and Expert Panel Selection

The research context is the processing plant of the Gohar Zamin Iron Ore Company, a pivotal entity in Iran's steel supply chain. The plant's complexity, scale, and exposure to multifaceted operational hazards make it an ideal revelatory case for studying industrial risk management. A purposive, criterion-based sampling strategy was used to constitute two panels [40]:

1. Delphi expert panel (n = 7): For the qualitative risk identification/validation phase. Selection criteria required: (a) minimum 10 years of experience in mineral processing or heavy industry, (b) current senior managerial or specialized technical role, and (c) direct familiarity with the case study plant's operations.

2. Assessment panel (n = 32): For the quantitative survey. This group comprised a broader set of managers and engineers from the steel industry, including representatives from Gohar Zamin, to ensure evaluative diversity while maintaining domain expertise.

4.3. Data Collection Procedures

Data collection was executed in a structured, sequential manner to build a reliable foundation for the model [33,41]:

Step 1, systematic risk identification: An initial set of 43 potential operational risks was compiled through a systematic review of academic literature and industry failure reports relevant to mineral processing and heavy industry.

Step 2, risk validation and finalization (modified Delphi): This initial list was subjected to a three-round modified Delphi process with the 7-member expert panel. Rounds involved anonymous scoring of risk relevance, iterative feedback with statistical summaries (mean, interquartile range), and controlled feedback until consensus was achieved on a final list of 26 non-redundant, critical operational risks.

Step 3, survey development and administration: A structured questionnaire was developed where each of the 26 risks was evaluated against four key performance criteria: Time, Cost, Quality, and Safety. To capture expert judgement under uncertainty, a 5-point linguistic scale (e.g., "Very Low Impact" to "Very High Impact") was used, with each point corresponding to a predefined interval grey number (Table 3). This design directly translates subjective assessments into computable grey data. The questionnaire's face and content validity were affirmed by five independent scholars. Its reliability, tested on a pilot sample, yielded a Cronbach's Alpha coefficient of 0.82, indicating high internal consistency. In the present study, all evaluation criteria were treated as cost-type attributes because each criterion represents an undesirable characteristic associated with operational risk. Higher values indicate greater risk severity, higher probability of occurrence, larger operational consequences, or more significant adverse impacts on plant performance. Consequently, lower criterion values correspond to more favourable operational conditions. Therefore, the assumption that all criteria are cost-type is consistent with the inherent nature of the operational risk assessment problem considered in this study, and no benefit-type criteria were included in the proposed evaluation framework. If benefit-type criteria are considered in future applications, the proposed framework can readily accommodate them by applying the corresponding normalization procedure prior to the Grey Entropy weighting stage.

Table 3. Linguistic variables and corresponding interval grey numbers for impact assessment.

Linguistic Term	Interpretation (Impact Level)	Corresponding Interval Grey Number (⊗)
Very Low (VL)	Negligible impact on the criterion	[0.0, 0.2]
Low (L)	Minor impact on the criterion	[0.1, 0.3]
Medium (M)	Moderate impact on the criterion	[0.3, 0.5]
High (H)	Significant impact on the criterion	[0.5, 0.8]
Very High (VH)	Severe, critical impact on the criterion	[0.7, 1.0]

4.4. Analytical Framework: The Integrated GST-MCDM-GRA Model

The core analysis employs an integrated grey-based model, comprising three main analytical stages as follows:

4.4.1. Stage 1: Grey Multi-Criteria Decision-Making for Prioritization

A. Construction of the aggregate Grey decision matrix (D): Responses from the 32 assessors were aggregated using the averaged intervals method to form a consolidated group decision matrix $D = \left[\otimes x_{ij}\right]_{m\times n}$, where $\otimes x_{ij} = \left[\underline{x}_{ij}, \overline{x}_{ij}\right]$ is the Grey evaluation of risk i (I = 1, . . ., 26) with respect to criterion j (j = 1, 2, 3, 4) for time, cost, quality, and safety [42].

B. Normalization of the grey matrix (R): Given all criteria are "cost" type (i.e., lower impact is better), linear normalization was applied to preserve the property of the grey numbers [42]:

$$\otimes r_{ij} = \left[\frac{\min_i \underline{x}_{ij}}{\overline{x}_{ij}}, \frac{\min_i \underline{x}_{ij}}{\underline{x}_{ij}} \right] \quad (1)$$

yielding the normalized matrix $R = \left[\otimes r_{ij}\right]_{26\times 4}$.

Additional details regarding the expert evaluation procedure, linguistic assessment scale, and the general structure of the Grey Decision Matrix are provided in Supplementary Materials S2 of the Supplementary Materials.

C. Determination of criteria weights using Grey entropy: Grey Entropy weighting was adopted because it objectively derives criterion importance directly from the dispersion of expert evaluations without requiring subjective pairwise comparisons. Compared with conventional weighting techniques, Grey Entropy is particularly suitable for operational risk assessment problems characterized by incomplete, interval-valued, or uncertain information, where preserving uncertainty throughout the weighting process is essential. Furthermore, objective weighting minimizes potential evaluator bias and improves the reproducibility of the decision-making process, making it well suited for complex industrial applications involving multiple experts. Objective weights were calculated to minimize bias. First, the information entropy E_j for each criterion was computed from the normalized matrix [42]:

$$p_{ij} = \frac{\left(\underline{r}_{ij} + \overline{r}_{ij}\right)/2}{\sum_{i=1}^{26}\left(\underline{r}_{ij} + \overline{r}_{ij}\right)/2}, \; E_j = -\frac{1}{\ln 26}\sum_{i=1}^{26} p_{ij} \ln p_{ij} \quad (2)$$

The weight w_j for criterion j is then:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^{4}(1 - E_j)}, \text{ satisfying } \sum_{j=1}^{4} w_j = 1 \quad (3)$$

A concise description of the Grey Entropy weighting procedure and the corresponding computational steps is provided in Supplementary Materials S3 of the Supplementary Materials.

D. Calculation of the Grey possibility degree and composite score: The Grey Possibility Degree (GPD) was employed because it provides a robust mechanism for comparing interval grey numbers without converting them into crisp values. Unlike deterministic ranking approaches, GPD preserves interval uncertainty during pairwise comparisons and therefore offers a more reliable basis for prioritizing operational risks under incomplete information. This property has contributed to its widespread adoption in Grey System Theory-based decision-making studies. The Grey Positive Ideal Solution (GPIS) for each criterion was defined as $\otimes r_j^+ = \left[\min_i\left(\underline{r}_{ij}\right), \min_i\left(\overline{r}_{ij}\right)\right]$. The Grey Possibility Degree (GPD), measuring the probability that a risk's performance is less than or equal to the ideal, was calculated for each risk-criterion pair [39,42]:

$$P\left(\otimes r_{ij} \le \otimes r_j^+\right) = \frac{\max(0, L^* - \max(0, \underline{r}_j^+ - \overline{r}_{ij}))}{L^*} \quad (4)$$

where $L^* = \left(\overline{r}_{ij} - \underline{r}_{ij}\right) + (\overline{r}_j^+ - \underline{r}_j^+)$. The composite Grey Risk Priority Score (RPS_i) for each risk is the weighted sum:

$$RPS_i = S_i = \sum_{j=1}^{4} w_j \cdot P(\otimes r_{ij} \le \otimes r_j^+) \quad (5)$$

Lower RPS_i values indicate higher criticality. Risks were then stratified into Critical, Significant, and Controllable tiers based on natural breaks in the RPS distribution. Natural-break classification was employed because it partitions observations according to inherent discontinuities within the data distribution rather than imposing arbitrary interval boundaries. Consequently, the resulting risk categories more accurately reflect the underlying structure of operational risk severity and reduce classification bias compared with equal-interval or manually defined thresholds.

4.4.2. Stage 2: Grey Relational Analysis for Interdependency Assessment

The upper bounds of the grey relational coefficients were selected for the interdependency analysis because the objective of this stage was to identify potential worst-case operational interactions among risks. Considering upper-bound values enables conservative estimation of risk propagation, which follows the precautionary approach recommended in grey-based risk assessment literature (e.g., [33]). Since the framework aims to support strategic mitigation planning under uncertainty, emphasizing the maximum plausible interaction provides a more robust basis for identifying critical cascading effects than midpoint or lower-bound estimates. To map systemic connections between risks, Grey Relational Analysis was conducted on the normalized matrix R. The Grey Relational Coefficient $\zeta_{ik}(j)$ between risk i and risk k concerning criterion j was computed [43]:

$$\zeta_{ik}(j) = \frac{\max_i \max_k \Delta_{ik}(j) + \rho \max_i \max_k \Delta_{ik}(j)}{\Delta_{ik}(j) + \rho \max_i \max_k \Delta_{ik}(j)} \quad (6)$$

where $\Delta_{ik}(j) = \left|\bar{r}_{ij} - \bar{r}_{kj}\right|$ (using the upper bounds as representatives for distance), and $\rho = 0.5$ is the distinguishing coefficient. The overall Grey Relational Grade γ_{ik} was obtained by averaging across criteria [43]:

$$\gamma_{ik} = \frac{1}{4}\sum_{j=1}^{4} \zeta_{ik}(j) \quad (7)$$

A threshold of $\gamma_{ik} > 0.75$ was set to identify strong interdependencies, revealing critical risk clusters. The threshold value ($\gamma > 0.75$) was selected to identify only strong interdependencies among operational risks while avoiding excessive network complexity resulting from weak associations. This threshold is consistent with values commonly adopted in grey relational analysis studies (e.g., [32,39]). Sensitivity analysis presented in Section 5.4 further confirms that the identified critical relationships remain stable under uncertainty perturbations, indicating that the selected threshold does not materially influence the overall analytical conclusions.

4.4.3. Stage 3: Aggregate Burden Analysis and Model Validation

The model validation for different steps was performed as follows:

A. Cumulative impact score (CIS): The total risk burden on each criterion j was calculated as [39]:

$$CIS_j = \sum_{j=1}^{26} w_j \cdot P(\otimes r_{ij} \leq \otimes r_j^+) \quad (8)$$

This quantifies the aggregate pressure on each performance objective.

B. Validation and robustness checks: To evaluate the robustness and reliability of the proposed framework, two complementary validation approaches were employed. Monte Carlo simulation was used to assess the stability of the obtained rankings under uncertainty, while a comparative analysis with the Fuzzy AHP–TOPSIS method was conducted to examine the consistency of the prioritization results obtained using an established multi-

criteria decision-making technique. The combination of these two validation strategies provides both stochastic and methodological verification of the proposed framework.

- Sensitivity analysis: A Monte Carlo simulation (1000 iterations) was run, randomly varying criterion weights (±25%) and grey interval midpoints (±10%) to test ranking stability [44].
- Comparative analysis: The results were benchmarked against those from a Fuzzy AHP-TOPSIS model applied to the same dataset, with agreement measured via Kendall's W coefficient [45]. Fuzzy AHP–TOPSIS was selected as the benchmark method because it is among the most widely adopted hybrid MCDM techniques for industrial risk assessment under uncertainty. It combines subjective criteria weighting with fuzzy representation of linguistic judgments and therefore provides an appropriate state-of-the-art reference for evaluating the consistency of the proposed grey-based framework. Furthermore, both approaches address uncertainty using interval-type information while relying on different mathematical paradigms, making their comparison suitable for assessing convergent validity rather than algorithmic superiority.
- Internal consistency: The stability of the expert-derived risk list from the Delphi process was assessed by calculating the interquartile range (IQR) convergence across rounds.

In addition to the quantitative validation procedures, the final prioritization results and identified interdependency patterns were independently reviewed by senior operational managers and domain experts familiar with large-scale mineral processing plants. Their qualitative assessment confirmed that the identified critical risks, including energy interruptions, raw material supply instability, human competency deficiencies, and cyber-physical vulnerabilities, are consistent with practical operational experience and current risk management priorities within continuous mineral processing systems. Although this expert-based assessment does not replace long-term historical validation, it provides additional evidence supporting the practical relevance of the proposed framework. Generally, the validation results demonstrate that the proposed framework provides stable, consistent, and reliable risk prioritization under uncertain operational conditions. The complementary use of Monte Carlo simulation and comparative analysis with the Fuzzy AHP–TOPSIS method confirms both the robustness of the obtained rankings and the methodological reliability of the proposed framework. These findings support the applicability of the proposed approach as a practical decision-support tool for operational risk assessment in mineral processing plants. Supplementary Materials provide additional methodological details supporting the expert evaluation procedure, Grey Entropy weighting process, computational workflow, and reproducibility of the proposed framework.

4.5. Ethical Considerations and Software Tools

The study adhered to strict ethical protocols: informed consent was obtained from all participants, anonymity and confidentiality of responses were guaranteed, and participants retained the right to withdraw at any stage. The primary analytical computations for the GST-MCDM and GRA models were performed in MATLAB R2021a. Supporting statistical analyses, including reliability testing and descriptive statistics, were conducted using SPSS Statistics v26 and STATISTICA v13.

5. Results and Discussion

5.1. Comprehensive Risk Prioritization and Stratification

The implementation of the integrated Grey System Theory-based Multi-Criteria Decision-Making model yielded a sophisticated, multi-dimensional prioritization of the 26 operational risks identified within the Gohar Zamin iron ore processing plant. The

composite Grey Risk Priority Score (RPS_i) for each risk, computed using Equation (5), demonstrated significant dispersion across a normalized spectrum (0.19 to 0.81), where lower values indicate greater proximity to the negative ideal solution and thus higher criticality. Leveraging natural breaks in the RPS distribution and aligning with established risk management frameworks, the risks were stratified into three distinct managerial tiers: Critical ($RPS_i \leq 0.35$), Significant ($0.35 < RPS_i \leq 0.55$), and Controllable ($RPS_i > 0.55$), as provided in Figure 2 and Table 4. This stratification transforms a simple ranked list into an actionable resource allocation framework, clarifying which risks demand strategic, tactical, or operational responses. The prioritization results indicate that operational risks associated with process continuity, equipment reliability, and maintenance management exert the greatest influence on the overall performance of mineral processing plants. These risks directly affect production stability, equipment availability, operational costs, and downstream process efficiency. Consequently, the proposed integrated framework assigns higher priority to risks capable of triggering cascading operational disruptions across interconnected processing units. The obtained prioritization pattern is generally consistent with previous studies on operational risk assessment in mineral processing and other industrial systems, where equipment failures, maintenance deficiencies, and process interruptions have been recognized as dominant contributors to operational instability. Unlike conventional weighting and ranking techniques, the proposed Grey-based framework explicitly incorporates uncertainty in expert judgments while simultaneously accounting for interdependencies among operational risks, thereby providing a more comprehensive representation of real industrial conditions.

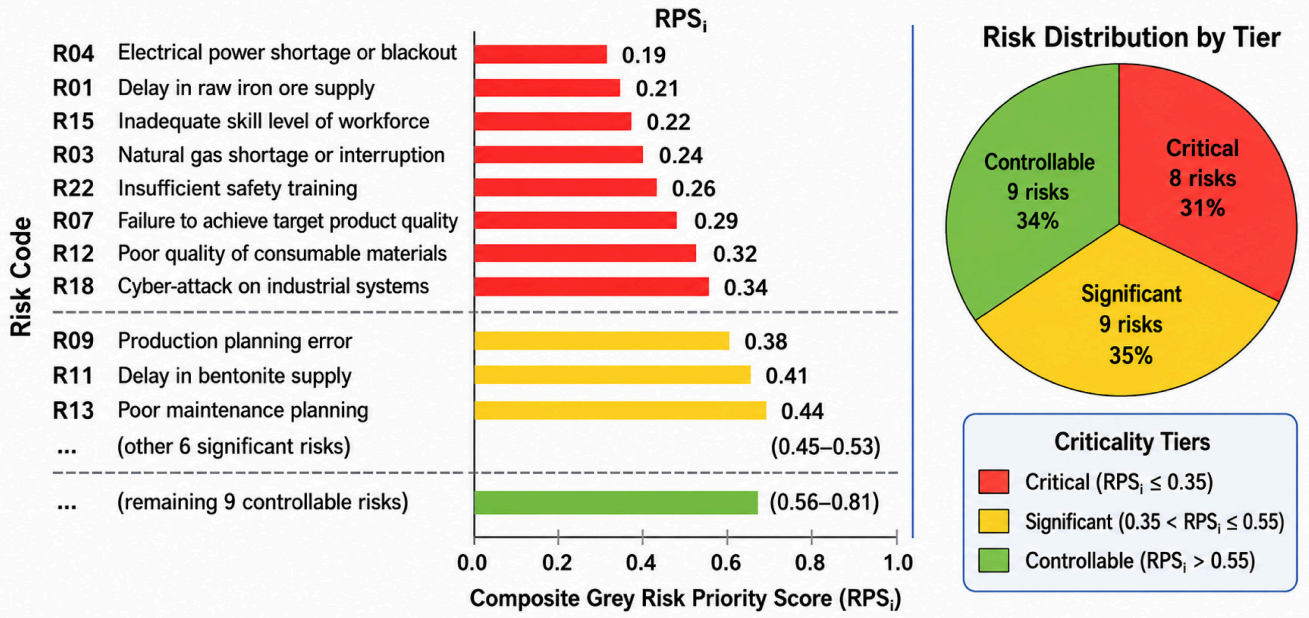


Figure 2. Risk prioritization and stratification results (GST-MCDM).

The eight risks constituting the Critical tier are presented in Table 5. The emergence of "Electrical power shortage or blackout" (R04) and "Natural gas interruption" (R03) as the foremost risks starkly highlights the profound vulnerability of continuous, capital-intensive mineral processing to energy supply instability. This finding resonates with global literature emphasizing the severe operational and financial consequences of energy insecurity in heavy industry, where stoppages incur not only lost production but also significant restart energy penalties and equipment stress (e.g., [46–52]).

Table 4. Stratified prioritization and management framework for operational risks.

Criticality Tier	Risk Count	Composite RPS Range	Key Characteristics	Recommended Management Approach
Critical	8	0.19–0.34	High-impact, multi-criteria effects; potential for cascading failures.	Immediate, strategic intervention with dedicated resources and senior management oversight. Requires formal treatment plans and Key Risk Indicators (KRIs).
Significant	9	0.36–0.53	Moderate to high impact, often dominant in one or two criteria.	Proactive management through optimized operational procedures, targeted investments, and continuous monitoring.
Controllable	9	0.56–0.81	Localized impact, lower probability, or effective existing controls.	Management through routine procedures, standard operating protocols, and general continuous improvement initiatives.

Table 5. Composition and primary impact profile of critical risk tier.

Rank	Risk Code	Risk Description	Composite RPS (S_i)	Primary Impact Criteria (Weighted Contribution > 20%)
1	R04	Electrical power shortage or blackout	0.19	Cost (38%), Time (35%)
2	R01	Delay in supply of raw iron ore	0.21	Time (42%), Quality (33%)
3	R15	Inadequate skill level of workforce	0.22	Safety (45%), Quality (30%)
4	R03	Natural gas shortage or interruption	0.24	Cost (40%), Time (37%)
5	R22	Insufficient safety training and awareness	0.26	Safety (68%)
6	R07	Failure to achieve target product quality	0.29	Quality (62%)
7	R12	Poor quality of consumable materials (e.g., reagents)	0.32	Quality (52%), Cost (28%)
8	R18	Cyber-attack on industrial automation systems	0.34	Safety (41%), Time (31%)

The high ranking of "Delay in raw iron ore supply" (R01) underscores the plant's dependency on a robust and timely supply chain. The grey model effectively captures its cascading impact, affecting "Time" through production idling and "Quality" by forcing the processing of alternative, potentially sub-optimal ore blends. The prominence of human-factor risks R15 and R22 in the critical tier quantitatively validates the central tenet of High-Reliability Organization (HRO) theory: human competence and mindfulness are foundational, non-negotiable prerequisites for safe and effective operation in complex socio-technical systems.

5.2. Criterion-Wise Decomposition and Cumulative Impact Burden

To enable targeted mitigation, the impact of each risk was decomposed across the four fundamental performance objectives: Time, Cost, Quality, and Safety. Table 6 presents the top risks specific to each criterion, based on their criterion-specific Grey Possibility Degree.

To understand the aggregate risk burden on each organizational objective, the Cumulative Impact Score (CIS) was calculated per Equation (8) and presented in Figure 3 and Table 7. This metric sums the weighted, criterion-specific Grey Possibility Degrees for all risks, providing a macro-level view of where the total operational risk load is concentrated. The analysis reveals a critical strategic insight. While "Cost" and "Time" overruns typically dominate operational reviews, the "Safety" criterion bears the largest aggregate burden of risk (32%). This is not driven by a single catastrophic threat but by the combined weight of human competency gaps (R15), cultural/practice deficiencies (R22), and emerging tech-

nological vulnerabilities (R18). This finding effectively supports reframing investments in safety culture, training, and cybersecurity not as discretionary compliance costs but as the most significant lever for reducing the plant's overall risk profile. The concentrated nature of the "Quality" burden (heavily influenced by R07 and R12) suggests that targeted improvements in raw material control and process stability could yield substantial returns in product consistency and market premium.

Table 6. Specifications of criterion-specific leading risks.

Risk Type	Rank	Risk Code	Description	Risk Type-Specific Score
Time	1	R01	Delay in raw ore supply	0.12
	2	R04	Electrical power shortage	0.15
	3	R11	Delay in bentonite supply	0.18
Cost	1	R04	Electrical power shortage	0.09
	2	R03	Natural gas interruption	0.14
	3	R09	Production planning error	0.19
Quality	1	R07	Failed quality target	0.11
	2	R12	Poor consumable quality	0.14
	3	R11	Delay in quality bentonite	0.17
Safety	1	R15	Inadequate workforce skills	0.08
	2	R22	Insufficient safety training	0.10
	3	R13	Poor maintenance planning	0.20

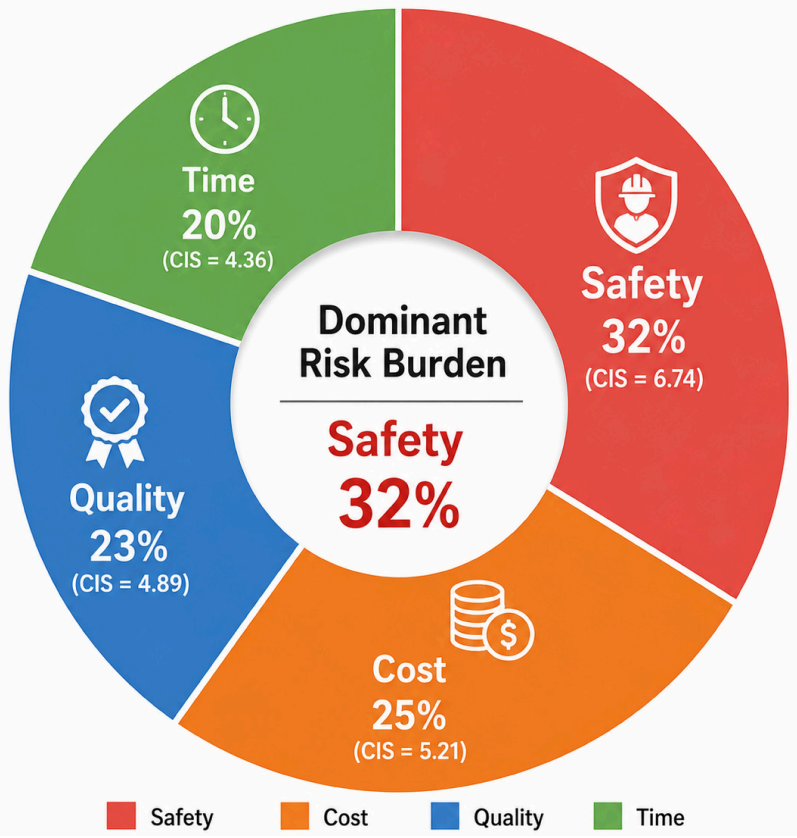


Figure 3. Cumulative impact burden across performance cirteria.

Table 7. Aggregate risk burden analysis via cumulative impact scores.

Performance Criterion	Assigned Weight (w_j)	Cumulative Impact Score (CIS_j)	Proportion of Total Risk Burden	Primary Contributing Risks
Safety	0.28	6.74	32%	R15, R22, R18
Cost	0.25	5.21	25%	R04, R03, R09
Quality	0.24	4.89	23%	R07, R12, R01
Time	0.23	4.36	20%	R01, R04, R11
Total	1.00	21.20	100%	

5.3. Analysis of Risk Interdependencies and Cascading Pathways

Recognizing that risks do not act in isolation, Grey Relational Analysis (GRA) was employed to quantify the strength of connections between risks. The Grey Relational Grade (γ_{ij}) between risks i and j was calculated using Equation (7), with $\gamma_{ij} > 0.75$ indicating a strong interdependency warranting clustered management. Results provided in Figure 4 and Table 8 indicate that the "Quality Cascade (R12 $\rightarrow$ R07)" demonstrates that final product failure is often a direct symptom of poor input quality, arguing for an integrated supplier-to-shipping quality management system rather than isolated departmental controls. The strong "Maintenance-Safety Nexus (R13 $\rightarrow$ R15)" exposes a latent, high-consequence scenario where poor planning forces complex repairs to be executed by inadequately skilled personnel, creating a potent mix of procedural and human error. These interdependencies mandate a shift from "linear, siloed risk mitigation" to a "networked, systemic risk management" approach.

5.4. Model Validation, Sensitivity, and Comparative Analysis

The robustness of the GST-MCDM model was subjected to robust validation. A comprehensive sensitivity analysis via Monte Carlo simulation (1000 iterations) perturbing criterion weights ($\pm$25%) and grey interval bounds ($\pm$10%) confirmed high stability as listed in Table 9 and Figure 5. The Critical tier composition remained unchanged in 94% of simulations, with the mean Spearman rank correlation coefficient (ρ) between original and perturbed rankings being 0.91. The model was benchmarked against a well-established Fuzzy AHP-TOPSIS methodology applied to the same dataset [53]. While mid-tier rankings showed expected minor variations due to differing aggregation philosophies, the strong concordance (Kendall's W = 0.85) and, most importantly, the identical identification of the eight Critical risks, confirm the validity of the core findings. The GST framework offers a distinct advantage in preserving the inherent uncertainty of expert judgement through interval grey numbers, whereas fuzzy methods often lose this nuance during defuzzification. The limited variation observed in the simulated rankings indicates that the proposed framework is relatively insensitive to small perturbations in the input data. This stability demonstrates that the identified priority risks are not the result of random fluctuations in expert judgments but reflect the inherent characteristics of the operational risk structure. The close agreement between the proposed framework and the Fuzzy AHP–TOPSIS method further supports the validity of the obtained rankings. Minor differences in the ranking positions are expected because the proposed Grey-based framework explicitly considers uncertainty and interdependencies among operational risks, whereas conventional approaches generally evaluate risks independently. These differences therefore reflect methodological characteristics rather than inconsistencies in the obtained results.

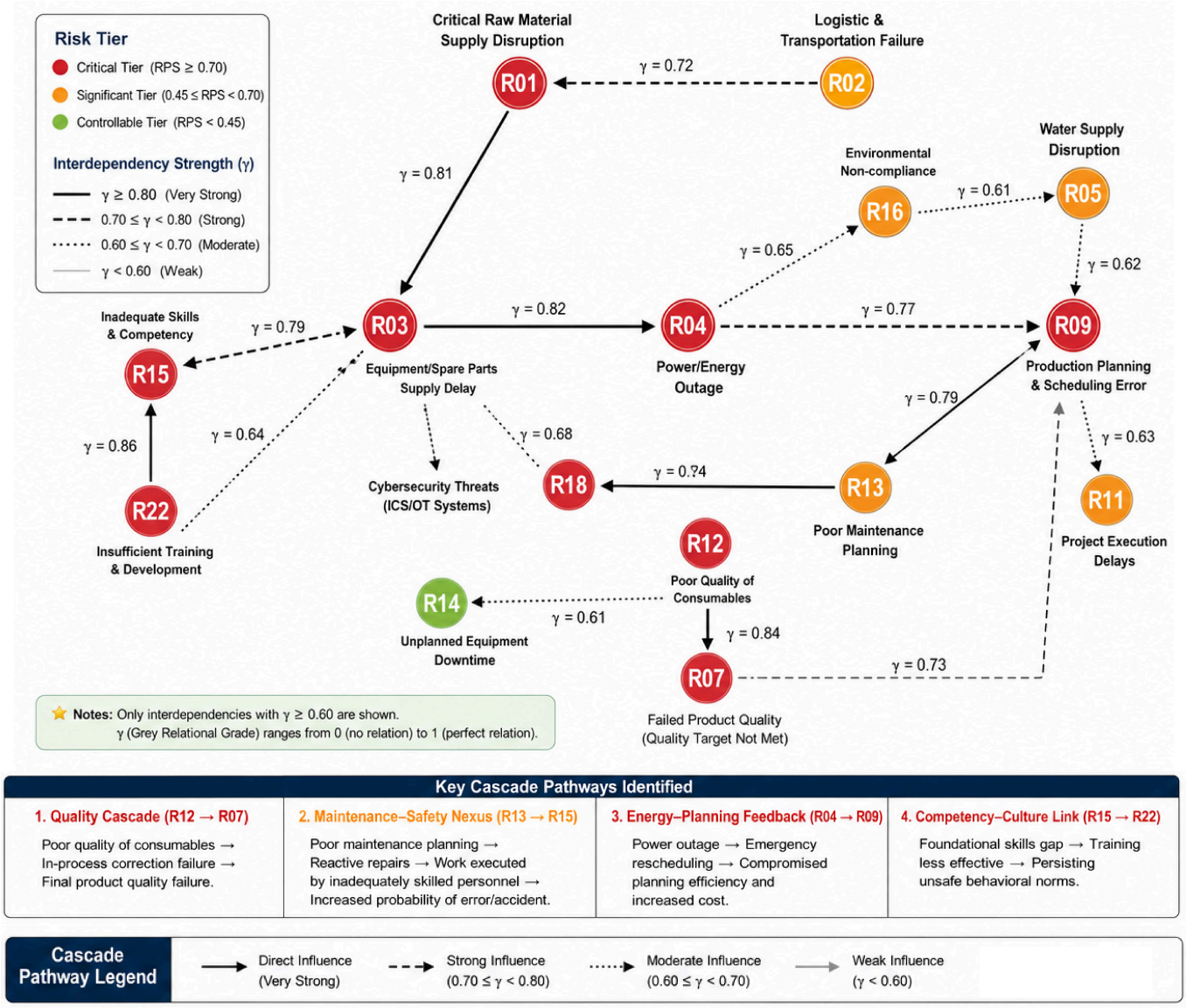


Figure 4. Critical risk interdependencies and cascade pathways (GRA).

Table 8. Critical risk interdependencies and implied cascade paths.

Risk Cluster	Central Risk	Correlated Risk (γ > 0.75)	Relational Grade (γ)	Implied Cascade Pathway
Quality Cascade	R12 (Poor consumables)	R07 (Failed quality target)	0.84	Input quality failure → In-process correction failure → Final product rejection.
Maintenance-Safety Nexus	R13 (Poor maintenance planning) *	R15 (Inadequate skills)	0.79	Reactive, unplanned maintenance → Assignment to undertrained personnel → Increased probability of procedural error or accident.
Energy-Planning Feedback	R04 (Power outage)	R09 (Production planning error)	0.77	Unplanned disruption → Emergency rescheduling → Compromised planning efficiency and increased cost.
Competency-Culture Link	R15 (Inadequate skills)	R22 (Insufficient training)	0.86	Foundational skill gap → Rendered safety training less effective → Persistent unsafe behavioural norms.

* R13 is a Significant-tier risk with a critical link to a Critical-tier risk.

Table 9. Sensitivity and comparative analysis summary.

Validation Test	Methodology	Key Result	Interpretation
Weight Sensitivity	Monte Carlo Simulation (n = 1000)	Mean ρ = 0.91; Critical tier stable in 94% of runs.	Model outputs are robust to reasonable uncertainties in expert-derived criterion weights.
Comparative Analysis	Benchmarking vs. Fuzzy AHP-TOPSIS	Kendall's W = 0.85 ($p < 0.001$). Identical Critical tier identification.	High convergent validity. GST advantage lies in more natural handling of interval uncertainty without mandatory defuzzification.
Grey Threshold Analysis	Derivation of practical Risk Tolerance Threshold	Threshold: RPS = 0.45. Risks below this (12 risks) account for >80% of potential impact.	Provides a clear, data-driven cut-off for focusing strategic management resources.

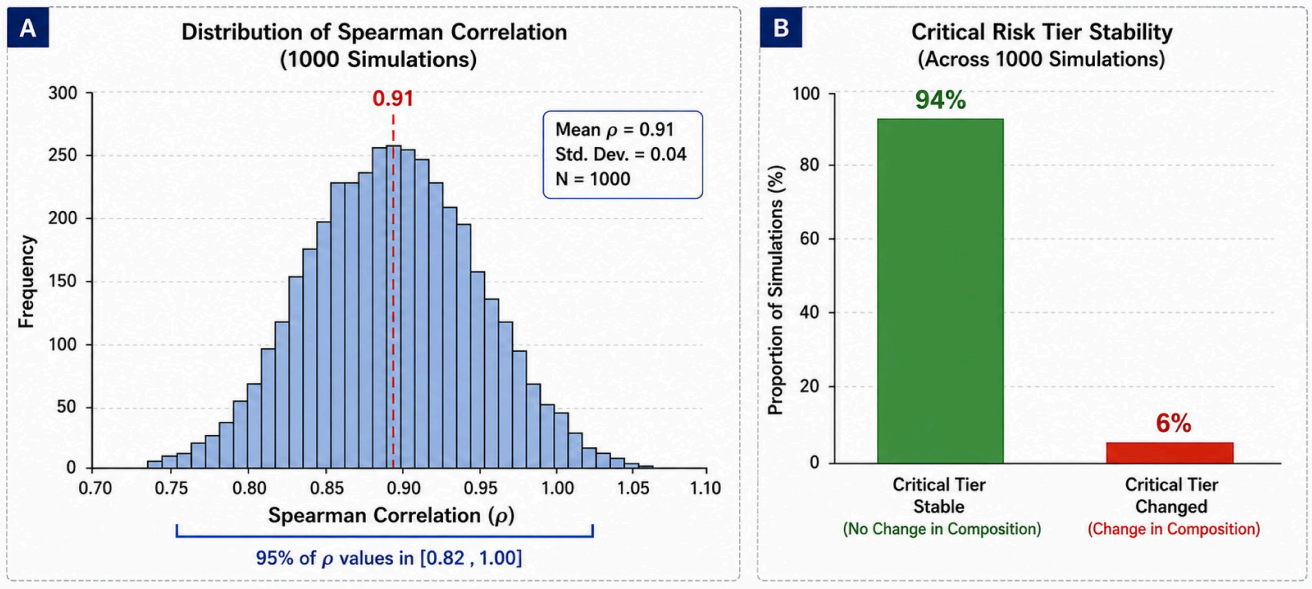


Figure 5. Monte Carlo sensitivity analysis demonstrating the robustness of the GST-MCDM framework under uncertainty perturbations: (**A**) Distribution of Spearman rank correlation between original and simulated rankings, and (**B**) Stability of the critical risk tier across 1000 simulations.

5.5. Synthesis, Managerial Implications, and Future Research

This study demonstrates that an integrated Grey System approach provides an integrated lens for operational risk assessment. It moves from mere identification to delivering: (1) a stratified priority list, (2) a decomposition of impact across key objectives, (3) a quantification of the total risk burden per objective, and (4) a map of critical interdependencies. The results paint a picture of a system where external supply-chain and energy vulnerabilities (R01, R04, R03) interact dangerously with internal human-factor and planning weaknesses (R15, R22, R09, R13), all under the emerging threat of digital disruption (R18). The integration of Grey Entropy weighting, Grey MCDM, Grey Relational Analysis, and Cumulative Impact Score within a unified framework provides richer decision-support outputs than standalone techniques, enabling managers to understand not only risk priorities but also systemic interactions and cumulative operational vulnerabilities.

From managerial perspective, the following implications may be suggested to provide a robust decision-making strategy:

- Adopt a Tiered Response Strategy: Implement distinct governance mechanisms for Critical, Significant, and Controllable risks. Critical risks require board-level visibility, dedicated mitigation budgets, and defined KRIs.
- Manage Risk Clusters, Not Isolated Risks: Formulate mitigation strategies for interdependent clusters (e.g., the "Quality Cascade" or "Maintenance-Safety Nexus"). This requires cross-functional teams and integrated action plans.
- Reconceptualize Safety and Training as Core Risk Mitigation: The high CIS for Safety indicates that investments in competency (R15) and culture (R22) are among the most effective ways to reduce the plant's overall risk load. This should inform capital and operational budgeting.
- Elevate Cyber-Physical Security: The criticality of R18 demands the formal integration of Operational Technology (OT) cybersecurity into the plant's core engineering safety and risk management protocols, necessitating collaboration between IT and operational departments.

From an industrial perspective, the proposed framework provides decision-makers with a practical tool for systematically identifying and prioritizing operational risks in mineral processing plants. The resulting prioritization can support maintenance planning, resource allocation, operational reliability improvement, and proactive risk mitigation, thereby contributing to safer and more efficient plant operation under uncertain conditions. The study's limitations include its static, snapshot nature and reliance on expert judgement. Furthermore, model validation was conducted using a single industrial case study and benchmark comparison with an established Fuzzy AHP—TOPSIS approach. Validation against historical operational records or independent industrial datasets was not feasible within the scope of this study. Although these validation procedures demonstrated high consistency and robustness, broader validation across multiple mineral processing plants and comparison with long-term operational performance records would further strengthen the generalizability of the proposed framework. Consequently, the current findings should be interpreted as strong evidence of methodological applicability rather than universal industrial generalizability. Future research should focus on:

- Dynamic Grey Models: Integrating real-time sensor data, market feeds, and maintenance logs to create a live, forecast-enabled risk dashboard.
- Resilience-Enhanced Criteria: Incorporating explicit metrics for "adaptive capacity," "recovery time," and "robustness" into the MCDM framework to assess not just risk, but resilience.
- Cross-Industry Validation: Applying this integrated GST-GRA-CIS framework to other continuous-process industries (e.g., chemicals, power generation) to test its generalizability and refine risk archetypes and clusters.

From a practical perspective, the proposed framework provides plant managers with a structured decision-support tool for prioritizing mitigation strategies under uncertain operational conditions. The resulting risk rankings may assist decision-makers in allocating maintenance resources, scheduling preventive actions, and improving operational reliability while supporting more effective long-term risk management planning.

6. Conclusions

This study developed and applied an integrated Grey System Theory (GST) framework to assess operational risks in a complex mineral processing plant. By fusing Grey Multi-Criteria Decision-Making (GST-MCDM) with Grey Relational Analysis (GRA), the research moves beyond simple risk listing to provide a systemic analysis that prioritizes risks, maps their interdependencies, and quantifies their cumulative burden across key performance objectives. Overall, the following concluding remarks can be merged from this study:

- The risk landscape is dominated by external vulnerabilities (energy and supply-chain disruptions) critically intertwined with internal weaknesses (human factors, planning deficits).
- Safety carries the highest cumulative risk burden (32%), driven largely by human competency gaps and insufficient training, reframing safety investment as a primary risk-mitigation strategy.
- Cyber-risk to industrial control systems emerged as a critical safety threat, highlighting the new paradigm of cyber-physical security in modern industry.
- Analysis of interdependencies revealed high-probability cascade paths, such as poor input quality leading directly to final product failure, necessitating cluster-based rather than siloed risk management.
- The integrated framework provides a unified analytical architecture that preserves uncertainty while delivering risk prioritization, interdependency mapping, cumulative impact evaluation, and cluster-based managerial recommendations.

The framework provides managers with an actionable, data-driven blueprint for strategic resource allocation and systemic risk control. Future studies should focus on: (1) dynamic grey models using real-time data for predictive analytics; (2) integrating resilience metrics like recovery time into the criteria; and (3) validating the framework in other continuous-process industries (e.g., chemicals, power) to generalize findings. This research establishes a replicable, replicable approach for navigating uncertainty and building operational resilience in capital-intensive sectors.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/min16080781/s1, Materials S1: Computational Workflow; Materials S2: Expert Evaluation Procedure and Grey Decision Matrix; Materials S3: Grey Entropy Weighting Procedure; Materials S4: Reproducibility and Data Availability.

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Abbreviations

The following abbreviations are used in this manuscript:

MCDM	Multi Criteria Decision Making
GST	Grey System Theory

GRA	Grey Relational Analysis
FMEA	Failure Mode and Effects Analysis
HAZOP	Hazard and Operability Study
FTA	Fault Tree Analysis
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	Vise Kriterijumska Optimizacija i Kompromisno Resenje (in Serbian)
DEMATEL	Decision Making Trial and Evaluation Laboratory
CIS	Cumulative Impact Score
GPIS	Grey Positive Ideal Solution
GPD	Grey Possibility Degree
IQR	Interquartile Range
KRI	Key Risk Indicator
RPS	Risk Priority Score

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