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A Theoretical and Practical Project-Based Questionnaire for the Mining Industry Risks

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Abstract

As mining industry is one of the deadliest industries in the world there are many risks in different types (categories), which they are involved in it. Here we have dedicated all efforts in order to develop a questionnaire in a way that: 1) it encompasses all the risks in order (phase by phase), and 2) the risks are addressed according to Project Management Body of Knowledge (PMBOK) approach. Ultimately the risks are prioritized using a novel fuzzy score-based theoretical method and addressed to minimize the casualties. As proof of concept, a case study was conducted in the mining industry upon the questionnaire.

Keywords: Mining industry risks, Questionnaire mining risks, Questionnaire risks, Risk management, Project risks.

1 | Introduction

The mining industry is a cornerstone of the global economy, generating substantial revenue and attracting significant Foreign Direct Investment (FDI). Its economic importance is especially pronounced in low-income countries, where Artisanal and Small-scale Mining (ASM) frequently provides essential livelihoods for rural populations and contributes materially to national Gross Domestic Product (GDP) [1]. Even in advanced economies, targeted mining investment can produce large regional spillovers; for example, initiatives such as Canada's Plan Nord in Quebec illustrate how mining-led investment stimulates infrastructure, housing, and allied industries [2]. Estimates also highlight the sector's multiplier effect: Every dollar invested in mining is associated with multiple dollars of broader economic activity [3].

This economic promise, however, exists alongside severe human, environmental, and financial costs. Mining remains one of the world's most hazardous industries, exposed to immediate catastrophic events (collapses, explosions) and long-term health risks (respirable dust and chronic lung disease), which contribute to large numbers of premature deaths and disease burden [4]. The financial toll is similarly large: unsafe working

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conditions impose substantial macroeconomic costs (ILO estimates running into the trillions annually), and individual fatality costs in developed settings are also high [5], [6].

Industrial actors have adopted a range of risk responses – from structured safety programs and insurance to risk transfer mechanisms – and empirical studies suggest such measures can reduce organizational costs substantially by 15-25% [7], [8]. The continued prevalence of tragedies and liabilities – from persistent high fatality rates and chronic health burdens to enduring environmental damage and severe financial losses – points to a deep-seated systemic flaw rather than isolated incidents [9]. Current approaches are demonstrably insufficient, often being dangerously fragmented and fundamentally reactive. This fragmentation is not merely organizational but intellectual, where risk is compartmentalized into neat boxes like "operational hazards" or "financial safeguards", ignoring the dynamic interplay between them. Existing risk management models are ill-equipped for the realities of modern mining because they are built on a flawed premise of predictable, linear causality. They fail to account for the interconnected, multi-dimensional nature of risk where social, environmental, technical, and financial threats are deeply intertwined. This critical deficiency is magnified by a top-down approach that undervalues the crucial, ground-level intelligence of the broader workforce. Without a comprehensive risk framework that actively empowers and incorporates the situational awareness of every staff member, organizations are effectively operating blind to the emergent, cascading failures that threaten their very existence [10].This fragmentation points to a clear research gap: lack of a robust, integrative framework that simultaneously captures operational, health, environmental, and financial risks and the causal linkages among them. Addressing this gap is particularly urgent in many Asian contexts, where regulatory heterogeneity, diverse ownership structures (formal and informal), and high ASM prevalence create complex risk interdependencies that differ from Western settings.

Accordingly, this study develops a holistic risk management framework tailored to the mining sector. The central research question is: How can a holistic risk management framework be structured to effectively identify, assess, and respond the interconnected operational, health, environmental, and financial risks in the mining industry?

As the result in this paper we are going to address following questions:

I. How to map the different types/categories of interdependent risks in an integrated, systematic, and comprehensive risk management framework?

II. How to achieve authentic information about the risks in an efficient and effective way?

III. How to prioritize the most critical risks in order. Which for, we introduce a novel fuzzy score-based analysis theory.

2 | Literature: Theoretical Lesnses

2.1 | General System Theory

General System Theory was introduced for the first time by von Bertalanffy [11]. It emphasizes the importance of subsystems'/processes' interactions with each other, also their dynamic influence on each other over a period of time, which ultimately leads to better recognition of a greater and a more complex system. In fact, it states that a complete risk picture requires assembling fragmented insights from all organizational levels. Research highlights a "hierarchical blindness," where management's perception of risk differs from the reality experienced by frontline workers [12]. Integrating these crucial worker perspectives requires a culture of psychological safety and combining qualitative insights with quantitative data [13]. The Business Triage Theory dictates the next step.

2.2 | Business Triage Theory

At first place it was stemmed from the "medical triage theory" which was originated by Barron Domonique Jean Larry, in the Napoleonic battlefield for treating the wounded soldiers. In the 1990s business practitioners took advantage of it as a decision-making framework in which the critical risks are coloured as red, then the important and ordinary ones in order of yellow and green are coloured. Business Triage Theory dictates the strategic allocation of finite resources to the most critical threats. Effective prioritization is essential. Research utilizes models like fuzzy logic and the Analytic Hierarchy Process (AHP) to rank hazards and guide targeted resource allocation [14], [15]. This triage is vital for both immediate safety and achieving long-term strategic goals [16].

2.3 | Mosaic Theory

Finally, the Mosaic Theory frames risk management as a continuous, iterative lifecycle, with variety of categories of risks. This requires dynamic adaptation, such as embedding Human Factors (HF) throughout a project's entire lifecycle [17]. Frameworks like the Hazard Identification-Assessment-Check-Action (HACA) model which ensures different types of risks are identified and perpetually monitored [18], and necessary approaches for navigating evolving threats like climate change are taken into account [19].

Together, these three theories shape the comprehensive roadmap to address the questions of the paper, by:

Module 1 (Questionnaire design). Designing a standard questionnaire, which encompasses all types of risks within the organization/project.

Module 2 (Novel fuzzy theory proof). A novel fuzzy theory is proved for effective risk prioritization.

Module 3 (Result analysis). A case study is conducted which, prioritizes and analyses the mining risks.

3 | Module 1 (Questionnaire Design)

The questionnaire is based on the risk management lifecycle detailed in the Project Management Body of Knowledge (PMBOK) Guide, Sixth Edition [20] and The Standard for Risk Management [21]. It encompasses the complete risk management process: planning, identification, analysis, response planning, implementation, and monitoring.

To capture the entire lifecycle of a risk, from its conception to its resolution, the questionnaire is structured with the following columns:

- *Risk ID*
- *Risk name*
- *Risk phase*
- *Cause of risk*
- *Risk consequence*
- *Risk severity*
- *Risk occurrence (likelihood)*
- *Risk detectability*
- *Risk Priority Number (RPN) (novel fuzzy grey)*
- *Risk response strategy*
- *Risk control method*

3.1 | Risk Phase

Experts will assign each risk to one of the four distinct phases of the mining lifecycle: 1) exploration, the initial search for and evaluation of viable ore deposits, 2) development (construction), which involves the feasibility studies, financing, and construction of the mine and its infrastructure, 3) operation (extraction), the active mining and processing of ore, which constitutes the longest phase, and 4) closure (reclamation), the final phase involving the safe decommissioning and environmental rehabilitation of the site [22].

3.2 | Cause of Risk

The potential causes of risks are grouped into four main categories to identify root issues. These include human (organizational) causes, such as lack of competence, human error, or non-compliance with protocols [23]; technical issues, which are deficiencies or failures related to hardware, control systems, or monitoring equipment [24]; systemic flaws that are inherent hazards stemming from poor design of equipment or processes [25]; and external factors, which are uncontrollable events like inherent geological hazards, extreme weather, or socio-political disruptions [15], [19].

3.3 | Risk Consequence

The potential consequences of an identified risk are classified into four distinct types based on their primary effect. These are life casualty, where the primary impact is a fatality or life-altering injury; time waste and financial waste, a major disruption where operational delays and financial losses are of equal importance; more time waste, less financial waste, which describes situations where the primary consequence is a schedule delay with a relatively low immediate financial cost; and more financial waste, less time waste, which covers events causing a significant and immediate financial loss without a major operational stoppage.

3.4 | Risk Response Strategy

Focusing on threats (negative risks), the response strategies are aligned with the PMBOK Guide [26]:

I. Avoid: Acting to eliminate the threat entirely.

II. Transfer: Shifting ownership and impact of the threat to a third party (e.g., through insurance).

III. Mitigate: Taking action to reduce the likelihood or impact of the threat.

IV. Accept: Acknowledging the risk and not taking proactive action, which can be passive or active (e.g., creating a contingency plan).

3.5 | Risk Control Measures

The most effective controls are Avoidance/Redesign, which involves canceling a project or designing out the hazard from the start [27]. This is followed by engineering controls, which physically separate people from hazards through automation, monitoring, or physical barriers. The other reliable one is administrative controls, which depend on human behavior and include methods like training and Standard Operating Procedures (SOPs) [28]. Finally, consequences can be managed through risk transfer and financing, which involves using financial instruments like warranties and contingency budgets.

3.6 | Risk Severity, Occurrence, and Detection Rating

The theoretical foundation for the Novel Fuzzy Grey Score is the RPN method, which calculates a risk score by multiplying ratings for Severity (S), Occurrence (O), and Detection (D), each on a 1-to-10 scale [29]. However, the traditional RPN method contains two fundamental obstacles:

I. Time and position constraint: In other words, the process is too time-consuming, asking experts to assign precise scores for S, O, and D using detailed tables, on top of completing other qualitative columns of the questionnaire, creates an excessive workload, which highly likely leads to decline of the quality and accuracy of responses.

II. The RPN formula ($S \times O \times D$) has a critical flaw, it gives equal weight to Severity, Occurrence, and Detection. This is unsuitable for the mining industry, where Severity is significantly more important than the other two factors. For example, a risk with high Severity ($S=8$, $O=4$, $D=4$) gets the same RPN score of 128 as a less severe but more frequent risk ($S=4$, $O=8$, $D=4$). The standard RPN method cannot differentiate between these two scenarios, failing to prioritize the potentially catastrophic event (like a mine collapse) over a more common but less impactful one.

In order to tackle the first obstacle, we are using 5-level fuzzy linguistic.

And in order to tackle the second obstacle, we give different weights to the criteria (S, O, D) based on the fuzzy pair-wise comparison.

4 | Module 2 (Novel Fuzzy Theory Proof)

This theory – Fuzzy Grey Weighted Analysis Method – introduces a novel risk analysis framework that integrates three distinct methodologies. The approach is characterized by the full compatibility and high accordance of its components, which work in cohesively as:

I. Grey Relational Analysis (GRA) forms the foundational method for comparing and ranking risks based on their similarity to an ideal reference [30].

II. Fuzzy Theory is exploited to transition the classic GRA into a fuzzy context, effectively handling the imprecision and subjectivity inherent in risk data [31].

III. Chang's Fuzzy Extent Analysis Method is applied to assign differential, appropriate weights to each of the three risk factors: Severity, occurrence, and detection [32].

4.1 | Grey Relational Analysis

Ri: m Risks, denoted as $R_1, R_2, \ldots, R_m$,

Criterion: n Criteria, indexed by $k = 1, 2, \ldots, n$,

Where in decision-making matrix as shown in *Table 1*; x_i (k) is the value of factor i under criterion k.

Table 1. Decision-making matrix.

$x_1(1)$	$x_1(2)$	…	$x_1(n)$
$x_2(1)$	$x_2(2)$	…	$x_2(n)$
⋮	⋮	⋱	⋮
$x_m(1)$	$x_m(2)$	…	$x_m(n)$

Normalization (if the criteria intervals not the same):

$$x^*_i(k) = \begin{cases} x_i^*(k) = \frac{\max t\, x_t(k) - x_i(k)}{\max t\, x_t(k) - \min t\, x_t(k)}, (\text{cost} - \text{type}), \\ x_i^*(k) = \frac{x_i(k) - \min t\, x_t(k)}{\max t\, x_t(k) - \min t\, x_t(k)}, (\text{benefit} - \text{type}). \end{cases}$$

$x^*_0 = [1, 1, \ldots, 1]$ (Ideal) => $x^*_0(k) = 1$ ($\forall k$), Which:

Higher Grey Relational Grade (Γ_i) => Less Cost

Higher Grey Relational Grade (Γ_i) => More Benefit

Absolute deviation matrix:

$$\Delta_i(k) = \text{abs. value}(x^*_0(k) - x_i^*(k)) = |x^*_0(k) - x^*_i(k)| = 1 - x^*_i(k). \quad (1)$$

Global extrema:

$$\Delta_{min} = \min_i \min_k \Delta_i(k) = 0.$$
$$\Delta_{max} = \max_i \max_k \Delta_i(k) = 1. \quad (2)$$

Grey relational grade:

$$\gamma_i (k) = \frac{\Delta \min + \zeta \Delta\max}{\Delta i(k) + \zeta \Delta\max},$$

$$\gamma_i (k) \in (0,1],$$

$$\gamma_i (k) = 1 \text{ if } \Delta_i (k) = \Delta\min = 0, \quad (3)$$

$$\Gamma_i = \frac{1}{N} \sum_{K=1}^{N} \gamma i(k).$$

4.2 | Fuzzy Theory: Required Fuzzy Theory for GRA Transition into Fuzzy Context

Once we have fuzzy triangular values as following:

TFN A = (a_1,a_2,a_3).

TFN B = (b_1,b_2,b_3).

Alpha-cut of A: $[a_1+\alpha(a_2-a_1), a_3-\alpha(a_3-a_2)]$.

Alpha-cut of B: $[b_1+\alpha(b_2-b_1), b_3-\alpha(b_3-b_2)]$.

Minimum Aα and Bα: $[\min (a_1+\alpha(a_2-a_1), b_1+\alpha(b_2-b_1)), \min (a_3-\alpha(a_3-a_2), b_3-\alpha(b_3-b_2))]$.

$$=> \begin{cases} \left(a_1 + \alpha(a_2 - a_1),\ b_1 + \alpha(b_2 - b_1)\right) = \min(a_1, b_1) + \alpha(\min(a_2, b_2) - \min(a_1, b_1)), \\ \text{and} \\ \left(a_3 - \alpha(a_3 - a_2),\ b_3 - \alpha(b_3 - b_2)\right) = \min(a_3, b_3) - \alpha(\min(a_3, b_3) - \min(a_2, b_2)). \end{cases}$$

For lower bound: α = 0

$$\alpha = 0 => \begin{cases} \min(a_1, b_1) + 0^*(\min(a_2, b_2) - \min(a_1, b_1)) = \min(a_1, b_1), \\ \text{and} \\ \min(a_3, b_3) - 0^*(\min(a_3, b_3) - \min(a_2, b_2)) = \min(a_3, b_3). \end{cases} => \min (a_1, b_1)$$

For modal: α = 1

$$\alpha = 1 => \begin{cases} \min(a_1, b_1) + 1^*(\min(a_2, b_2) - \min(a_1, b_1)) = \min(a_2, b_2), \\ \text{and} \\ \min(a_3, b_3) - 1^*(\min(a_3, b_3) - \min(a_2, b_2)) = \min(a_2, b_2). \end{cases} => \min (a_2, b_2)$$

For upper bound: α = 0

$$\alpha = 0 => \begin{cases} \min(a_1, b_1) + 0^*(\min(a_2, b_2) - \min(a_1, b_1)) = \min(a_2, b_2), \\ \text{and} \\ \min(a_3, b_3) - 0^*(\min(a_3, b_3) - \min(a_2, b_2)) = \min(a_2, b_2). \end{cases} => \min (a_3, b_3)$$

As the result, it was proven that for minimum of two triangular – TFN A, TFN B – we have:

TFN A = (a_1,a_2,a_3).

TFN B = (b_1,b_2,b_3).

Min (TFN A, TFN B) = $(\min (a_1, b_1), \min (a_2,b_2), \min (a_3,b_3))$. **(4)**

Similarly, for maximum we would have:

$$\text{Max (TFN A, TFN B)} = (\max(a_1, b_1), \max(a_2, b_2), \max(a_3, b_3)). \tag{5}$$

4.3 | Chang's Fuzzy Extent Analysis Method

We have m rows and n columns for a pairwise comparison matrix, which:

$m = n.$

$a'ij = (1,1,1), \quad \forall\, i = j.$

$a'ij = (aij^{(l)}, aij^{(m)}, aij^{(u)}), \qquad \forall\, i \neq j.$

$G'i = \sum_{j=1}^{n} a'ij = (\sum_j aij^{(l)}, \sum_j aij^{(m)}, \sum_j aij^{(u)}).$

$G'global = \sum_{i=1}^{n} G'i = \sum_i (G'i(l), G'i(m), G'i(u)).$

$G'global\text{-}1 = (\sum_{i=1}^{n} G'i)^{-1} = (\sum_i (G'_i{}^{(l)}, G'_i{}^{(m)}, G'_i{}^{(u)}))^{-1}.$

where: $(aij^{(l)}, aij^{(m)}, aij^{(u)})\text{-}1 = (\frac{1}{aij^{(u)}}, \frac{1}{aij^{(m)}}, \frac{1}{aij^{(l)}}).$

$Si = \sum_{j=1}^{n} G'i \otimes G'global\text{-}1,$

where: $(a,b,c) \otimes (d,e,f) = (ad, be, cf)$ and $m = n$.

Degree of possibility of $M_2 \geq M_1$ as it is indicated in *Fig. 1*:

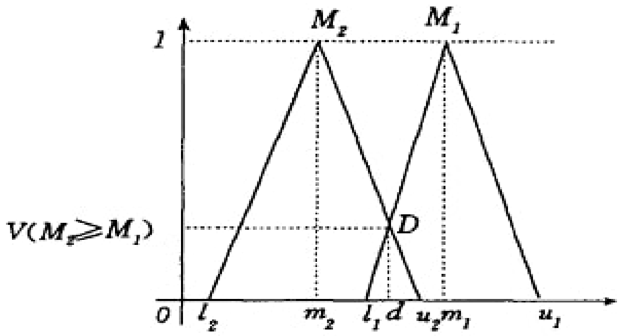

Fig. 1. Degree of possibility.

$$V(M_2 \geq M_1) = \sup(\min(\mu M_1(x), \mu M_2(y))). \tag{6}$$

$$\Rightarrow \begin{cases} V(M_2 \geq M_1) = 1 \text{ if and only if } m_2 \geq m_1, \\ \text{otherwise} \\ V(M_2 \geq M_1) = \text{hgt}\,(M_1 \cap M_2) = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}. \end{cases} \tag{7}$$

$V(M \geq M_1, M_2, \ldots, M_k) = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and } \ldots \text{ and } (M \geq M_k)] \Rightarrow$

$V(M \geq M_1, M_2, \ldots, M_k) = V(M \geq M_i), \qquad i = 1, 2, \ldots, k.$

$d'(Ai) = \min\{V(M_i >= M_k)\}, \quad k = 1,2, \ldots,n, \quad k \neq i$

$W' = (d'(A1), d'(A2), \ldots, d'(An))^T$

With W' normalization we have: $W = \{w_1, w_2, \ldots, w_n\}$.

Thus, w_1, w_2, and w_3 represent the weights of risk severity, risk occurrence, and risk detection, in order.

4.4 | Fuzzy Grey Weighted Risk Priority Analysis Method

Suppose that x'i (k), is a fuzzy triangular value = $(a_{ij}^{(l)}, a_{ij}^{(m)}, a_{ij}^{(u)})$ as indicated in *Table 2*:

Table 2. Fuzzy decision-making matrix.

$x'_1(1)$	$x'_1(2)$	$\cdots$	$x'_1(n)$
$x'_2(1)$	$x'_2(2)$	$\cdots$	$x'_2(n)$
$\vdots$	$\vdots$	$\ddots$	$\vdots$
$x'_m(1)$	$x'_m(2)$	$\cdots$	$x'_m(n)$

We proved that for the minimum (maximum) values of Triangular Fuzzy Numbers (TFN) (4) , (5):

I. For the lower bound, the smallest (greatest) lower bound among all fuzzy values is selected.

II. For the modal value (middle), the smallest (greatest) modal value among all fuzzy values is selected.

III. For the upper bound, the smallest (greatest) upper bound among all fuzzy values is selected.

$$\text{Min}\ (x'_1(1), x'_1(2), \ldots, x'_m(n)) = \min\ (a_{11}^{(l)}, a_{12}^{(l)}, \ldots, a_{mn}^{(l)})\ ,\ \min\ (a_{11}^{(m)}, a_{12}^{(m)}, \ldots, a_{mn}^{(m)})\ ,\ \min\ (a_{11}^{(u)}, a_{12}^{(u)}, \ldots, a_{mn}^{(u)})$$

$$\text{Max}\ (x'_1(1), x'_1(2), \ldots, x'_m(n)) = \max\ (a_{11}^{(l)}, a_{12}^{(l)}, \ldots, a_{mn}^{(l)})\ ,\ \max\ (a_{11}^{(m)}, a_{12}^{(m)}, \ldots, a_{mn}^{(m)})\ ,\ \max\ (a_{11}^{(u)}, a_{12}^{(u)}, \ldots, a_{mn}^{(u)}).$$

Therefore, among hundreds of risks, the fuzzy minimum will be $(a^{*(l)},a^{*(m)},a^{*(u)})$.

Ideal reference sequence (as it is cost-type):

$$x'_0(k) = \min x'i(k) = (a^{*(l)},a^{*(m)},a^{*(u)}).$$

Absolute deviation matrix:

$$\Delta'_i\ (k) = \text{abs. value}\ (x'_i(k) - x'_0(k)) = |x'_i(k) - x'_0(k)| =$$

$$|((a_{ij}^{(l)} - a^{*(u)}), (a_{ij}^{(m)} - a^{*(m)}), (a_{ij}^{(u)} - a^{*(l)}))| =$$

$$[(a_{ij}^{(l)} - a^{*(u)}) + (a_{ij}^{(m)} - a^{*(m)}) + (a_{ij}^{(u)} - a^{*(l)})] \div 3 = \tag{9}$$

$$[(a_{ij}^{(l)} - a^{*(l)}) + (a_{ij}^{(m)} - a^{*(m)}) + (a_{ij}^{(u)} - a^{*(u)})] \div 3 =$$

$$|((aij^{(l)} - a^{*(l)}), (a_{ij}^{(m)} - a^{*(m)}), (a_{ij}^{(u)} - a^{*(u)}))|.$$

Global extrema:

$$\Delta'_{min} = \min_i \min_k \Delta'_i\ (k).$$
$$\Delta'_{max} = \max_i \max_k \Delta'_i\ (k).$$

Grey relational grade:

$$\gamma'_i(k) = \frac{\Delta' \min + \zeta\ \Delta' \max}{\Delta' i(k) + \zeta\ \Delta' \max}.$$

As the result for Fuzzy Grey Weighted RPN we have:

$$\Gamma' i = w_1 * \gamma'_i\ (k = 1) + w_2 * \gamma'_i\ (k = 2) + w_3 * \gamma'_i\ (k = 3)\ \ |\ \ i = 1, 2, \ldots, m. \tag{10}$$

Where k denotes the criteria = $\begin{cases} k = 1: \text{Risk severity}, \\ k = 2: \text{Risk occurrence}, \\ k = 3: \text{Detectability}. \end{cases}$

Defuzzification (crisp conversion): $\Gamma_i = \Gamma'_i \div 3.$ **(11)**

5 | Module 3 (Result Analysis)

We selected the headquarter of a multi-branch industrial-minerals (non-metallic) mining company in Tehran, Iran, as the site for questionnaire distribution pilot test. The headquarter consisted of 5 senior managers, 7 general managers and expert engineers, and 9 general staff. To ensure relevance and precision, to be more reliable, we first conducted semi-structured interviews, and then administered the questionnaire. 147 general risks were yielded; although specific risks could be taken into account, too, but in order to be effective, the management board requested that only general risks be retained for use in future company projects. Out of the 147 identified risks, 40 (≈27%) were assigned to the exploration phase, 37 (≈25%) to development/construction, 54 (≈37%) to operation/extraction, and 16 (≈11%) to closure/reclamation. Then for the questionnaire, risks were organized phase by phase, in Excel files in order to be more user-convenient.

Table 3. Risk score and ranking of phase.

Phase/Score	Fuzzy Score	Crisp Score	Rank
Exploration	(0.36,0.48,0.769)	0.536	2
Development	(0.36,0.48,0.772)	0.535	1
Operation	(0.37,0.49,0.79)	0.548	3
Closure	(0.43,0.57,0.98)	0.662	4

5.1 | Heatmap

In order to determine the strength of association among categorical variables we have illustrated the heatmap based on the Cramer's V statistical measure, *Fig. 2* shows it:

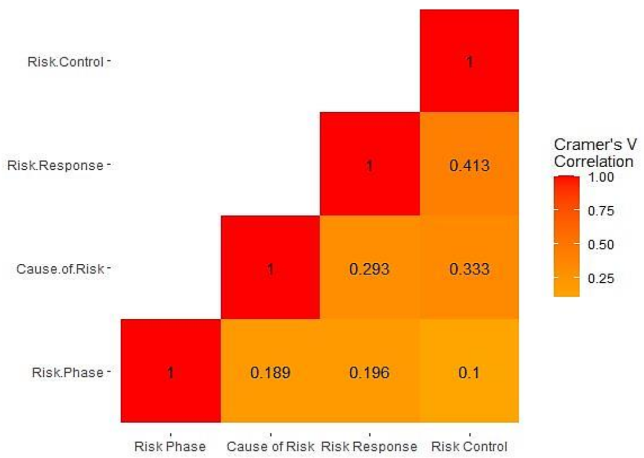

Fig. 2. Cramer's V Heatmap.

6 | Conclusion

The aim of this study was to establish a foundational methodology for systematic identification and management of the risks. To establish this foundation, we reviewed the relevant works of prominent researchers and pioneers in the field. Our goal was to find the common grounds in their work and to pinpoint gaps where improvements could be made. Ultimately resulted in an enhanced systematic questionnaire in a way that:

I. The questionnaire incorporates the standard PMBOK framework, covering the complete risk lifecycle from identification through assessment (qualitative first by fuzzy linguistic, then quantitative by novel fuzzy scoring), response, and control. In other words, essentially from inception to death/reduction in a structured way.

II. Using a multi-choice categorized design, so the questionnaire minimizes completion time for respondents/senior engineers.

III. Expert-determined response and control measures reduce critical outcome variables: budget overruns, schedule delays, and loss of life.

IV. Scoring risk with considering uncertainties and weighting in risk severity, occurrence, and detection with a novel Fuzzy Grey Weighted Analysis Method, effectively computes risk score.

As for future work, it is highly suggested to try to build a probabilistic model, which could predict the best response; that would act as an administrative advisor for the risk management decisions.

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