

Article

Developing an Alternate Mineral Transportation System by Evaluating Risk of Truck Accidents in the Mining Industry—A Critical Fuzzy DEMATEL Approach

Binay Prakash Pandey and Devi Prasad Mishra * Department of Mining Engineering, Indian Institute of Technology (Indian School of Mines),
Dhanbad 826 004, Jharkhand, India

* Correspondence: dpmishra@iitism.ac.in

Abstract: The innovative transportation system is a pertinent need for the mining industry. Truck haulage is currently the most common mode of mineral transportation between the excavation sites and end use plants. However, besides being resource-intensive and inefficient, this mode of transportation accounts for a high number of accidents and injuries. In order to reduce the occurrence of accidents, it is important to first understand the primary contributors to truck-related occupational risks and then develop strategies to eliminate such risks. The available literature predominantly advocates for the use of statistical or probabilistic methodologies that suffer from considerable limitations. This paper utilizes the Fuzzy DEMATEL (Fuzzy Decision-Making Trial Evaluation Laboratory) approach to conduct an in-depth assessment of the critical factors that result in mining accidents involving trucks and the relationships between these factors, presented using a cause-and-effect diagram. The study also includes a sensitivity analysis for validating the robustness of the fuzzy model. The results show that high speed and aggressive driving is the most important causal factor behind accidents. The negative impact on socio-economic conditions of local community members is also discussed. Among other preventive measures, the paper emphasizes the pipe conveyor system as an alternate and safer mineral transportation system.



Citation: Pandey, B.P.; Mishra, D.P. Developing an Alternate Mineral Transportation System by Evaluating Risk of Truck Accidents in the Mining Industry—A Critical Fuzzy DEMATEL Approach. *Sustainability* **2023**, *15*, 6409. <https://doi.org/10.3390/su15086409>

Academic Editors: Jurgita Antuchevičienė and Elżbieta Macioszek

Received: 8 March 2023
Revised: 6 April 2023
Accepted: 7 April 2023
Published: 9 April 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: mining truck accidents; risk evaluation; Fuzzy DEMATEL; mineral transportation planning; decision making; mine safety

1. Introduction

Safety remains a contentious issue in the mining industry. It is reported that the industry accounts for 8% of all workplace fatalities while employing just 1% of the global workforce [1]. In countries such as the United States (US), as per the most recent data available, the rate of fatal mining accidents is more than four times higher than the average for all industries [2]. The number of mining accidents is expected to be even higher in India when compared to the US [3,4]. Despite year-on-year improvements in safety performance, the incident frequency rates for fatal as well as serious accidents is concerning. As per data presented by the Minister of State for Labor and Employment in the Lok Sabha (the lower house of India's parliament), 268 mine workers lost their lives and 748 suffered serious injuries between 2016 to 2019, i.e., on average, one mine worker's life was lost every six days [5]. These numbers indicate that government regulations and managerial oversight have proven insufficient in reducing the exposure of workers to the inherent risks involved in mine-related activities. Restructuring some of the fundamental components of the industry, therefore, gains urgency.

It is in this context that innovating the mineral transportation system becomes a pertinent need. According to a report published by the International Council on Mining and Metals (ICMM), transportation-related accidents accounted for 24% of all fatal accidents in the mining industry between 2015 and 2019 [6]. In Indian mines, the Director General

of Mine Safety (DGMS) reported that 37.64% of all lethal accidents and 34.57% of all mortalities during the period from 2000 to 2013 were transportation-related [7]. In 2019, transportation-related accidents accounted for 62% of all accidents in Indian mines [8].

Among different modes of power-driven transportation, haul trucks are the most widely used mobile gear to move ore and waste from mines to manufacturing units and account for approximately 50% of all mining fatal accidents that occur every year globally [9,10]. In India, they are the third most common group of vehicles to be involved in all road accidents (12.3%) and road-accident fatalities (15.8%), with 10% of all victims being drivers or passengers in trucks [11]. Data on accidents involving mining trucks and/or dumpers in coal mines and non-coal mines over the years as reported by the Ministry of Labor and Employment, Government of India, are presented in Figure 1 [12]. In the Karnataka state, particularly in the Ballari district, a hotspot for mining activities in India, media outlets have reported that in the year 2021, of a total of 180 road fatalities occurred, 110 involved mining trucks. Those who lost their lives were either two-wheeler riders or pedestrians and the accidents resulted from reckless driving of mining trucks [13].

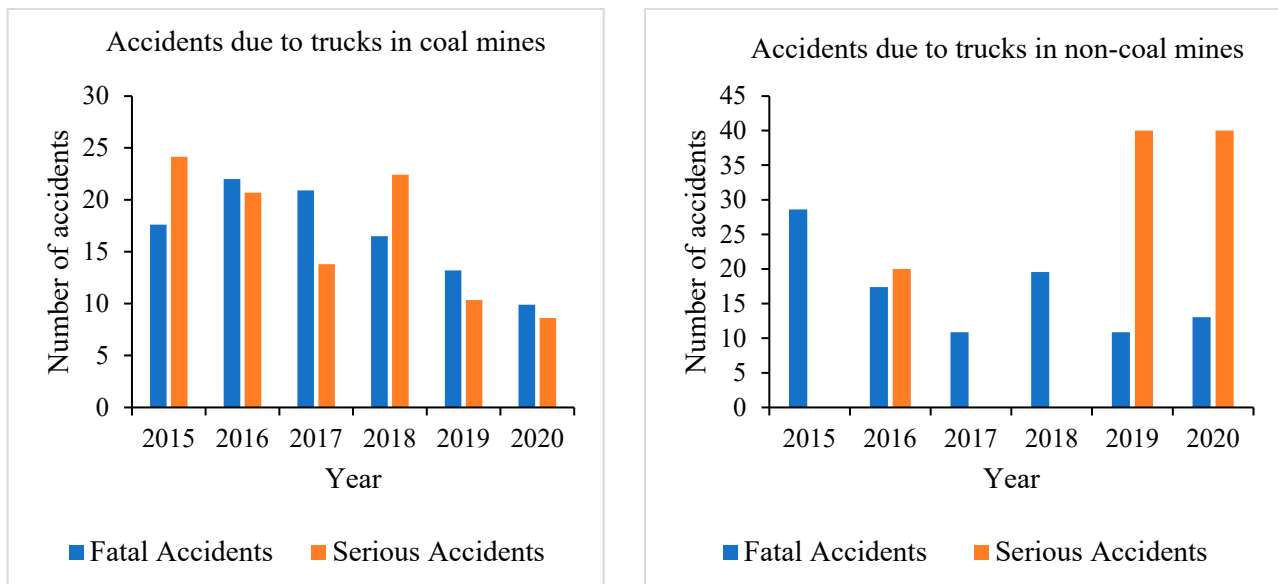


Figure 1. Fatal and serious accidents in mines involving trucks.

Various causal factors have been identified for transport accidents in the mining industry, ranging from failure in operating compliance, where the violated policies related to seat belts, pre-shift inspections, and traffic control, to site requirements failures, which refers to faulty roadway and equipment design and conditions, as well as human performance failures including driver fatigue and distraction from either long working hours or irregular sleep patterns [14–16]. A joint study in 2018 by the market research and consultancy firm Kantar IMRB and automotive lubricant maker Castrol India, which covered 1000 truckers, identified a range of self-reported causes behind truck accidents (Figure 2). While 53% of truck drivers reported psychological issues such as fatigue, obesity, backache, joint and neck pain, or breathlessness, 23% reported struggling with sleep deprivation [17].

However, despite the wide range of data on the matter, there is a scope to clear the ambiguity around the context within which transport-related mine accidents take place as well as to further explore the interrelationships between the critical causal factors. It is evident to the authors that identifying the risks that might result in mining truck accidents using a single technique proves insufficient, and an integrated approach is certainly required. The shortcomings of the conventional methods used in analyzing the cause–effect relationships underlying mineral transport accidents have been discussed in some detail in Section 2 of this paper.

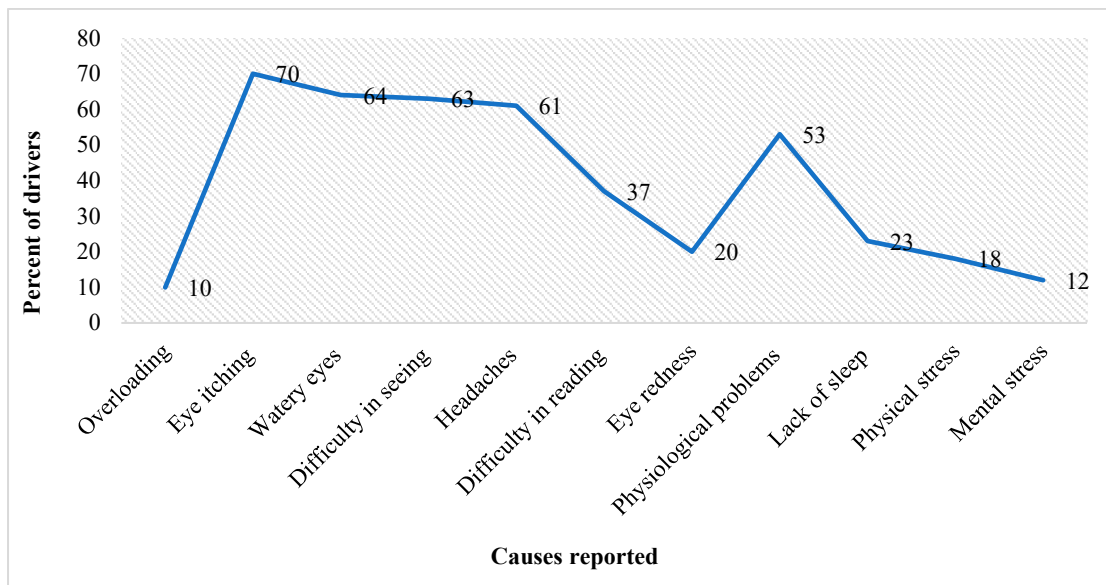


Figure 2. Causes of accidents as reported by truck drivers.

The remainder of this paper is structured as follows. In Section 3, we introduce our research methodology, which is an improved Fuzzy DEMATEL modeling approach, and illustrate our findings. Section 4 captures the results and its interpretation. Finally, Section 5 presents recommendations to promote transportation safety in the mining industry and Section 6 presents the conclusions drawn.

2. Review of Literature: Risk Analysis in the Mining Industry

Traditional methodologies commonly used to identify the risk factors in various industries include the Hazard and Operability Study (HAZOP) methodology, the Failure Mode and Effects Analysis (FMEA), the Job Hazard Analysis (JHA), the Bowtie Analysis, and the Structured What-if Technique (SWIFT), among others. The limitations and shortcomings of such risk assessment methodologies have been previously researched by numerous academics [18–21]. One such limitation is their reliance on quantitative data and statistical analysis to estimate the likelihood and consequences of different risks. However, in many cases, the available data may be incomplete or uncertain, which can lead to inaccurate risk assessments.

It is in this context that fuzzy concept-based risk assessment methods can prove to be better suited. They allow for a more flexible and nuanced approach to risk assessment by incorporating the concept of uncertainty and imprecision into the decision-making process, whilst guaranteeing accuracy and reliability of results. This is particularly useful in complex systems where there are many interacting factors that contribute to risk. More importantly, fuzzy concept-based risk assessment methods can help to identify the most critical risk factors and prioritize risk mitigation efforts accordingly.

Owing to such advantages, fuzzy methods have become common place in managing workplace safety and mitigating risks. For example, in the construction industry, there is literature on the use of the Fuzzy Analytic Hierarchy Process (AHP) to develop a Safety Management System (SMS) as well as on the application of the Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method for analyzing occupational risks using cause–effect diagrams as well as a sensitivity analysis in the construction industry [22,23]. Within the mining industry, the relationship between the specific context of various mining activities and human error rate has previously been modeled using a fuzzy mapping approach [24]. Risk-based maintenance systems have also been developed using fuzzy logic [25].

Upon noting some of the limitations of common fuzzy concept-based risk assessment methods (as captured in Table 1), the authors opted for the use of the Fuzzy DEMATEL methodology to assess the causal influences of haul truck accidents in Indian mines. The authors reviewed previous research that utilizes the Fuzzy DEMATEL approach to analyze variables for cause-and-effect relationships in the mining industry in India, Iran, China, and other geographies [26–29]. The gap in literature that utilizes this methodology to particularly assess the transportation-related risks in Indian mines inspired the present research.

Table 1. Different fuzzy models or risk assessments and their limitations.

S. No.	Different Models Used to Assess the Risk	Limitation
1	Failure Mode and Effects Analysis (FMEA)	Time consuming and tedious, with uncertainty and ambiguity.
2	Technique for order of preference by similarity to ideal solution with fuzzy information (TOPSIS-F)	Fails to give clear information in the real-world application. In this model, decision makers express their opinion in natural language as “Poor or Good”.
3	Fuzzy Analytic Network Process (FANP)	Uncertainty and ambiguity.
4	Fuzzy Analytic Hierarchy Process (AHP)	There is discrepancy in placing when comprising or removing options applied as a portion of the data set.

3. Methodology

This study utilizes the fuzzy DEMATEL described to assess potential risk factors in the mining transportation system. The research methodology detailed in the following sections is depicted systematically in the flow chart (Figure 3).

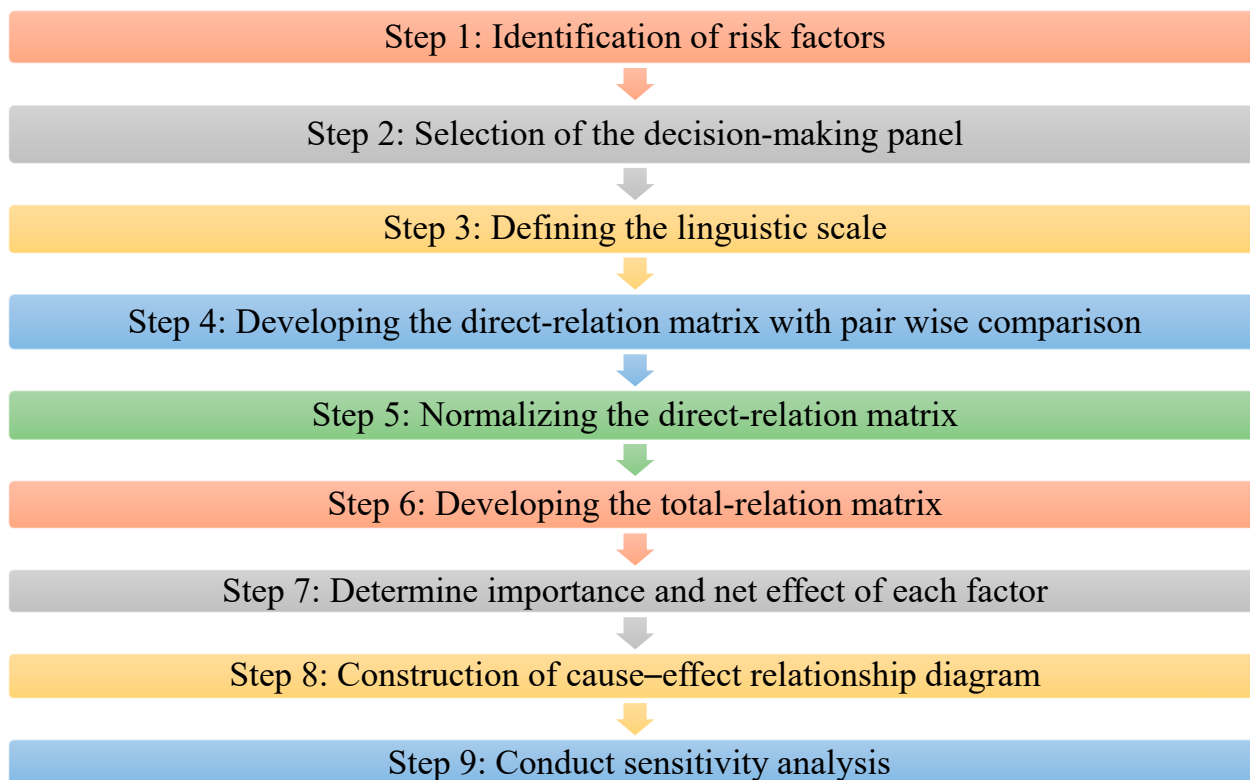


Figure 3. Schematic representation of steps involved in relating cause and effect through fuzzy reasoning.

3.1. Identification of Risk Factors

In a fuzzy DEMATEL model, the identification of the set of risk factors is the crucial first step. The risk factors represent the various aspects or dimensions of the problem under consideration, mining truck accidents, and their selection which should be based on their relevance, significance, and measurability.

For our model, the potential risk factors causing mining truck accidents were identified after conducting an in-depth review of relevant literature. Evidence was also collected by consulting with experts and witnesses in the field from the Ballari–Hospet–Sandur (BHS) region, where the 1st author's (BPP) work is based, who referred to specific accident incidents to identify the causal factors (Figures 4 and 5). The 20 selected risk factors are listed in Table 2.



Figure 4. A mining truck accident occurred in the BHS region due to hazardous weather conditions and speeding/aggressive driving.



Figure 5. A mining truck accident occurred in the BHS region due to drunken driving and improper vehicle maintenance.

Table 2. Causal risk factors linked to mining transport accidents.

S. No.	Code	Causal Factors	Description
1	E1	Inadequate supervision	Lack of maintaining a record of and/or validating drivers' licenses, scheduling regular health examinations, maintaining records on health status, past trainings or other qualifications of the drivers, and substance abuse records; lack of training or inadequate training provided to new drivers, lack of regular drug screening of drivers, employing drivers without background checks.
2	E2	Inadequate planning in operations	Lack of standardized guidelines or operating procedures include rapid response frameworks that can guide daily operations and aid with risk management.
3	E3	Failure to correct known problems	Lack of initiative to correct known mechanical problems in vehicles such as brake failure, steering failure, tire issues, transmission failure, issues with trailer coupling, or failure in addressing the issues reported by drivers such as unmanageable work schedules.
4	E4	Supervisory problems	Imposing unrealistic or tightly packed schedules and/or delivery timelines to meet client commitments, leading to many issues such as overloading, high stress, and driver fatigue.
5	E5	Overloading	Causing vehicle to over-weigh, disturbing the center of gravity and influencing physical condition/movement of trucks including bursting of the tire and loss of balance.
6	E6	Adverse physiological state of the driver	Caused by conditions such as obesity, poor vision, back, joint or neck pain, high levels of stress, lack of proper sleep.
7	E7	Physical health of the driver	Level of physical fitness impacted by lifestyle habits such as smoking, drinking alcohol, as well as disease and infections.
8	E8	Mental health of the driver	Impacted by depression, anxiety, loneliness, personality disorders, chronic sleep disturbance.
9	E9	Driver distraction	Caused by use of cell phones or other such actions that influence attentiveness.
10	E10	Working capabilities of the driver	Skill and driving experience, driving without improper training, or those uncertified or driving with fake licenses.
11	E11	Site condition	Road closures or construction zones without proper signs, sudden stops, dangerous curves or slopes, muddy roads, debris, equipment.
12	E12	Working schedule	Multiple shifts in a day, back-to-back shifts, long hours of driving without rest.
13	E13	Inadequate safety training	Lack of training and awareness on safety, protocols to manage risk, recommended precautions to be taken on duty.
14	E14	Lack of safety management	Lack of regular safety meetings, lack of safety training, no safety manuals distributed.
15	E15	Lack of safety awareness	Lack of awareness of job-related risks or site-specific safety regulations.
16	E16	Alcohol consumption	Driving under the influence.
17	E17	Unsafe climatic conditions	Trucks losing control and/or toppling during unfavorable environmental conditions such as strong winds, heavy rainfall, snow.
18	E18	Improper vehicle maintenance	Vehicle parts and systems not checked/upgraded when needed, causing issues to go unnoticed.
19	E19	Speeding or aggressive driving	Driving above speed limits, reckless driving, display of road rage.
20	E20	Poor lighting	Resulting in poor visibility particularly during night time.

3.2. Selection of the Decision-Making Panel

In a fuzzy DEMATEL model, the decision-making panel consists of a group of experts or stakeholders who provide their subjective judgments on the cause-and-effect relationships among the risk factors identified. The decision-making panel also plays a key role in interpreting the results of the fuzzy DEMATEL model and using them to support decision-making. It is, therefore, important to consult with specialists who were well-versed in the subject matter and had sufficient hands-on experience with producing logical evaluations.

Our panel of evaluators was selected based on their total, relevant work experience, age, and nature or duties performed within the mining sector. It was important to consult with specialists who were well-versed in the subject matter and had sufficient hands-on experience with producing logical evaluations. Ten external evaluators were selected from the age group 35–65 years with their total professional experience ranging from 15 to 30 years (Table 3). The chosen evaluators work at mining sites and have personally been tasked with the responsibility to evaluate the reasons for accidents at some point in their career. Therefore, despite the variation in level of expertise of panel experts, their understanding of the factors causing haul-truck accidents in the mining industry was satisfactory for the purposes of the present research.

Table 3. Characteristics of selected evaluators.

S. No.	Qualification	Designation	Experience (in Years)	Roles and Responsibilities
Evaluator 1	B. Tech Mining	Associate Vice-President, JSW, Bellary, Karnataka	30	Project management, business and financial advising, risk management, and cost reduction strategizing.
Evaluator 2	B.E. Mechanical	CEO, JSW, Bellary, Karnataka	30	Project management, business and financial advising, risk management, and cost reduction strategizing.
Evaluator 3	M. Tech Instrumentation	Director, Oracle, Bangalore, Karnataka	22	Project head with research experiences concerning safety issues of mining workers.
Evaluator 4	B. Tech Mining	Assistant Professor, IIT (ISM), Dhanbad, Jharkhand	25	Excellent subject-matter expertise and vast experience in field-based mining research.
Evaluator 5	B.E. Mechanical	National Accreditation Board for Education and Training (NABET), Visakhapatnam, Andhra Pradesh	25	Manage processes around resolution of disputes and complaints regarding accreditation and related matters.
Evaluator 6	B. Tech Mining	Associate Vice-President E2E Mining Services, Bangalore, Karnataka	15	Excellent subject-matter expertise and vast experience in field-based mining research.
Evaluator 7	B. Tech Mining	Director, Ecomen Laboratories Private Limited, Bangalore, Karnataka	21	Project management, business and financial advising, risk management, and cost reduction strategizing.
Evaluator 8	M. Tech Mining	MD, Ecomen Laboratories Private Limited, Lucknow, Uttar Pradesh	28	Environmental management, including water and energy resource management, city planning, and public education.

Table 3. Cont.

S. No.	Qualification	Designation	Experience (in Years)	Roles and Responsibilities
Evaluator 9	M. Tech	Director, Ecomen Laboratories Private Limited, Bangalore, Karnataka	30	Project management, assuring a safe operational atmosphere for workers, addressing risk factors, implementing safety standards, training workers and drivers on safety precautions.
Evaluator 10	B. Tech Mining	Director and Safety Expert, Ecomen Laboratories Private Limited, Bellary, Karnataka	28	Implementing safety standards, training workers and drivers on safety precautions.

3.3. Defining the Linguistic Scale

In the fuzzy DEMATEL model, a linguistic scale is a tool used to represent the degree of importance or influence of a risk factor being analyzed. This scale is used to capture the subjective judgments of experts in numerical terms that can be analyzed for effective decision making. The scale typically consists of a set of labels or terms that are used to describe the degree of importance or influence of a risk factor. Our panel experts described their judgement on the likelihood of each causal factor resulting in an accident using a five-point linguistic scale: no influence (NO), very low influence (VLI), low influence (LI), high influence (HI), and very high influence (VHI).

Next, triangular fuzzy numbers are assigned to each linguistic label. The triangular membership function is a commonly used mathematical function in fuzzy logic that assigns a degree of membership to a fuzzy set based on how close an input value is to a specific point or range of values. The function takes the form of a triangle, hence its name. The triangular fuzzy numbers are defined using three parameters: the minimum value, the most likely value, and the maximum value. These parameter values are obtained from the experts' knowledge [30]. The corresponding triangular fuzzy numbers used in our model are given in Table 4 [23]. Overall, this fuzzy linguistic scale is deemed appropriate in handling the full range of uncertainties and vagueness associated with subjective judgments.

Table 4. The fuzzy linguistic scale considered for the evaluation.

S. No.	Fuzzy Linguistic Terms Considered with Abbreviations	Corresponding Triangular Fuzzy Numbers (TFNs)
1	No influence (NO)	(0, 0, 0.25)
2	Very low influence (VLI)	(0, 0.25, 0.5)
3	Low influence (LI)	(0.25, 0.5, 0.75)
4	High influence (HI)	(0.5, 0.75, 1)
5	Very high influence (VHI)	(0.75, 1, 1)

3.4. Developing the Direct-Relation Matrix with Pair-Wise Comparison

The initial direct-relation matrix, represented by Z^k , where k is the number of evaluators, is a set obtained using the Fuzzy scale. It is developed to capture the judgement of panel experts on the relationship between any two risk factors, represented in an $n \times n$ matrix. Any given element in the matrix $[z_{ij}]$ represents the direct impact of factor i on j [23]. All diagonal elements are listed as NI since $i = j$. The pair-wise comparison matrix is constructed using the linguistic terms given by the evaluators. The pair-wise direct-relation matrix developed is provided in Table A1.

3.5. Normalizing the Direct-Relation Matrix

In this step, the direct relation matrix, Z^k , is scaled so that the sum of each row is equal to one, reflecting the fact that the relationships between the variables in the row are complete and consistent. Normalizing the direct-relation matrix involves dividing each element in a row by the sum of that row. The mathematical equation to obtain the normalized direct-relation matrix, denoted by N is as follows [23]:

$$N = \frac{Z^k}{\max_{1 \leq i \leq n} \sum_{j=1}^n Z_{ij}} \quad (1)$$

where $i, j = 1, 2, \dots, n$.

Normalization is done to ensure that the matrix accurately reflects the degree of relationship between the factors, without being skewed by variations in the scale used to describe the relationships between any two factors. The normalized direct relation matrix is given in Table A2.

3.6. Developing the Total-Relation Matrix

The total-relation matrix (T) is developed by multiplying the N by itself. This matrix squaring process captures the cumulative effect of all the intermediate factors on the relationship between each pair of factors, resulting in a matrix that reflects the total degree of relationship between all the factors in the risk assessment. The total-relation matrix T is obtained using the following equation [22]:

$$T = N(I - N)^{-1} \quad (2)$$

where $T = N + N^2 + \dots = \sum_{i=1}^{\infty} N^i$, $I = n \times n$ matrix, and $^{-1}$ denotes the matrix inverse operation. The diagonal elements represent the total relations of each factor with itself, which is always equal to 1. The obtained matrix is presented in Table A3.

3.6.1. Calculating Row and Column Sums from the Total-Relation Matrix

The row (r_i) and column (c_j) sums for each row i and column j in the total-relation matrix (T) are calculated to provide a measure of the overall degree of relationship between each risk factor and all the other factors in the risk assessment [23]. The row sum for each row i reflects the total degree of relationship between factor i and all the other factors in the assessment, while the column sum for each column j reflects the total degree of relationship between all the factors in the assessment and factor j . This is an important step in identifying the most important factors, as those with higher row and column sums will have a greater influence on the overall risk landscape. The following equations were used to calculate r_i and c_j , and the calculated (fuzzy) values are presented in Table A4. This information can be used to prioritize risk management efforts and allocate resources more effectively.

$$T = [t_{ij}]_{n \times n} \quad (3)$$

$$r_i = \sum_{j=1}^n t_{ij} \quad (4)$$

$$c_j = \sum_{i=1}^n t_{ij} \quad (5)$$

where $i, j = 1, 2, 3, \dots, n$.

3.7. Determining Importance and Net Effect of Each Factor

The $(r_i + c_j)$ and $(r_i - c_j)$ values based on results from Section 3.6.1 are calculated. If the $(r_i - c_j)$ value is positive, the factor is in the cause group, and if the $(r_i - c_j)$ value is negative, the factor is in the effect group. The $(r_i + c_j)$ value represents the degree of

importance of a factor and $(r_i - c_j)$ refers to the strength of influence. Using the Centre of Area (COA) defuzzification technique, $(r_i + c_j)$ and $(r_i - c_j)$ are defuzzified and Best Non-fuzzy Performance (BNP) or crisp values are obtained [23]. The COA is mathematically expressed as follows:

$$x \text{ centroid} = \frac{\sum_i \mu(x_i)x_i}{\sum_i \mu(x_i)} \quad (6)$$

where $\mu(x_i)$ is the membership value for the point and x_i is the universe of discourse. The values are presented in Tables A4 and A5.

3.8. Construction of Cause–Effect Relationship Diagram

The diagrammatic representation of the cause-and-effect relationship takes on the $(r_i + c_j)$ values on the horizontal axis, with the vertical axis taking on the $(r_i - c_j)$ values (Figure 6).

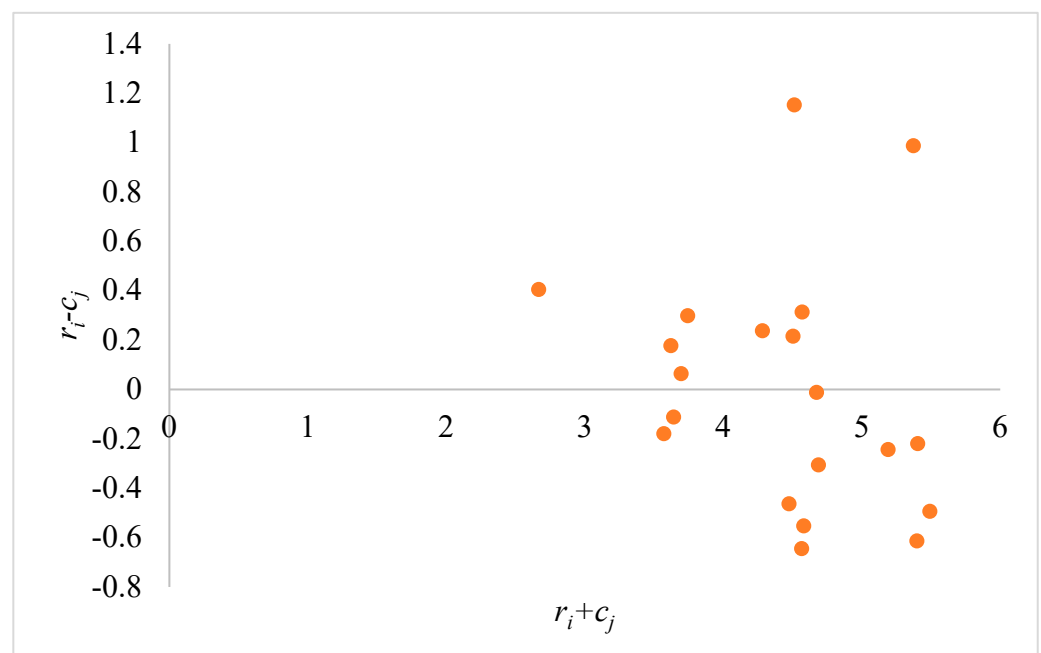


Figure 6. Cause-and-effect diagram.

3.9. Conduct Sensitivity Analysis

To test the reliability of the fuzzy logic model, we add and deduct a fixed percentage (10%) from each fuzzy set value. This also helps us investigate the impact of uncertainties in the input data on the model's output by rerunning the fuzzy logic model to observe the changes. The crisp value obtained in these scenarios is then compared with the actual values. The results show that the ranking of the factors as categorized under cause and effect remains unchanged (Table A6). The graphical representation of the results is shown in Figure 7.

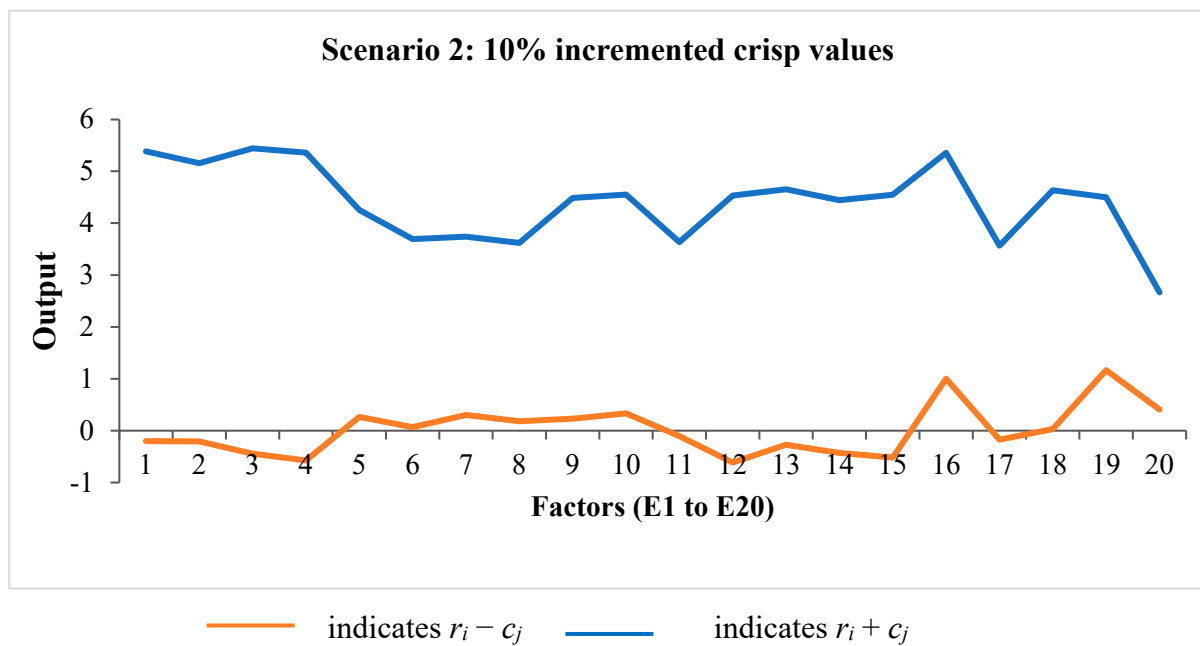
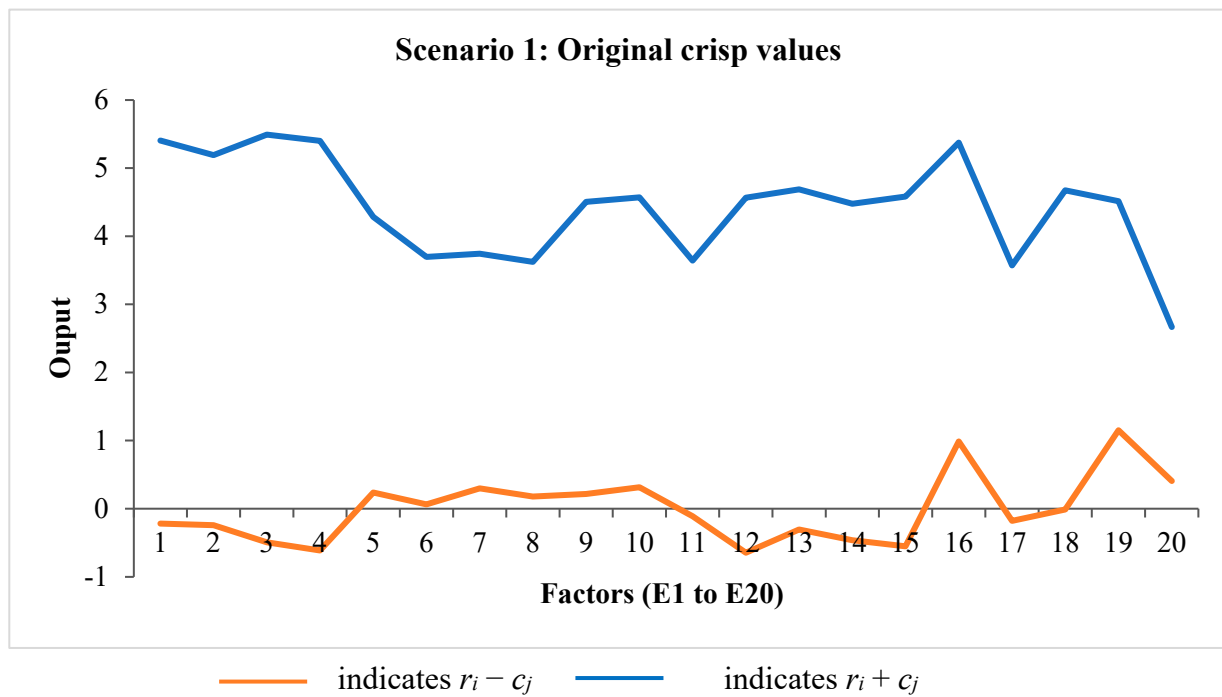


Figure 7. Cont.

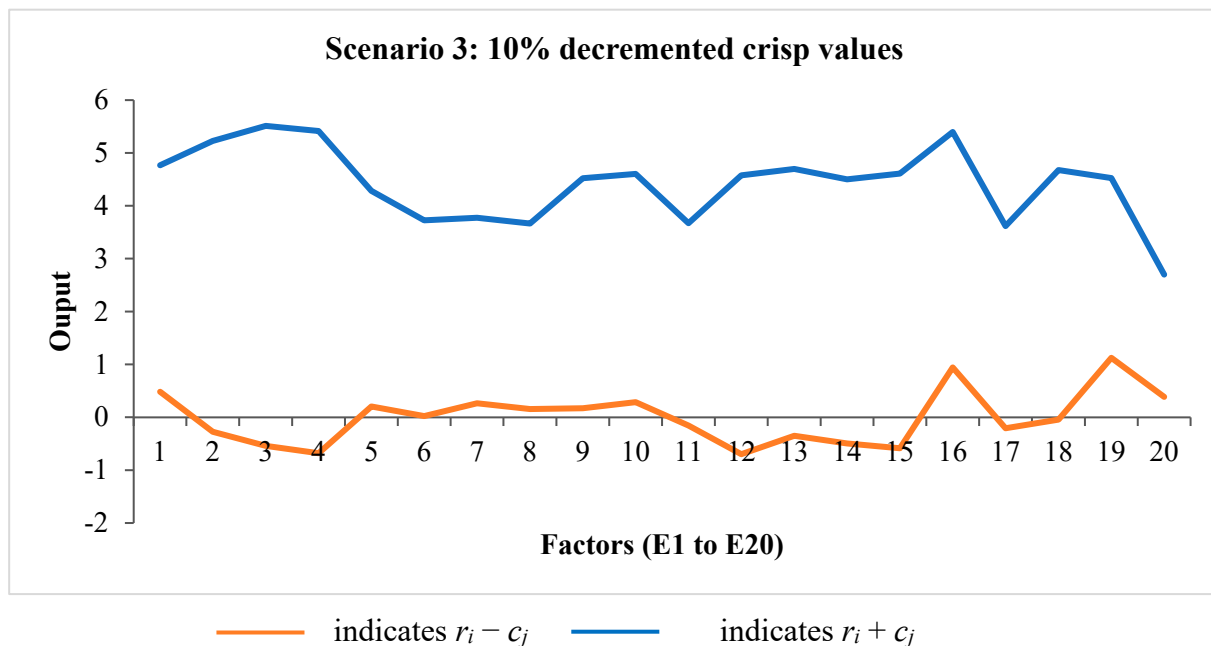


Figure 7. Results of the sensitivity analysis.

4. Results and Discussion

Based on the cause-and-effect diagram (Figure 6) and sensitivity analysis (Figure 7), the causal factors responsible for mining truck accidents are identified as follows: alcohol consumption (E16), speeding and aggressive driving (E19), working capabilities of the drivers (E10), physical limitation of the drivers (E7), overloading (E5), adverse physiological state (E6), mental limitation (E8), driver's behavior (E9), and poor lighting (E20). The following effects are identified: inadequate supervision (E1), planned inappropriate operations (E2), failure to correct the known problems (E3), supervisory problem (E4), site condition (E11), working schedule (E12), inadequate safety training (E13), lack of safety management (E14), lack of awareness (E15), unsafe climatic condition (E17), and improper vehicle maintenance (E18). Causal factors have a direct or indirect influence on other factors and need to be prioritized for improvement. The effect factors can be used to determine the effectiveness of any solutions developed to prevent the occurrence of the accidents.

The most significant causal factors behind mining truck accidents are identified as speed and aggressive driving (E19) with the uppermost ($r_i - c_j$) value of 1.152, followed by alcohol consumption (E16) ($r_i - c_j = 0.9806$). E16 also has the highest r_i value. Further, failure to correct known problems with the vehicle (E3) and inadequate supervision (E1) are identified as important factors with the two highest ($r_i + c_j$) values. Moreover, their ($r_i - c_j$) values are above average, meaning they have an impact on the other causal factors.

These results align with the analysis found in existing literature, and are not limited to the study of Indian mines. Speeding by operators is identified as the leading causal factor resulting in the loss of control and/or unexpected movement of haul trucks [15]. This has been tied to driver distraction and fatigue that impacts decision-making abilities around when to decrease speed or the ability to make controlled maneuvers at high speed [31]. In our results as well, driver distraction [E9] scores a high r_i value of 2.3596 as well as a high ($r_i + c_j$) value of 4.504.

It is evident that investigating the role of human error in accidents is increasingly commonplace. Identified contributing factors has pre-dominantly focused on the unsafe acts of individuals, in this case, the truck drivers. Through our results, we aim to balance this approach with an organizational approach that identifies shortfalls of the over-arching systems [32]. The findings reported in the previous section can guide decision making around risk assessment and management strategies in the mining sector to address these shortfalls.

Supervisors and managers can plan and prioritize the adaptation and implementation of relevant preventive measures (outlined in Table 5).

Table 5. Preventive measures against the critical causal factors responsible for mining truck accidents.

Factor Code	Causal Factor	Preventive Measures
E19	Speeding and aggressive driving	<ul style="list-style-type: none"> • Setting speed limits that are safe and realistic. • Educating drivers on the risks involved in speedy driving. • Appropriate engineering measures and safe road designs to control/ regulate speed. • Recruitment of enforcement officers and training them on the use of speed measuring devices such as radars, lidars. • Strict punitive actions against the speeding drivers.
E16	Alcohol consumption	<ul style="list-style-type: none"> • Regular alcohol screening. • Educating drivers regarding side-effects of alcohol consumption and alcohol-impaired driving. • Rehabilitation of alcohol addicts. • Establishment of regular checkpoints and patrols to monitor the drink and drive cases, especially in accident-prone regions.
E10	Working capabilities of the drivers	<ul style="list-style-type: none"> • Training drivers to watch out for blind spots. • Regular assessment of driver's capabilities and detecting changes. • Encouraging drivers to practice signaling while changing lanes even if they do not spot other vehicles. • Training drivers to slow down during bad weather and poor visibility. • Pre-trip and post-trip inspections. • Real-time GPS to monitor the safety of drivers.
E7	Physical health of the drivers	<ul style="list-style-type: none"> • Install temperature-controlled driving cabins. • Well devised insurance benefits. • Annual physical, full-body check-ups. • Tie-ups with local clinics and hospitals.
E5	Overloading	<ul style="list-style-type: none"> • Training drivers to properly distribute the load. • Using the weighbridge tool to prevent overloading. • Mandatory weighting before the trip begins. • Advise drivers to consider each axel after loading. • Monitor mechanical components of the truck and plan for proper servicing for worn down parts. • Regular checkpoints need to be maintained to monitor the truckload.
E6	Adverse physiological state of the driver	<ul style="list-style-type: none"> • Encouraging drivers to take breaks intermittently. • Recommending a minimum of seven hours of sleep before a driving shift. • Proper planning of driving shifts. • Compensation for drivers working late night shifts. • Encouraging drivers to report any sleep disorders or mental ailments to supervisors.
E8	Mental health of the driver	<ul style="list-style-type: none"> • Promoting awareness of proper diet and regular exercises. • Providing treatment options to address mental health gaps. • Ensuring work-life balance and prioritizing family time. • Tie-ups with rehabilitation centers. • Regular check-ins to monitor drivers' mental health and well-being.
E9	Driver distraction	<ul style="list-style-type: none"> • Education on consequences of texting or attending a call while driving. • Punitive measures to address indiscipline behavior of drivers.
E20	Poor lighting	<ul style="list-style-type: none"> • Promoting awareness of high beam and low beam lighting practices on highways among drivers. • Installing lamp posts at regular intervals. • Educating drivers on using anti-glare eyeglasses. • Implementing reflective sign boards on curves, crossings, and intersections.

Linkages to Socio-Economic Conditions of Local Community

The authors' interactions with local community members revealed that truck accidents are usually seen as an unavoidable occupational hazard by mining workers and their family members. Many of the risk factors identified negatively impact the drivers and their families as they relate to the drivers' health outcomes, employment status, earning levels and overall quality of life. For drivers involved in truck accidents, there are also reputational damages that in turn impact levels of self-confidence and self-esteem. The individual's role within the society as well as within their household might change, causing deep instability. Despite such enormous costs, there is surprisingly minimal effort taken by the industry to explore new mitigative measures or innovate the transportation system.

5. Recommendation

While strategies to address the various causal factors influencing mining haul truck accidents are discussed in this paper, driver training, strict monitoring, and enforcement of safety policies may be more feasible and cost-effective in the short-run. To achieve safer outcomes in the long-run, an alternative transportation system might be better suited. The authors recommend replacing the road-based movement of trucks in mining sites with a conveyor belt system. This energy-efficient method of using conveyor belts for transporting ore reduces the burden on both road and rail transport infrastructure and, importantly, prevents accidents. Alongside minimal particulate emissions at loading and unloading points, the conveyor belt system ensures no spillage of valuable mineral resources, does not contribute to dust or noise pollution, and is a faster means of transportation. On the other hand, it is also important to note certain limitations of the pipe conveyor systems, including the need for regular maintenance to prevent equipment failure such as belt deviation or belt damage, power outages that can halt operations, cost intensive repairs, and other general issues caused by wear and tear. However, there is ongoing research on utilizing innovative technologies to make the system more efficient and reliable [33,34].

Despite the above limitations, switching to mechanical methods, such as pipe conveyors, has been directed by the Honorable Supreme Court of India, specifically for mines transporting ore in excess of 0.7 MTPA (million tons per annum). In response, techno-economic feasibility reports for the transportation and loading of iron ore using a downhill conveyor system have already been developed by the KSMCL (Karnataka State Minerals Corporation Limited) and other private mining lease owners. Moreover, one of the largest steel plants operating in the state of Karnataka, M/s JSW Steel, has implemented the use of pipe conveyors to transport raw material from the mines located in Sandur to its integrated steel plant in Vijayanagar, as part of the company's commitment to promote environmental outcomes (Figure 8). Further research should be conducted on strategies to make the implementation of the pipe conveyor belt system economically viable for mining companies dealing in smaller quantities of ore, while replacing the conventional truck transport system in a phased manner. This will ensure that this mode of transportation becomes the new standard in the mining industry.



Figure 8. Closed pipe conveyor belt system used for transportation of iron ore.

6. Conclusions

The truck haulage system is a continuing challenge for the mineral industry. The results of the fuzzy DEMATEL model identified the most critical human and systematic errors resulting in mining transport accidents, thereby enabling multi-criteria decision making. While targeted steps can be taken to address the safety concerns due to conventional transportation systems, the authors recommend a shift to an automated/mechanical transportation system in the mineral industry for a long-term sustainable improvement in resource efficiency.

As evident from our research, the conventional truck haulage is the cause of increasing road accidents, resulting in loss of manpower and increased costs. The carbon emissions released from the trucks also add to the pollution load on the environment. The paper concludes that the conveyor system is a better replacement for the truck haulage system depending upon the scale of mining operation. It would reduce the number of accidents caused due to human error, while reducing the risk of dust exposure and various environmental hazards. As next steps, the project managers in both large and small mining companies must conduct feasibility studies to assess the impacts of shifting to the conveyor system, considering the business, environmental, and social and governance (ESG) impacts, including any disruptive impacts on local communities. Nevertheless, the success of mining projects is closely tied to public perception and therefore, investments in building a safety culture in the mining industry is the need of the hour.

Author Contributions: B.P.P.: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing—original draft; D.P.M.: Supervision, Methodology, Writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy.

Acknowledgments: This research forms a part of the Ph.D. work carried out by the first author. The authors are thankful to Prajwal Prabhu, Research Scholar, IISc, Bangalore, Karnataka, India for providing valuable inputs in completing the study successfully.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Direct-Relation Matrix.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18	E19	E20
E1	NI	HI	VHI	HI	HI	VLI	VLI	VLI	LI	LI	VLI	HI	HI	HI	HI	LI	VLI	VHI	LI	NI
E2	LI	NI	VHI	HI	HI	VLI	VLI	VLI	VLI	LI	VLI	HI	HI	HI	HI	LI	VLI	VHI	LI	NI
E3	HI	HI	NI	HI	HI	VLI	VLI	VLI	VLI	LI	VLI	HI	HI	HI	HI	LI	VLI	VHI	LI	NI
E4	VHI	LI	VHI	NI	HI	VLI	VLI	VLI	VLI	VLI	VLI	HI	HI	HI	HI	LI	VLI	VHI	LI	NI
E5	HI	HI	HI	VHI	NI	VLI	VLI	VLI	VLI	LI	VLI	LI	LI	LI	VLI	VLI	HI	HI	LI	NI
E6	LI	LI	LI	LI	VLI	NI	VLI	VLI	LI	LI	VLI	LI	VLI	VLI	LI	HI	VLI	VLI	VLI	VLI
E7	LI	LI	LI	LI	VLI	HI	NI	HI	LI	VLI	VLI	LI	VLI	VLI	LI	HI	VLI	VLI	VLI	VLI
E8	VLI	VLI	LI	LI	VLI	HI	HI	NI	LI	VLI	VLI	LI	VLI	VLI	LI	HI	VLI	VLI	VLI	VLI
E9	HI	HI	LI	HI	VLI	HI	HI	NI	VLI	VLI	LI	LI	LI	VLI	VHI	VLI	VLI	VLI	VLI	VLI
E10	LI	HI	LI	HI	VLI	LI	LI	HI	NI	VLI	VHI	LI	LI	LI	LI	HI	HI	VLI	VLI	VLI
E11	LI	LI	LI	LI	VLI	VLI	VLI	VLI	LI	LI	NI	VLI	VLI	VLI	LI	VLI	HI	LI	VLI	VLI
E12	HI	HI	VLI	HI	VLI	VLI	VLI	VLI	HI	LI	LI	NI	VLI	LI	LI	VLI	VLI	VLI	VLI	VLI
E13	HI	HI	HI	HI	VLI	VLI	VLI	VLI	HI	LI	LI	NI	LI	LI	HI	VLI	VLI	VLI	VLI	LI
E14	LI	HI	HI	HI	VLI	VLI	VLI	VLI	VLI	VLI	LI	LI	HI	NI	HI	VLI	VLI	VLI	VLI	VLI
E15	LI	HI	HI	HI	VLI	VLI	VLI	VLI	VLI	LI	LI	HI	LI	NI	VLI	VLI	VLI	VLI	VLI	VLI
E16	VHI	VHI	VHI	HI	VLI	HI	HI	HI	VHI	VHI	HI	LI	HI	VHI	VHI	NI	HI	LI	VHI	HI
E17	VLI	VLI	LI	VLI	VLI	LI	LI	LI	VLI	VLI	VLI	VLI	LI	LI	VLI	VLI	NI	HI	VLI	LI
E18	HI	LI	HI	HI	HI	VLI	VLI	VLI	VLI	LI	HI	LI	LI	VLI	VLI	HI	NI	LI	LI	LI
E19	HI	LI	HI	LI	HI	LI	LI	LI	VHI	VHI	LI	HI	LI	LI	VHI	VLI	LI	NI	LI	LI
E20	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VLI	VHI	VLI	VLI	VLI	VLI	VLI	HI	VLI	LI	NI

Table A2. Normalized Direct-Relation Matrix.

	E1	E2	E3	E4	E5
E1	(0,0,0.0144)	(0.054,0.0535,0.0579)	(0.081,0.0714,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)
E2	(0.027,0.0357,0.0434)	(0,0,0.0144)	(0.081,0.0714,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)
E3	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0,0,0.0144)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)
E4	(0.081,0.0714,0.0579)	(0,0.0178,0.0289)	(0.081,0.0714,0.0579)	(0,0,0.0144)	(0.054,0.0535,0.0579)
E5	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.081,0.0714,0.0579)	(0,0,0.0144)
E6	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)
E7	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)
E8	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)
E9	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.027,0.0357,0.0434)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)
E10	(0.027,0.0357,0.0434)	(0.054,0.0535,0.0579)	(0.027,0.0357,0.0434)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)
E11	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)
E12	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)
E13	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)
E14	(0.027,0.0357,0.0434)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)
E15	(0.027,0.0357,0.0434)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)

Table A2. Cont.

	E16	E17	E18	E19	E20
E7	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E8	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E9	(0.081,0.0714,0.0579)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E10	(0.054,0.0535,0.0579)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E11	(0,0.0178,0.0289)	(0.054,0.0535,0.0579)	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E12	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E13	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E14	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E15	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E16	(0,0,0.0144)	(0.054,0.0535,0.0579)	(0.027,0.0357,0.0434)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E17	(0,0.0178,0.0289)	(0,0,0.0144)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)	(0,0.0178,0.0289)
E18	(0,0.0178,0.0289)	(0.054,0.0535,0.0579)	(0,0,0.0144)	(0.027,0.0357,0.0434)	(0.027,0.0357,0.0434)
E19	(0.081,0.0714,0.0579)	(0,0.0178,0.0289)	(0.027,0.0357,0.0434)	(0,0,0.0144)	(0.027,0.0357,0.0434)
E20	(0,0.0178,0.0289)	(0.054,0.0535,0.0579)	(0,0.0178,0.0289)	(0.027,0.0357,0.0434)	(0,0,0.0144)

Table A3. Total-Relation Matrix.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
E1	0.217712	0.256785	0.264922	0.272532	0.220192	0.181245	0.176208	0.176208	0.210052	0.209344
E2	0.239051	0.20814	0.257925	0.265146	0.214598	0.175911	0.171022	0.171022	0.19083	0.203857
E3	0.255971	0.253395	0.21992	0.268933	0.217657	0.17843	0.173471	0.173471	0.193748	0.206766
E4	0.246007	0.216343	0.251042	0.21619	0.209099	0.170855	0.166107	0.166107	0.185387	0.184761
E5	0.241642	0.238634	0.247153	0.253302	0.165463	0.168528	0.163845	0.163845	0.181874	0.194971
E6	0.208058	0.206058	0.212385	0.218742	0.161884	0.140679	0.150665	0.150665	0.180422	0.17906
E7	0.216191	0.213905	0.221074	0.227491	0.168487	0.190108	0.143138	0.184825	0.187638	0.172128
E8	0.195948	0.193549	0.213809	0.22002	0.162445	0.185145	0.180000	0.138313	0.182068	0.166387
E9	0.246617	0.243965	0.238555	0.258968	0.182437	0.20259	0.196959	0.196959	0.173293	0.185515
E10	0.239023	0.250187	0.244433	0.265383	0.186692	0.193304	0.187931	0.187931	0.220096	0.175896
E11	0.202137	0.186086	0.206916	0.212305	0.157836	0.150721	0.146533	0.146533	0.175061	0.173949
E12	0.226901	0.224632	0.204513	0.238212	0.166822	0.158442	0.154039	0.154039	0.197916	0.182679
E13	0.240559	0.238345	0.245672	0.25276	0.177854	0.168094	0.163422	0.163422	0.208759	0.193856
E14	0.216471	0.227684	0.235234	0.241443	0.169486	0.159475	0.155043	0.155043	0.172573	0.17184
E15	0.216785	0.227997	0.235361	0.241776	0.169725	0.159945	0.1555	0.1555	0.173233	0.185792
E16	0.283403	0.280716	0.290454	0.298602	0.211831	0.230548	0.22414	0.22414	0.245788	0.24331
E17	0.184845	0.182527	0.203224	0.194819	0.154625	0.161953	0.157452	0.157452	0.158491	0.157207
E18	0.248763	0.23177	0.254268	0.260588	0.212601	0.174162	0.169322	0.169322	0.188254	0.201104
E19	0.270535	0.254291	0.27576	0.270574	0.228502	0.205846	0.200125	0.200125	0.234785	0.23276
E20	0.173607	0.171022	0.17806	0.182445	0.145627	0.139956	0.136066	0.136066	0.149918	0.148672
	E11	E12	E13	E14	E15	E16	E17	E18	E19	E20
E1	0.183736	0.250253	0.246113	0.242727	0.247846	0.212156	0.184477	0.228212	0.187739	0.124831
E2	0.17876	0.243645	0.239631	0.236332	0.24148	0.206168	0.179482	0.222394	0.182832	0.121257
E3	0.181313	0.247122	0.243051	0.239705	0.244924	0.209116	0.182045	0.225565	0.185441	0.122992
E4	0.173855	0.236956	0.233246	0.230032	0.235033	0.200288	0.174172	0.216665	0.178006	0.117733
E5	0.16999	0.220301	0.216267	0.213486	0.204108	0.184545	0.199015	0.215162	0.175942	0.115456
E6	0.155562	0.200955	0.183542	0.181015	0.199249	0.196467	0.15672	0.169086	0.147191	0.118807
E7	0.161933	0.208985	0.190814	0.188185	0.207408	0.204577	0.16274	0.175974	0.15321	0.123698
E8	0.156895	0.202122	0.184065	0.181528	0.200608	0.198764	0.157683	0.169712	0.148061	0.120279
E9	0.17435	0.225312	0.220364	0.21751	0.210289	0.218764	0.175004	0.190466	0.165365	0.132376
E10	0.179167	0.244345	0.226367	0.223436	0.228904	0.222994	0.207625	0.195696	0.169386	0.135969
E11	0.136833	0.181513	0.178278	0.175639	0.193142	0.163843	0.180642	0.178935	0.143553	0.116349
E12	0.172833	0.178096	0.18879	0.199698	0.204332	0.173283	0.160289	0.173983	0.151348	0.121444

Table A3. *Cont.*

	E11	E12	E13	E14	E15	E16	E17	E18	E19	E20
E13	0.182996	0.219286	0.18728	0.212304	0.231121	0.184242	0.170109	0.185448	0.161011	0.128454
E14	0.175547	0.209056	0.219325	0.174414	0.221733	0.174541	0.162049	0.17672	0.153587	0.122858
E15	0.175597	0.209547	0.219423	0.202887	0.180146	0.175214	0.162682	0.176983	0.153806	0.123041
E16	0.230278	0.260448	0.26894	0.265038	0.272337	0.207708	0.231884	0.235593	0.19172	0.15325
E17	0.14901	0.177866	0.187802	0.185215	0.176222	0.160952	0.135486	0.188532	0.140818	0.114888
E18	0.20378	0.2266	0.222444	0.219573	0.210722	0.190444	0.206269	0.179603	0.181473	0.147428
E19	0.206634	0.261002	0.241953	0.238819	0.244616	0.237484	0.194936	0.223863	0.16786	0.159415
E20	0.168399	0.16699	0.163807	0.16155	0.1656	0.151497	0.170122	0.152759	0.146894	0.094735

Table A4. Fuzzy Values $r_i, c_j, r_i + c_j, r_i - c_j$.

E1	(1.3151,2.1681,4.2932)	(1.4891,2.3763,4.5702)	(2.8042,4.5444,8.8635)	(−0.1739,−0.2081,−0.2769)
E2	(1.203,2.0643,4.1494)	(1.3759,2.2703,4.506)	(2.5789,4.3346,8.6555)	(−0.1728,−0.206,−0.3565)
E3	(1.2058,2.0657,4.223)	(1.7,2.5777,4.7006)	(2.9058,4.6435,8.9237)	(−0.4941,−0.512,−0.4776)
E4	(1.1547,2.0163,4.0078)	(1.6391,2.5209,4.8602)	(2.7938,4.5372,8.8681)	(−0.4843,−0.5045,−0.8523)
E5	(0.9864,1.8583,3.9335)	(0.7424,1.6436,3.6838)	(1.7289,3.502,7.6173)	(0.2439,0.2147,0.2496)
E6	(0.5994,1.5204,3.5172)	(0.4812,1.473,3.4959)	(1.0806,2.9934,7.0131)	(0.1182,0.0473,0.0212)
E7	(0.7152,1.6445,3.7025)	(0.4053,1.3892,3.3709)	(1.1205,3.0338,7.0734)	(0.3098,0.2553,0.3315)
E8	(0.5994,1.5386,3.5574)	(0.4053,1.3892,3.3709)	(1.0048,2.9279,6.9283)	(0.1941,0.1494,0.1864)
E9	(1.0606,1.9626,4.0556)	(0.8308,1.7938,3.8101)	(1.8915,3.7564,7.8658)	(0.2298,0.1688,0.2454)
E10	(1.1096,2.0297,4.1847)	(0.8379,1.7785,3.7698)	(1.9476,3.8082,7.9546)	(0.2717,0.2511,0.4149)
E11	(0.4677,1.4219,3.4068)	(0.5822,1.5321,3.5174)	(1.05,2.954,6.9242)	(−0.1145,−0.1102,−0.1106)
E12	(0.6599,1.5902,3.6322)	(1.2743,2.1728,4.3704)	(1.9343,3.7631,8.0026)	(−0.6143,−0.5826,−0.7381)
E13	(0.8699,1.7894,3.9149)	(1.1739,2.0553,4.2615)	(2.0439,3.8447,8.1764)	(−0.304,−0.2659,−0.3465)
E14	(0.6944,1.6284,3.6941)	(1.1669,2.0528,4.189)	(1.8613,3.6812,7.8832)	(−0.4724,−0.4243,−0.4949)
E15	(0.705,1.6354,3.7009)	(1.2445,2.1372,4.3198)	(1.9496,3.7727,8.0207)	(−0.5394,−0.5017,−0.6188)
E16	(1.8934,2.7943,4.8501)	(0.869,1.8376,3.873)	(2.7624,4.632,8.7231)	(1.0244,0.9566,0.977)
E17	(0.3955,1.3603,3.3293)	(0.5542,1.5201,3.5534)	(0.9497,2.8805,6.8828)	(−0.1586,−0.1598,−0.224)
E18	(0.9823,1.9134,4.0984)	(1.1358,2.0141,3.8813)	(2.1181,3.9276,7.9798)	(−0.1534,−0.1006,0.2171)
E19	(1.533,2.4159,4.5498)	(0.4098,1.346,3.2852)	(1.9428,3.762,7.8351)	(1.1232,1.0699,1.2646)
E20	(0.2626,1.2438,3.1037)	(0.0957,0.7811,2.5152)	(0.3583,2.0249,5.619)	(0.1669,0.4627,0.5885)

Table A5. Crisp Values $r_i, c_j, r_i + c_j, r_i - c_j$.

	r_i	c_j	$r_i + c_j$	$r_i - c_j$	Identify
E1	2.5922	2.8123	5.405	−0.2201	effect
E2	2.4732	2.7171	5.19	−0.2439	effect
E3	2.4989	2.9932	5.492	−0.4943	effect
E4	2.3922	3.0066	5.399	−0.6144	effect
E5	2.26	2.023	4.283	0.237	cause
E6	1.8797	1.8165	3.696	0.0632	cause
E7	2.0207	1.7223	3.743	0.2984	cause

Table A5. Cont.

	r_i	c_j	$r_i + c_j$	$r_i - c_j$	Identify
E8	1.8996	1.7223	3.622	0.1773	cause
E9	2.3596	2.1443	4.504	0.2153	cause
E10	2.4417	2.1286	4.57	0.3131	cause
E11	1.7649	1.8773	3.642	-0.1124	effect
E12	1.9604	2.6059	4.566	-0.6455	effect
E13	2.1909	2.4971	4.688	-0.3062	effect
E14	2.0059	2.4693	4.475	-0.4634	effect
E15	2.014	2.5669	4.581	-0.5529	effect
E16	3.1798	2.1932	5.373	0.9866	cause
E17	1.6959	1.8757	3.572	-0.1798	effect
E18	2.3309	2.3433	4.674	-0.0124	effect
E19	2.8328	1.6807	4.514	1.1521	cause
E20	1.5361	1.1313	2.667	0.4048	cause

Table A6. Results of Sensitivity Analysis, Comparing Original Crisp Values with Results from Two Different Scenarios: 10% Increment and Decrement to Original Fuzzy Values.

Scenario 1 (Original Crisp Value)		Scenario 2 (10% Increment Crisp Value)		Scenario 3 (10% Decrement Crisp Value)	
$r_i + c_j$	$r_i - c_j$	$r_i + c_j$	$r_i - c_j$	$r_i + c_j$	$r_i - c_j$
5.4045	-0.2201	5.384	-0.200	4.764	0.481
5.1903	-0.2439	5.155	-0.208	5.225	-0.276
5.4921	-0.4943	5.443	-0.446	5.511	-0.542
5.3988	-0.6144	5.360	-0.576	5.414	-0.680
4.283	0.237	4.254	0.266	4.280	0.205
3.6962	0.0632	3.693	0.067	3.725	0.021
3.743	0.2984	3.740	0.301	3.772	0.263
3.6219	0.1773	3.619	0.180	3.664	0.155
4.5039	0.2153	4.487	0.232	4.521	0.170
4.5703	0.3131	4.551	0.332	4.601	0.286
3.6422	-0.1124	3.635	-0.105	3.671	-0.156
4.5663	-0.6455	4.533	-0.612	4.576	-0.697
4.688	-0.3062	4.654	-0.273	4.697	-0.351
4.4752	-0.4634	4.442	-0.430	4.498	-0.495
4.5809	-0.5529	4.548	-0.520	4.607	-0.587
5.373	0.9866	5.356	1.003	5.395	0.943
3.5716	-0.1798	3.566	-0.174	3.615	-0.208
4.6742	-0.0124	4.633	0.029	4.676	-0.045
4.5135	1.1521	4.498	1.168	4.523	1.126
2.6674	0.4048	2.666	0.407	2.699	0.386

References

1. ILO Sectoral Policies and Governance. *Safety and Health in Mining*; International Labour Organization: Genève, Switzerland, 2018. Available online: https://www.ilo.org/global/topics/safety-and-health-at-work/events-training/WCMS_633314/lang-en/index.htm (accessed on 7 January 2023).
2. National Institute for Occupational Safety and Health (NIOSH). Mining: The Leading Cause of Fatalities; Centers for Disease Control and Prevention (CDC), 16 October 2020. Available online: <https://www.cdc.gov/niosh/mining/features/mining-fatalities.html> (accessed on 7 January 2023).
3. Mine Safety and Health Administration. *2019 Year End Summary of Mining Fatalities*; US Department of Labor: Washington, DC, USA, 2020. Available online: <https://www.msha.gov/data-reports/fatality-reports/2019> (accessed on 10 January 2023).

4. Directorate General of Mines Safety. *Annual Report 2019*; Ministry of Labour and Employment, Government of India: New Delhi, India, 2020. Available online: https://www.dgms.gov.in/writereaddata/uploadedfile/statistics/Annual_Report_2019_Eng.pdf (accessed on 14 January 2023).
5. The Mining Sector's Human Cost: Over 260 Miners Died in Accidents in 3 Years. *The Hindu Business Line*, 31 January 2020. Available online: <https://www.thehindubusinessline.com/economy/mining-sector-sees-over-260-fatalities-in-3-years/article30684708.ece> (accessed on 9 January 2023).
6. *Safety Performance Data: 2015-2019*; International Council on Mining and Metals: London, UK, 2020. Available online: <https://www.icmm.com/-/media/documents/publications/safety-performance-data-2015-2019.pdf> (accessed on 12 January 2023).
7. Dash, A.K.; Bhattcharjee, R.M.; Paul, P.S.; Tikader, M. Study and Analysis of Accidents Due to Wheeled Trackless Transportation Machinery in Indian Coal Mines—Identification of Gap in Current Investigation System. *Procedia Earth Planet. Sci.* **2015**, *11*, 539–547. [[CrossRef](#)]
8. *Safety in Coal Mines*; Directorate General of Mines Safety: Dhanbad, India, 2019. Available online: <https://www.dgms.gov.in/writereaddata/uploadedfile/Coal%20Safety%20Report%202018-19.pdf> (accessed on 27 December 2022).
9. *Safety Performance in the Mining Industry*; International Council on Mining and Metals: London, UK, 2019. Available online: www.icmm.com/en-gb/publications/safety-performance-in-the-mining-industry (accessed on 27 December 2022).
10. National Institute for Occupational Safety and Health (NIOSH). Haul Truck Research Roadmap Report 2020; Centers for Disease Control and Prevention (CDC). Available online: <https://www.cdc.gov/niosh/mining/researchprogram/strategicplan/HaulTruckRoadmap2020.html> (accessed on 10 January 2023).
11. *Road Accidents in India—2018*; Ministry of Road Transport and Highways, Government of India: New Delhi, India, 2019. Available online: https://morth.nic.in/sites/default/files/Road_Accidents_in_India_2018.pdf (accessed on 17 January 2023).
12. *Annual Report 2020-2021*; Ministry of Labour and Employment, Government of India: New Delhi, India, 2021. Available online: https://labour.gov.in/sites/default/files/annual_report-21-22.pdf (accessed on 21 January 2023).
13. 180 Died in Accidents in Ballari in 2021, Mining Lorries, Bad Roads to Blame. *The New Indian Express*, 21 December 2021. Available online: <https://www.newindianexpress.com/states/karnataka/2021/dec/21/180-died-in-accidents-in-ballari-in-2021-mining-lorries-bad-roads-to-blame-2398215.html> (accessed on 24 December 2022).
14. Bellanca, J.L.; Ryan, M.E.; Orr, T.J.; Burgess-Limerick, R.J. Why Do Haul Truck Fatal Accidents Keep Occurring? *Min. Metall. Explor.* **2021**, *38*, 1019–1029. [[CrossRef](#)] [[PubMed](#)]
15. Drury, C.G.; Porter, W.L.; Dempsey, P.G. Patterns in Mining Haul Truck Accidents. *Proc. Hum. Factors Ergon. Soc. Annu. Meet.* **2012**, *56*, 2011–2015. [[CrossRef](#)]
16. Zhang, M.; Kecojovic, V.; Komljenovic, D. Investigation of haul truck-related fatal accidents in surface mining using fault tree analysis. *Saf. Sci.* **2014**, *65*, 106–117. [[CrossRef](#)]
17. Kantar IMRB and Castrol India. Truckers Battle Sleep Deprivation, Other Health Issues: Study. 2018. Available online: <https://www.asianage.com/life/health/200618/truckers-battle-sleep-deprivation-other-health-issues-study.html> (accessed on 23 January 2023).
18. Qin, J.; Xi, Y.; Pedrycz, W. Failure mode and effects analysis (FMEA) for risk assessment based on interval type-2 fuzzy evidential reasoning method. *Appl. Soft Comput.* **2020**, *89*, 106134. [[CrossRef](#)]
19. Dunj3, J.; Fthenakis, V.; Vilchez, J.A.; Arnaldos, J. Hazard and Operability (HAZOP) Analysis. A Literature Review. *J. Hazard. Mater.* **2009**, *173*, 19–32. Available online: <https://www.sciencedirect.com/science/article/pii/S0304389409013727> (accessed on 7 February 2023). [[CrossRef](#)] [[PubMed](#)]
20. Sii, H.S.; Wang, J.; Ruxton, T. Novel risk assessment techniques for maritime safety management systems. *Int. J. Qual. Reliab. Manag.* **2001**, *18*, 982–999. [[CrossRef](#)]
21. Tixier, J.; Dusserre, G.; Salvi, O.; Gaston, D. Review of 62 risk analysis methodologies of industrial plants. *J. Loss Prev. Process Ind.* **2002**, *15*, 291–303. [[CrossRef](#)]
22. Basahel, A.; Taylan, O. Using fuzzy AHP and fuzzy TOPSIS approaches for assessing safety conditions at worksites in construction industry. *Int. J. Saf. Secur. Eng.* **2016**, *6*, 728–745. [[CrossRef](#)]
23. Seker, S.; Zavadskas, E.K. Application of Fuzzy DEMATEL Method for Analysing Occupational Risks on Construction Sites. *Sustainability* **2017**, *9*, 2083. [[CrossRef](#)]
24. Gupta, S.; Kumar, P.; Karmakar, N.C.; Palei, S.K. Quantification of human error rate in underground coal mines—A fuzzy mapping and rough set-based approach. In Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management, Bangkok, Thailand, 10–13 December 2013; pp. 140–144. [[CrossRef](#)]
25. Tubis, A.; Werbińska-Wojciechowska, S.; Sliwinski, P.; Zimroz, R. Fuzzy Risk-Based Maintenance Strategy with Safety Considerations for the Mining Industry. *Sensors* **2022**, *22*, 441. [[CrossRef](#)] [[PubMed](#)]
26. Mohammadfam, I.; Khajevandi, A.A.; Deghani, H.; Babamiri, M.; Farhadian, M. Analysis of Factors Affecting Human Reliability in the Mining Process Design Using Fuzzy Delphi and DEMATEL Methods. *Sustainability* **2022**, *14*, 8168. [[CrossRef](#)]
27. Shahabi, R.S.; Basiri, M.H.; Qarahasanlou, A.N.; Mottahedi, A.; Deghani, F. Fuzzy MADM-Based Model for Prioritization of Investment Risk in Iran's Mining Projects. *Int. J. Fuzzy Syst.* **2022**, *24*, 3189–3207. [[CrossRef](#)]
28. Qi, R.; Li, S.; Qu, L.; Sun, L.; Gong, C. Critical factors to green mining construction in China: A two-step fuzzy DEMATEL analysis of state-owned coal mining enterprises. *J. Clean. Prod.* **2020**, *273*, 122852. [[CrossRef](#)]

29. Khaba, S.; Bhar, C. Quantifying SWOT analysis for the Indian coal mining industry using Fuzzy DEMATEL. *Benchmark. Int. J.* **2017**, *24*, 882–902. [[CrossRef](#)]
30. Azam, M.H.; Hasan, M.H.; Hassan, S.; Abdulkadir, S.J. Fuzzy Type-1 Triangular Membership Function Approximation Using Fuzzy C-Means. In Proceedings of the 2020 International Conference on Computational Intelligence (ICCI), Bandar Seri Iskandar, Malaysia, 8–9 October 2020; pp. 115–120. [[CrossRef](#)]
31. Schutte, P.C.; Maldonado, C.C. Factors affecting driver alertness during the operation of haul trucks in the South African mining industry. In *Safety in Mines Research Advisory Committee Final Report*; CSIR Mining Technology, SIM 020502; Safety in Mines Research Advisory Committee, South Africa: June 2003; p. 78. Available online: <https://hdl.handle.net/10204/1296> (accessed on 8 February 2023).
32. Dekker, S.W. Reconstructing human contributions to accidents: The new view on error and performance. *J. Saf. Res.* **2002**, *33*, 371–385. [[CrossRef](#)] [[PubMed](#)]
33. Zhang, M.; Jiang, K.; Cao, Y.; Li, M.; Hao, N.; Zhang, Y. A deep learning-based method for deviation status detection in intelligent conveyor belt system. *J. Clean. Prod.* **2022**, *363*, 132575. [[CrossRef](#)]
34. Carvalho, R.; Nascimento, R.; D'Angelo, T.; Delabrida, S.; GCBianchi, A.; Oliveira, R.A.; Azpúrua, H.; Uzeda Garcia, L.G. A UAV-Based Framework for Semi-Automated Thermographic Inspection of Belt Conveyors in the Mining Industry. *Sensors* **2020**, *20*, 2243. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.