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Analysis of Factors Affecting Human Reliability in the Mining Process Design Using Fuzzy Delphi and DEMATEL Methods

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Abstract: Design errors have always been recognized as one of the main factors affecting safety and health management and sustainable development in surface mines. Unfortunately, scant attention is paid to design errors and the factors causing them. Therefore, based on expert opinions, this study aimed to identify, rank, and investigate cause-and-effect relationships among variables influencing human error in surface mine design in Iran. The study variables were identified by reviewing previous literature on "latent human errors" and "design errors." After specifying effective variables, two rounds of the Fuzzy Delphi study were carried out to reach a consensus among experts. Nineteen variables with an influencing score of 0.7 and higher were screened and given to the experts to be analyzed for cause-and-effect relationships by the fuzzy DEMATEL method. The results of the study revealed that the following variables were the major factors affecting human error as root causes: poor organizational management (0.62), resource allocation (0.30), training level (0.27), and experience (0.25). Moreover, self-confidence (−0.29), fatigue (−0.28), depression (−0.25), and motive (−0.23) were found to be effect (dependent) variables. Our findings can help organizations, particularly surface mines, to opt for effective strategies to control factors affecting design errors and consequently reduce workers' errors, providing a good basis for achieving sustainable development.

Keywords: design errors; sustainable development; accident; multi-criteria decision-making

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1. Introduction

The mining industry is classified as one of the most dangerous and harsh work environments [1–3]. The consequences of mining accidents include occupational deaths and injuries, equipment damage [4], and environmental problems [5]. Besides, accidents and incidents in such a harsh work environment are very high (about 7–10 times) compared to other industries [1,6]. Identifying and eliminating the roots of mining accidents have always been one of the most important priorities of organizations and governments [7]. The analysis of mining accidents has shown that human error is the direct cause of 85% of these accidents. In recent years, many studies have been conducted to identify the factors affecting human error in mines. In most cases, the root cause of accidents resulting from human errors is a design error (DE), and thus the operator is just a victim of a poor design [8,9]. Liao asserts that despite efforts to reduce instances of human error by raising workers' awareness, not much progress has been achieved thus far. He regards DE as the main reason behind such a failure and states that it is one of the main causes of unsafe behaviors on workers' part in operational sectors [10]. DE is almost inevitable and can influence the safety of projects and their costs and timing [11]. More than 80% of the failures in buildings, bridges, hospitals, and civil engineering structures are caused by DE [12].

DE are important in various industries such as aviation [13], nuclear energy [14], process [15], and mining [16]. The diversity of mines, extensive operational space, and the extent of its consequences (occupational and public health, environmental, safety, social, and economic) have highlighted the role of design errors in this sector [17,18]. Unfortunately, the focus of human error studies for most of the 20th century has been on operational errors, which have been ignored [9]. The study by Thompson on road accidents in surface mines showed that design errors are the main causes of such accidents [19].

Flyrock is important in increasing the death rate and destroying mine equipment and structures. One of the main reasons for Flyrock production in blasting is DE in the blasting pattern [20]. Reason introduced this important construct as the latent human errors in 1998 because their consequences are not immediately known, and their identification takes longer. In other words, their identification needs a systematic approach [21]. Cho defines DE "as the result of a designer's actions and decisions in product development that lead to failure in the planned or intended outcome" [22].

Likewise, Mechlers believes that these latent human errors are cognitive processing errors, arguing that even the simplest forms of designs require cognitive functions [23]. From a cognitive psychological point of view, human error results from one or more deficits in human cognitive processes. Accidents happen due to perception, recognition, avoidance ability, and decision-making failures. Thus, failure in cognitive processes can lead to human errors and damage the system [24]. Studies show that design errors happen as a result of cognitive failure (CF) [25] influenced by individual, environmental, organizational, and task factors [26].

2. Review of Previous Research

In recent years, some studies have been conducted to find the effective factors behind human error in design. The results of the study by Kerli et al. [22] on DE showed that process (lack of design reviews), material (learning not shared amongst everyone), measurements (incomplete project tracking), tools (poor document traceability), people (loss of information and lack of making ability knowledge), and organization (scattered resources) are the main causes of such errors. Lopez et al. [12] reported that personal factors (loss of biorhythm and adverse behavior), organizational factors (training, experience, competitive professional fees, poor quality assurance), and project (time limitations and poor coordination) have a significant influence on DE in the construction sector. Some studies point out that errors result from individuals' tendency toward error or the conditions that induce error [27]. Also, some studies have classified the variables affecting DE into three groups: workplace, information flow, and organizational factors [28]. The study by Robert [29] revealed that designer knowledge, lack of standards, safety awareness, novel system, management of change, procedure, and lack of qualified staff were the most effective factors in design error. Zhaorong et al. [30] stated that defective workmanship, communication, lack of skill, contract issues, and external factors could lead to latent error and design error. Several studies have shown that these errors are influenced by individual, managerial, and social factors related to work, workplace, work methods and processes, task demands, workload, and physical work conditions [31]. However, DE has been considered as the major causes of accidents in many organizations [32]. There are many variables that directly or indirectly affect DE and are indeed the root causes of accidents. When a set of variables with complex relationships impact on a target variable, determining the most important variables requires extensive field studies, it is time-consuming and costly; and, moreover, the simultaneous controlling of all variables is not logical in system safety management and system safety engineering [33]. Therefore, using expert opinions to determine the most important variables based on scientific methods is a suitable strategy [34].

Multi-Criteria Decision-Making (MCDM) techniques are often adopted to solve complex problems based on experts' judgment. Previous studies have shown that MCDM methods, combined with a fuzzy set theory or other methods [35,36], can result in more reliable results. Several studies have used this approach in the areas of health [37], safety [38] and environment [39], and economy [40] for identifying and classifying relationships among variables. According to Fam et al. [41], the combination of fuzzy Delphi and DEMATEL is the best risk control strategy because DEMATEL can provide a cause-and-effect model. Similarly, in another study, Kumar et al. [42] reported that AHP and DEMATEL cannot determine the importance of the criteria. Therefore, the fuzzy Delphi method is very suitable to fill this gap. Renissa et al. [43] used the Delphi method and Fuzzy DEMATEL to identify the barriers to university technology transfer. Singh and Sardar [44] also used the Delphi method to determine the factors affecting sustainable product development and the Fuzzy DEMATEL method to illustrate the interrelationships among key factors by drawing a causal diagram in the automotive industry. The combination of these two methods can provide a deep understanding of a phenomenon.

Given the advantages of using fuzzy Delphi and DEMATEL methods and the lack of ample studies extensively surveying and prioritizing the factors affecting design error in Iranian surface mines, this study aimed to identify, rank, and investigate cause-and-effect relationships among variables influencing DE based on expert opinions.

Further, this study contributes to the literature in several ways:

(1) To our knowledge, this is one of the first studies investigating factors predicting DEs and their interactions. Thus, this study can contribute theoretically to the existing literature and fill the existing gaps in safety studies that addresses the role of latent errors in accidents;
(2) The proposed methodology of the present study provides a visual cause-and-effect model, which helps analyze DE. Mining managers and safety experts can update their goals and plan based on the results of the study;
(3) As a practical contribution, the study suggests strategic measures that may reduce DEs to avoid accidents; the study also presents evidence that helps improve health and safety at mines.

This study is organized as follows: Section 2 has the theoretical fundaments on DE, related literature gaps and the contribution of the study; in Section 3, the most important variables of DE in the mining design process are presented, followed by introducing Fuzzy Delphi and DEMATEL methods. The results and discussion are described in Sections 4 and 5; Section 6 specifies the conclusion and suggests future lines of research.

3. Materials and Methods

The methodology of this study comprised three phases: the identification of variables, the determination of effective variables via the Fuzzy Delphi method, and the analysis of cause-and-effect relationships among such variables via the Fuzzy DEMATEL method. The framework combining the two methods includes the following three phases, as shown in Figure 1.

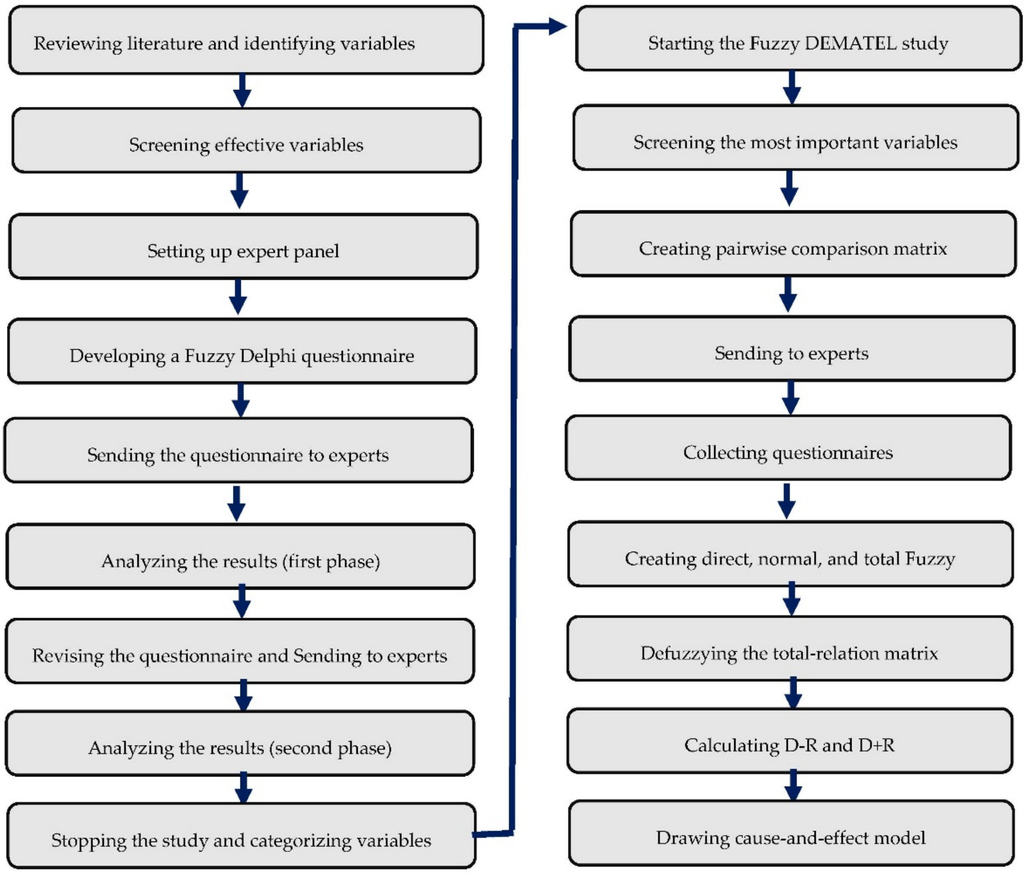

Figure 1. Research procedure.

3.1. Searching and Classifying the Variables Affecting DE

The important variables were first identified by a library research and literature review. Next, a panel of five experts in surface mine design was assigned to screen the most important variables and categorize them based on environmental, individual, external, organizational, and task factors for employing the Fuzzy Delphi method (Appendix A).

3.2. Identifying the Variables Affecting DE Using the Fuzzy Delphi Method

3.2.1. The Fuzzy Delphi Method

This method is a powerful tool used to reach a consensus based on expert opinions in a particular field of study [45]. In its classical form, the Delphi method makes use of expert opinions stated in the form of definite numbers. In this method, experts do not use their mental competence to state their opinions, showing a probability of uncertainty in the decisions made. Thus, to compensate for this drawback, a fuzzy set is used to collect the data in linguistic terms and interpret vague concepts stated by expert opinions [46,47]. Accordingly, the classical Delphi method was combined with fuzzy set theory to create the more effective Fuzzy Delphi method [48]. The Fuzzy Delphi method enjoys some advantages, including the unification of expert opinions to reach a consensus [49], the reduction of time and cost compared to the classical Delphi method [50], and the reduction of expert opinion collection rounds [41].

There are different types of fuzzy numbers, and this study used Triangular Fuzzy Numbers (TFN). In this study, TFN was shown using three real numbers M = (l, m, u), in which the upper bound is (u), lower bound is (l), infimum is (m), and 'M' is the most probable value of a fuzzy number [51]. TFN reflects the membership by the function, which can show the information of the experts more simply and accurately regarding a complex decision-making problem [52]. TFN has been applied in various domains, including risk, evaluation, anticipation, and expert systems [53].

3.2.2. Selection of Experts

In the MCDM method, the selection of experts is very important and vital. Powerful expert groups can ensure the accuracy of research results. Therefore, the expert panel in the study went through a rigorous selection process. In the first step, a database of experts active in surface mine design in Iran was collected. The inclusion criteria included being inclined to participate, having comprehensive knowledge, ample operational experience, and time adequacy. Due to the diversity of minerals, the difference in the size of the mines, the geography of the design environment, and the variety of techniques and tools used in the design, attempts were made to select decision-makers whose experience covered the listed items. Finally, out of 150 Iranian Open Mines Designers Association members, 25 were purposefully selected. The number of experts in the panel varies in various valid studies, and several studies have been conducted with fewer than 10 experts to higher numbers [54–56]. Among the experts, there were people with academic bachelor's degrees. These people are among the most famous mining designers in Iran who have a lot of experience in the field of exploration and extraction in surface mines. The demographic characteristics of the experts are shown in Table 1.

Table 1. Demographic characteristics of the experts.

	Delphi Study		DEMATEL Study	
Demographic Variables	**Total**	**Percentage**	**Total**	**Percentage**
Gender				
Male	16	84.21%	9	90.00%
Female	3	15.79%	1	10.00%
Educational				
Bachler	3	15.79%	-	-
Master	7	36.84%	2	20.00%
Doctoral	9	47.37%	8	80.00%
Experience in mine design				
<5 years	2	10.53%	-	-
5–15 years	6	31.58%	3	30.00%
>15 years	11	57.89%	7	70.00%

In line with previous literature using the Fuzzy Delphi method, a questionnaire with Likert-scale items was developed to be used in the study [50]. The expert panel was asked to review the developed semi-closed questionnaire and revise it by adding any important variables missing in the questionnaire.

3.2.3. First and Second Rounds Inquiry

Afterwards, the questionnaire was sent to three experts to be reviewed for face and content validities. Eventually, the finalized questionnaire was sent to 25 experts with a response rate of 76% (19 experts) in the first phase. In this phase, three new variables were suggested to be added to the questionnaire. After collecting expert opinions, the linguistic variables were changed into fuzzy numbers based on Table 2.

Table 2. Triangular fuzzy numbers corresponding to linguistic terms [54].

Linguistic Expressions	Triangular Fuzzy Numbers
No effect	(0, 0, 0.25)
Extremely weak effect	(0, 0.25, 0.5)
Weak effect	(0.25, 0.5, 0.75)
Strong effect	(0.5, 0.75, 1)
Extremely strong effect	(0.75, 1, 1)

The triangular fuzzy numbers set was measured for each expert's opinion based on Equation (1) [55]:

$$\widetilde{A}^{(i)} = \left(a_1^{(i)} \cdot a_2^{(i)} \cdot a_3^{(i)}\right) \; i = 1, 2, 3, \ldots, n. \tag{1}$$

Next, the mean of fuzzy numbers set ($\widetilde{A}_m^{(i)}$) out of all sets ($\widetilde{A}^{(i)}$) was measured based on Equation (2):

$$\widetilde{A}_m = (a_{m1} \cdot a_{m2} \cdot a_{m3}) = \left(\frac{1}{n}\sum_{i=1}^{n} a_1^i \cdot \frac{1}{n}\sum_{i=1}^{n} a_2^i \cdot \frac{1}{n}\sum_{i=1}^{n} a_3^i\right). \tag{2}$$

Then, the difference was calculated from the mean for each expert's opinion. After revisions and suggested variables were added, the questionnaire was re-sent to the experts to review and revise if needed. After collecting expert opinions in the second round based on Equations (1) and (2), expert opinions were aggregated, and their disagreements between the two rounds reached the minimum level of 0.2 [51]. At the end of the second round, the experts suggested that no new variable with disagreements reached the minimum level of 0.2. Accordingly, the Fuzzy Delphi study was stopped in this step [56].

3.2.4. Determination of the Most Important Variables

To defuzzy the numbers, the simple center of gravity method was used based on Equation (3):

$$S_j = \frac{l_j + m_j + u_j}{3}. \tag{3}$$

The ranking and determination of the most important variables were based on defuzzied scores: the higher the defuzzied score of a variable, the stronger the effect it exerted on human error, and hence more important. In this study, the screening process was conducted based on the 30–70 law, in which the threshold level for criterion acceptance was 7 [57]. Thus, if the amount of the defuzzied triangular number was found to be 0.7 or higher based on expert opinions, it was accepted as a criterion. Otherwise, it was removed from the study.

3.3. Determining Cause-and-Effect Relationships between the Variables

3.3.1. Fuzzy DEMATEL Method

Gabus et al. introduced a method called decision-making trial and evaluation laboratory (DEMATEL) in 1972 to analyze casual relationships and significant effects among variables with a strong validity [58]. This method works based on expert opinions expressed in linguistic terms; in order to avoid ambiguity and reach a unification of opinions, these linguistic terms need to be turned into fuzzy numbers. In 2008, Lin was the first person who used the DEMATEL method in a fuzzy environment [59]. The Fuzzy DEMATEL method investigates the relationships among criteria and sub-criteria and determines effective (cause) and affected (effect) criteria by the total-relation matrix [60,61]. This method is a multi-index decision-making technique [62]. One advantage of this method over other methods of investigation is that the process of decision-making is based on pairwise comparisons and the acceptance of relationships [63]. The Fuzzy DEMATEL method is frequently used in different fields of inquiry such as human resource management, risk assessment, and safety management system [24,64,65]. In this study, the following steps were taken to apply the Fuzzy DEMATEL method [66].

3.3.2. Setting up the Expert Panel

The first step aimed to identify experts qualified to participate in the inquiry process of the DEMATEL method. The respondent had to be a person who had adequate knowledge or experience related to the research problem. In this study, 15 experts with prominent experience and research history about mine design were selected, and the questionnaire was sent to them via email. Eventually, 10 experts collaborated in the study, performed the evaluation, and submitted the evaluation forms later.

3.3.3. Preparing Fuzzy DEMATEL Questionnaire

The Fuzzy DEMATEL questionnaire comprised a 20 × 20 matrix, which is not a symmetric matrix. The factors in these tables were assessed as a pairwise matrix. The experts used a 5-point Likert scale (Table 2) to express their opinions about the relationship among variables.

3.3.4. Analyzing the Data

(a) Based on experts' responses, the initial direct-relation fuzzy matrix was calculated

$$\widetilde{Z}_{ij}^{k} = \begin{pmatrix} 0 & \cdots & \widetilde{X}_{1n}^{k} \\ \vdots & \ddots & \vdots \\ \widetilde{X}_{n1}^{k} & \cdots & 0 \end{pmatrix}. K = 1, 2, 3, \ldots, P. \tag{4}$$

In this equation, P is the number of experts (10).

Then, using Equations (5)–(7) the aggregated mean of expert opinions was measured.

$$\widetilde{Z}_{ij} = \frac{\widetilde{X}^1 + \widetilde{X}^2 + \widetilde{X}^3 + \widetilde{X}^4 + \ldots + \widetilde{X}^P}{P}. \tag{5}$$

$\widetilde{X}^1$, $\widetilde{X}^2$, $\widetilde{X}^3$, and $\widetilde{X}^P$ are the pairwise comparison matrixes of the experts (expert 1, 2, 3, and P, respectively).

$$\widetilde{Z}_{ij} = \begin{pmatrix} 0 & \cdots & \widetilde{X}_{1n} \\ \vdots & \ddots & \vdots \\ \widetilde{X}_{n1} & \cdots & 0 \end{pmatrix}, \tag{6}$$

$$\widetilde{Z}_{ij} = \left(l_{ij} + m_{ij} + u_{ij}\right). \tag{7}$$

(b) Normalizing the direct-relation fuzzy matrix using Equations (8) and (9)

$$r = max \sum_{j=1}^{n} u'_{ij}, \tag{8}$$

$$\widetilde{H}_{ij} = \frac{\widetilde{z}_{ij}}{r} = \left(\frac{l'_{ij}}{r}.\frac{m'_{ij}}{r}.\frac{u'_{ij}}{r}\right) = \left(l''_{ij}.m''_{ij}.u''_{ij}\right). \tag{9}$$

(c) Determining the total-relation matrix.

The total-relation fuzzy matrix (T) was measured by the following Equations (12)–(14):

$$T = lim_{k\to\infty}\left(\widetilde{H}^1 + \widetilde{H}^2 + \widetilde{H}^3\right), \tag{10}$$

$$\widetilde{t}_{ij} = \left(l_{ij}^{t}.m_{ij}^{t}.u_{ij}^{t}\right), \tag{11}$$

$$\left[l_{ij}^{t}\right] = H_l \times (I - H_l)^{-1}, \tag{12}$$

$$\left[m_{ij}^{t}\right] = H_m \times (I - H_m)^{-1}, \tag{13}$$

$$\left[u_{ij}^{t}\right] = H_u \times (I - H_u)^{-1}. \tag{14}$$

(d) Defuzzying the total-relation fuzzy matrix base on Equation (15)

$$t_{ij} = \frac{l_{ij}^{t} + 2m_{ij}^{t} + u_{ij}^{t}}{4}. \tag{15}$$

(e) Measuring the D-value and R-value based on extracted variables from the total-relation defuzzied matrix base on Equations (16) and (17):

$$D = \sum_{J=1}^{n} t_{ij}.(j = 1, 2, 3, \ldots, n), \tag{16}$$

$$R = \sum_{i=1}^{n} t_{ij}.(i = 1, 2, 3, \ldots, n). \tag{17}$$

To do so, the elements of each row (Di) and each column (Ri) were totaled out of the total-relation defuzzied matrix. The total number of elements in each row (D) for each factor shows the degree to which that factor affects other factors in the system. On the contrary, the total number of elements in each column (R) for each factor shows the degree to which that factor is affected by other factors in the system.

(f) In the end, D and R values were used to measure D + R and D − R values.

The D + R values show how much one factor affects and is affected by other factors. In other words, the higher the D + R value, the more interaction between the factor and other factors in a system. On the other hand, D − R values show how strongly one factor affects other factors in a system. In general, if D − R is positive, the variable is considered a cause variable, and if it is negative, it is considered an effect variable. After defuzzying numbers, a Cartesian coordinate system is drawn in which the *x*-axis shows D + R values, and the *y*-axis shows D − R values.

4. Results

First, the relevant literature on DE and human error variables was reviewed, and important variables were identified and extracted. These variables were then screened by experts and categorized into five factors: organizational, external, environmental, task, and individual.

4.1. Ranking Variables Affecting DE Based on the Fuzzy Delphi Method

After specifying effective variables, the two phases of the Fuzzy Delphi study were carried out to reach a consensus among experts. Accordingly, the semi-closed questionnaire with Likert-scale items was developed and given to the experts. After collecting the questionnaires, the mean triangular fuzzy value and defuzzied value were measured for each of the phases based on Equations (1)–(3). Table 3 shows the absolute mean of experts' agreement corresponding to the importance of each factor. The results revealed that the following variables strongly affected human error in mine design: technical knowledge (designing and safety), poor organizational management, resource allocation (hardware and software), and experience. Environmental factors, noise, indoor air quality in the workplace, and lighting exerted the strongest effects on DE.

As for task factors, mental workload, multitasking in designing projects, and an unclear work process strongly influenced DE. Finally, technical knowledge, experience, and depression were the most effective individual factors. Poor organizational management, resource allocation (hardware and software), and a safe design culture were the most effective organizational factors.

Table 3. Selected variables of the Fuzzy Delphi study for cause-and-effect analysis.

Subgroup	Identification Code	Variable	Defuzzied Number
Individual variable	Va1	Technical knowledge (safety and designing)	0.81
	Va2	Experience	0.78
	Va3	Depression	0.74
	Va4	Motive	0.72
	Va5	Self-confidence	0.72
	Va6	Financial satisfaction	0.72
	Va7	Stress	0.71
	Va8	Intelligence coefficient	0.71
	Va9	Fatigue	0.70
Task variables	Va10	Unclear work process	0.76
	Va11	Multitasking	0.70
	Va12	Workload	0.70
Environmental variables	Va13	Noise	0.73
	Va14	Poor indoor air quality	0.72
	Va15	Inappropriate lighting	0.71
Organizational variables	Va16	Poor management	0.81
	Va17	Resource allocation	0.79
	Va18	Safe designing culture	0.73
	Va19	Training	0.71

4.2. Determining Cause-and-Effect Relationships among Variables Affecting DE (CF)

In this phase, variables with an influencing score of 0.7 and higher were screened from each variable group (individual, organizational, external, task, and environmental) and given to the experts in the form of a pairwise-matrix questionnaire analyzed for cause-and-effect relationships. Table A1 demonstrates the list of variables selected for the Fuzzy DEMATEL study. After collecting expert opinions regarding the effects of variables on each other, the mean of opinions was acquired by forming the direct-relation fuzzy matrix. Next, the normalized direct-relation matrix was formed, followed by the total-relation matrix (Appendix B). The variables in each row were added to measure the D value (Figure 2), and the variables in each column were added to measure the R-value (Figure 3); eventually, using D and R values, the interaction of variables (D + R) or dominance matrix (Figure 4) and the relationship among variables or the influence of variables and their pure influenceability (D − R) or relationship matrix (Figure 5) were determined. Factors with a positive D − R relationship were considered effective (causes) and those with a negative D − R relationship were considered affected (effects).

Based on D + R values, unclear work process, CF, multitasking, and fatigue had the highest level of interaction with other variables; on the contrary, poor indoor air quality, inappropriate lighting, and noise had the lowest level of interaction with other variables. According to D − R values, poor organizational management, resource allocation (hardware and software), training level, and experience were the most effective variables respectively, less influenced by other variables. In other words, these variables had a strong guiding power with minor dependence on other variables. Thus, if these variables are fortified, failures in cognitive function are reduced, leading to a significant decrease in design errors. On the other hand, CF, self-confidence, depression, and motive were the most affected variables (effects) respectively, more affected by other cause variables.

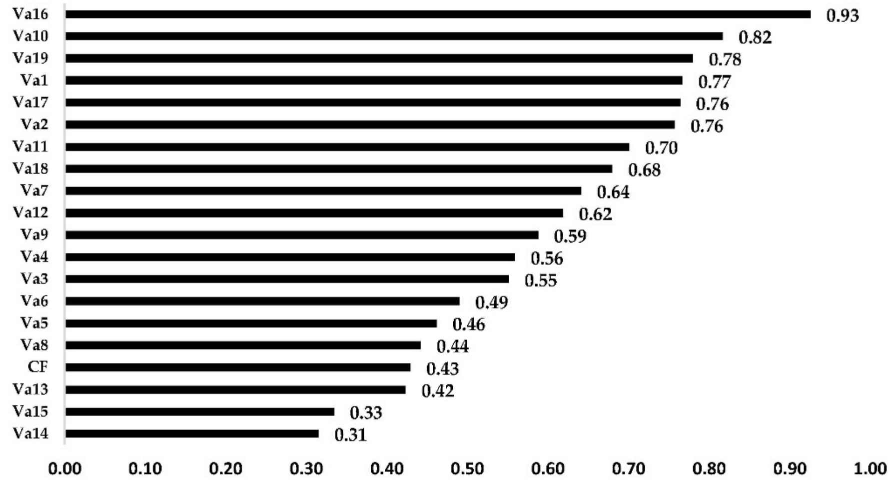

Figure 2. Influence of variable on other variables (D values).

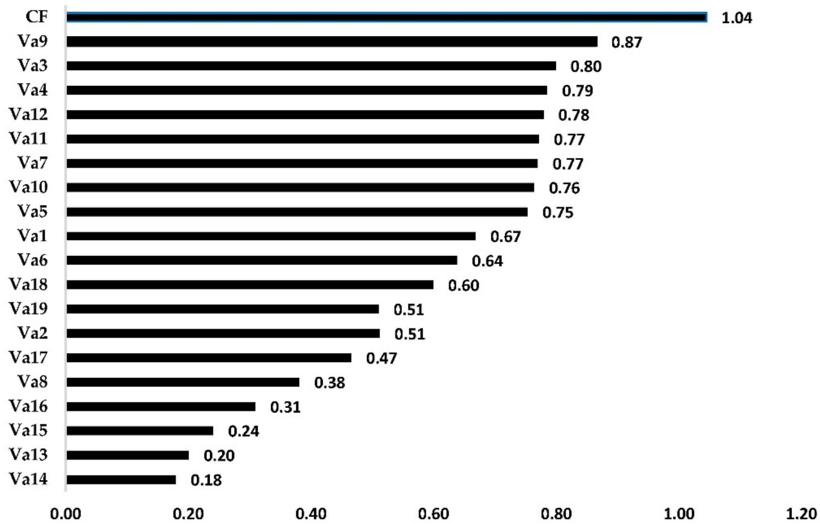

Figure 3. Influenced impact index variables (R values).

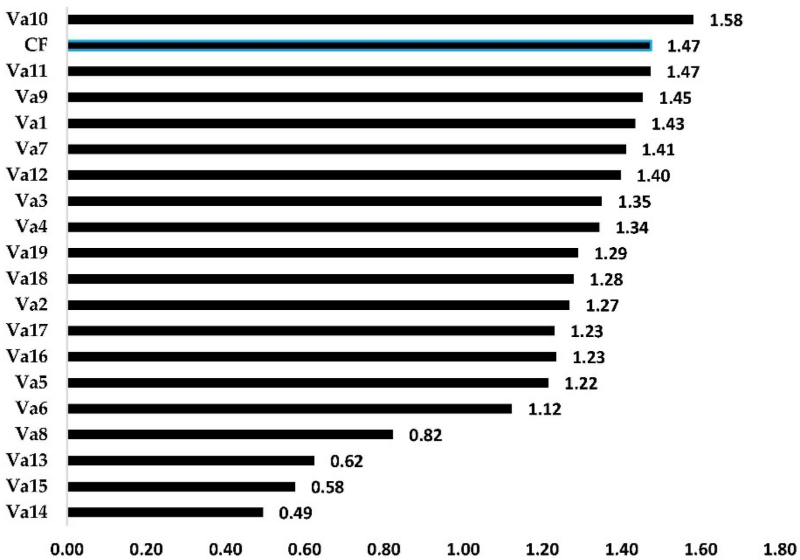

Figure 4. Interaction among variables (D + R values).

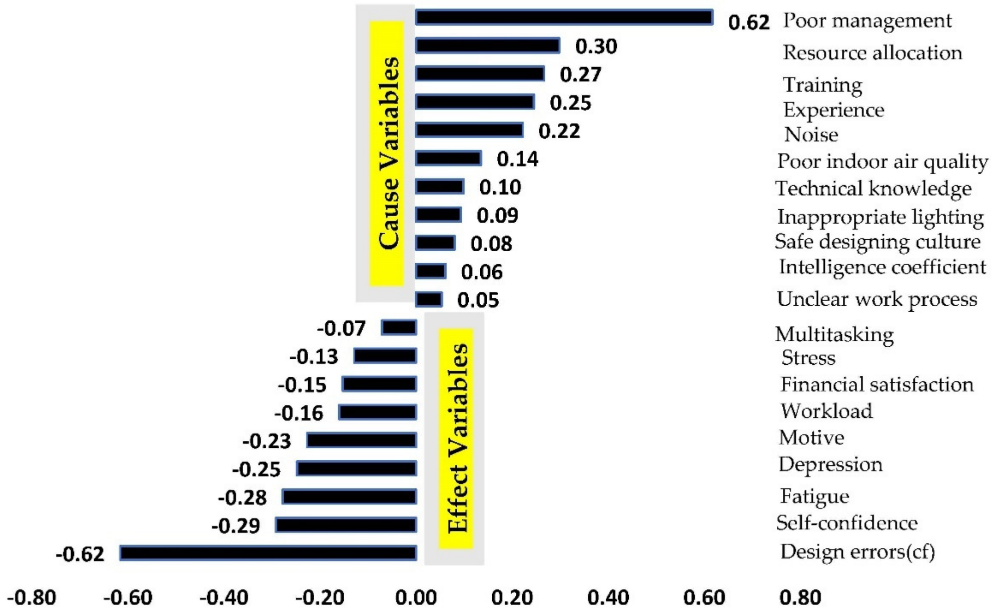

Figure 5. Cause-and-effect roles of the variables (D–R values).

According to the results of the cause-and-effect relationships presented in Figure 6, the variables of the study can be divided into four groups located in four different zones. The first group of cause (influencing) variables included poor organizational management, resource allocation (hardware and software), training, experience, technical knowledge (safety and designing), safe designing culture, and unclear work process. The second cause variables included noise, poor indoor air quality, and lighting. The third and fourth groups of variables were under the D + R axis including effect (influenced) variables. Financial satisfaction was the only variables present in this zone.

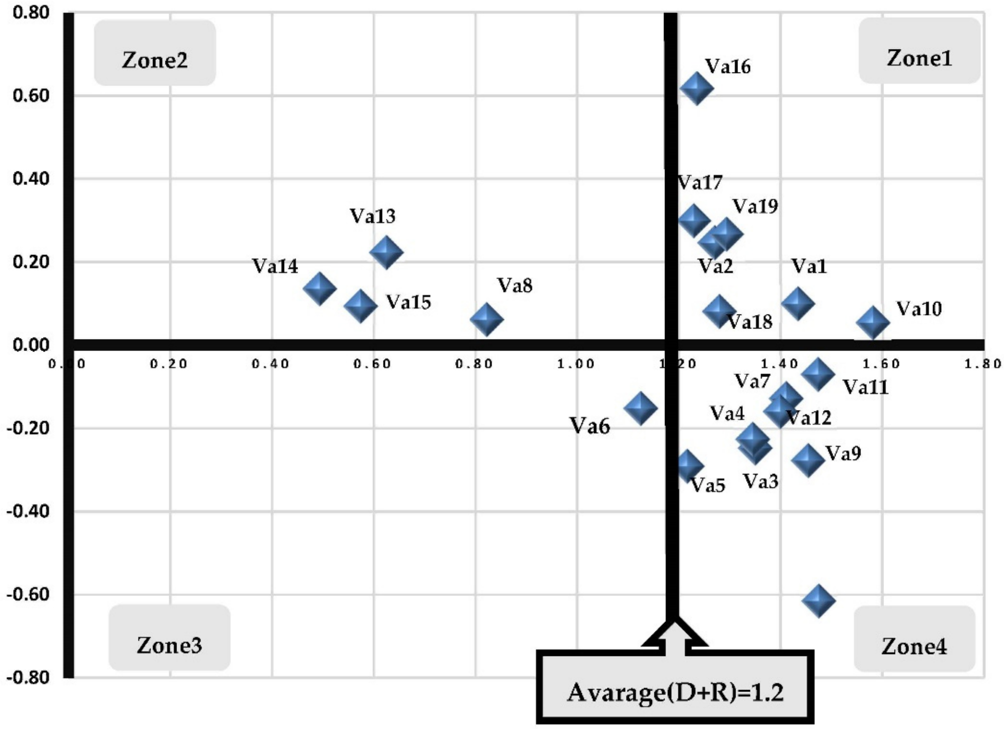

Figure 6. Cause-and-effect relationships among the variables.

This variable was affected by the variables of Zone 1 and Zone 2 but influenced variables of the fourth group. The fourth zone, however, as the most important group of effect variables, included CF, self-confidence, fatigue, depression, motive, workload, stress, and multitasking. Generally, to improve CF and reduce design errors, it is better to implement measures that consider Zone 1 variables followed by Zone 2 variables. If problems persist, the variable of Zone 3 needs to be considered. Zone 4 variables are the variables that are under the influence of variables present in previous zones, and thus no direct corrective action is performed for them. The study results demonstrate that environmental variables as one type of cause variables were the weakest variables in terms of affecting and being affected by other variables. In contrast, organizational variables were the strongest variables in terms of affecting other variables, showing that they are the most important variables affecting DE.

5. Discussion

In accordance with our findings, previous research also shows that organizational factors are one of the most important causes of DE [12,22]. Dedy et al. [67] named lack of training/education (training about design), poor resourcing, poor strategy and leadership, poor management, and lack of professionalism as the organizational factors affecting DE in construction projects. The results of Hafezi's study showed that organizational factors such as lack of training program for designers and poor use of technology had the highest priority in issues related to related to DE [68]. The results of Cho's study also revealed that poor management and lack of standard processes were the main organizational factors of DE [69]. Moreover, many studies focusing on human error have emphasized organizational factors, particularly management obligation [70–72], resource allocation [73], and safety culture [74].

The results of this study demonstrated that technical knowledge and experience were located in Zone 1; thus, these individual variables are the root cause of DE in surface mines. Similarly, the results of the study by Philemon et al. [75] showed that the lack of knowledge and experience of the design team was the most effective personal factor leading to DE and omission in construction projects in Tanzania. Lopez et al. also believe that employing inexperienced designers with low technical knowledge and engaging underqualified designers in important design projects are the main causes of DE in organizations [12]. Technical knowledge of designing, quality and quantity of training, and experience [76] are personal variables that can strongly affect cognitive function, especially in the early stages of detecting, noticing, understanding, and sense-making processes [77]. These two criteria are the most significant factors influencing cognitive function [78]. Continuous and adequate training and using experienced instructors are highly effective for preventing and controlling human errors on the one hand and reducing the risk of accidents on the other [79].

Environmental parameters such as noise, lighting, and indoor air quality were categorized into Zone 2 in this study, belonging to independent (cause) variables that could influence Zone 3 and Zone 4. To the researchers' knowledge, this important factor has been overlooked in DE studies. These factors can negatively influence the physiological balance of the human body; cognitive performance can cause stress, fatigue, depression, and workload, which in turn can result in the loss of focus and more human error [80,81]. Noise exposure can act as a stressor and increase mental workload, eventually impairing the mental performance required for one's responsibilities [82,83]. Noise can also lead to fatigue [84], significantly affecting one's performance while performing complex tasks requiring mental processing [85,86]. Appropriate lighting improves awareness and cognitive performance [87]. On the other hand, inappropriate lighting can result in depression, mental boredom, and sleep quality [88]. Research shows that indoor air quality in the workplace influences cognitive performance as chemical pollutants in the air, such as particles, and high levels of carbon dioxide in the air detrimentally affect cognitive performance [89].

Another dependent (effect) variable is financial satisfaction (Zone 3), which can affect a lot of variables in group 4, particularly cognitive function. For example, Tilley and McFallen conducted a study on Australian designers. They reported that most designers believed their payment was low despite their challenging job, which could eventually influence the quality of their designing performance [90]. Based on the study by Vaiana et al. [91], the contractor's lack of payment and inadequate cash flow was an important factor in increasing DE and accidents in Design and Build Projects in Malaysia. Financial dissatisfaction can demotivate designers, and low payments suggested by organizations can pave the way for inexperienced designers to take responsibility for important projects, increasing the risk of errors [12]. As for the fourth group of variables, the most important dependent (Zone 4) variables were located in this group, with the designer's cognitive function as the variable highly influenced by others. Other variables in this group, such as fatigue and depression, can also affect DE. From a cognitive point of view, chronic fatigue can lead to a decrease in the information processing capabilities of workers and designers and thus result in delayed reaction time, reduction in the field of vision, carelessness, unawareness, and lack of focus. Therefore, fatigue resulting from physical tiredness or insomnia negatively impacts cognitive resources and awareness [92]. Research shows that cognitive dissonance and well-being were the most important man factor of DE in the oil and gas industry [67]. Another variable belonging to Zone 4 was the workload. The increased workload can reduce mental health and stress, leading to cognitive overload, failures in cognitive performance, and increased human error [93,94]. Failures in cognitive function forge an important link between factors affecting performance and human error [26,95]. Thus, individual, environmental, task and organizational factors exert direct and indirect effects (fatigue, stress, demotivation, etc.) on the designer's cognitive function and lead to DEs eventually.

The comparison of the results of the abovementioned studies with the current study highlights some conflicting issues:

- Previous DE studies have focused on consequences such as rework, safety, and cost. Still, in mines, due to the diversity and wide operating spaces of the mines and the type and volume of equipment used, these consequences can be very significant. It can also have environmental, social, cultural, political, security and public health effects. Therefore, the role of design errors in this section is much more prominent than in other sections;
- Past studies focus only on identifying and categorizing the factors affecting design error. Still, in the present study, in addition to identifying and categorizing these factors, their relationships are also defined within a cause-and-effect model. This model aids decision-makers in focusing on the most important risks in mine design projects.

Based on the presented results, DE is one of the most important threats to sustainable development in mines. Therefore, identifying and prioritizing the factors affecting such errors is vital due to the financial and time constraints of organizations in eliminating and controlling them. This research proposes a comprehensive approach to managing design error in mines that, in addition to covering the existing theoretical gaps such as the lack of a comprehensive study in the field of design error and its factors affecting mines, provides important practical recommendations at all levels of the organization, especially for top management and mine safety experts. Concerning the findings of this study, inherently safe design culture, hardware and software resources, and individual factors such as insufficient experience and knowledge are the root causes of errors in mine design. Meanwhile, the role of top management is very important in developing, leading, and promoting an inherently safe design culture in the organization. The top management should be allocating the resources needed (hardware and software) to control errors in the design process, ensuring that engineers and designers are competent based on appropriate education, training, or experience, providing a safe and comfortable work environment based on ergonomic standards, and trying to improve the level of job satisfaction and motivation of the design team. In addition, based on the results, mining safety experts should pay special attention to design errors and predict the required resources in establishing objectives and planning to achieve them. They can reduce variables such as job stress, depression, and fatigue, and improve the designer's cognitive functions by conducting safe design training courses, implementing risk management and ergonomic programs, and monitoring physical factors in the workplace such as lighting and noise thermal comfort parameters. Moreover, the study can help legal organizations in mining safety to understand the nature of accidents and formulate strategic policies to implement safe design rules in the mining sector.

6. Conclusions and Future Research

Design error (DE), a latent human error, is a key factor behind many occupational accidents. Limited research, however, has been carried out investigating the relationship between the causes of human error and relevant negative consequences. This phenomenon is important, especially for the Iranian mining sector, which holds 7% of the mineral recourses in the world. Therefore, this study aimed to identify the most significant variables influencing surface mine designers' performance and investigate their cause-and-effect relationships. For this purpose, common effective factors were taken from the literature review and screened by the experts. One MCDM methodology, Fuzzy DEMATEL, was applied to investigate the relationships among variables and develop a cause-and-effect model. The results revealed that environmental variables (noise, lighting, and indoor air quality) had the weakest effects on other variables and were least affected by other ones; based on the cause-and-effect relationships model, it can be concluded that 'organizational factors' are vital for the DE control plan within the mining industry due to their effect on other factors.

Nevertheless, it should be noted that individual variables like training, experience, and technical knowledge were also found to influence DE. Similar to other studies, this study faced some limitations; therefore, this work can be extended in future studies. The most noticeable limitation is that the study is one of the first to study the most significant variables affecting DE in surface mines with the abovementioned methods. Hence it is not easy to generalize the findings to other industries. However, future studies may extend the research to different industries. In this study, the empirical analysis of the cause-and-effect relationship among variables was not conducted. For future research, empirical studies can be carried out to confirm the structural relationships found in the model. This study only investigated 19 variables, which are not exhaustive. More research should be conducted to determine the relationship between variables. Therefore, it is proposed that further studies should be done, focusing more on MCDM and new tools and approaches such as intuitionistic fuzzy set [96], type-2 fuzzy variable [97], and Rough interval [98], considering the challenges and control strategies for reaching a consensus via a group decision-making process [99,100]. In conclusion, the findings of this study can improve the status of health and environmental indicators and help achieve sustainable development goals in surface mines by identifying and prioritizing factors influencing DE and recommending practical solutions to eliminate and control such errors.

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Appendix A

Table A1. The Results of the Fuzzy Delphi Study Regarding the Rank of Variables Affecting DEs.

Subgroup	Variable
Individual factors	Technical knowledge (safety and designing)(0.81), Experience (0.78), Depression (0.73), Self-confidence (0.72), Financial satisfaction (0.72), Stress level (0.71), Intelligence coefficient (0.71), Work adaptation (0.69), Designing style (0.67), Fear of failure (0.65), Risk-taking (0.64), Understanding roles and responsibilities (0.62), Quality and quantity of sleep (0.62), Circadian rhythm (0.62), Risk Perception (0.61), Nutrition (0.52), Determinism (0.49), Disappointment (0.49), Personality type (0.35), Age (0.32), Lack of trust in performance (0.28), Gender (0.28).
Task factors	Workload (0.7), Multitasking (0.7), Time pressure (0.68), Instructions and procedure (0.67), Quality of human–system interaction (0.67), Lack of job security (0.65), Task complexity (0.62), Work posture (0.61), Work innovation (0.56), Freedom at work (0.55), Physical workplace (design) (0.51).
Organizational factors	Poor management (0.81), Resource allocation (0.79), Training (0.71), Employees' sense of belonging (0.69), Supervision level (0.63), Agreement between available and required information (0.62), Designers' sense of belonging (0.61).
Environmental factors	Noise (0.73), Poor indoor air quality (0. 0.72), Inappropriate lighting (0.71), Air circulation velocity (0.57), Hotness and coldness (0.56), Moisture (0.54), Radiation exposure (0.21).
External factors	Legal pressure (0.68), Conflict between work and family (0.51).

Appendix B

Table A2. Defuzzied Total-Relation Matrix.

CF	Va19	Va18	Va17	Va16	Va15	Va14	Va13	Va12	Va11	Va10	Va9	Va8	Va7	Va6	Va5	Va4	Va3	Va2	Va1	
0.07	0.05	0.06	0.04	0.02	0.02	0.01	0.01	0.05	0.06	0.03	0.05	0.02	0.05	0.04	0.05	0.05	0.04	0.04	0.02	Va1
0.06	0.05	0.05	0.03	0.01	0.01	0.01	0.01	0.05	0.06	0.03	0.05	0.03	0.05	0.03	0.07	0.04	0.04	0.01	0.05	Va2
0.05	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.04	0.03	0.02	0.04	0.02	0.03	0.02	0.05	0.05	0.03	0.02	0.03	Va3
0.05	0.03	0.03	0.02	0.02	0.01	0.01	0.01	0.05	0.03	0.02	0.05	0.02	0.03	0.03	0.04	0.02	0.02	0.03	0.04	Va4
0.05	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.03	0.04	0.02	0.03	0.03	0.03	0.02	0.01	0.03	0.03	0.02	0.03	Va5
0.06	0.02	0.06	0.04	0.05	0.01	0.01	0.01	0.05	0.06	0.05	0.04	0.03	0.04	0.02	0.05	0.05	0.04	0.05	0.06	Va6
0.06	0.04	0.02	0.01	0.01	0.02	0.01	0.01	0.05	0.06	0.03	0.06	0.03	0.02	0.03	0.04	0.05	0.05	0.02	0.03	Va7
0.04	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.02	0.03	0.01	0.02	0.03	0.04	0.03	0.03	0.03	0.03	Va8
0.06	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.04	0.05	0.03	0.02	0.02	0.05	0.03	0.03	0.04	0.05	0.03	0.05	Va9
0.05	0.03	0.05	0.03	0.01	0.01	0.01	0.01	0.04	0.03	0.26	0.06	0.02	0.04	0.02	0.03	0.03	0.03	0.02	0.03	Va10
0.06	0.05	0.03	0.03	0.01	0.01	0.01	0.01	0.06	0.02	0.03	0.06	0.03	0.06	0.04	0.05	0.05	0.05	0.03	0.04	Va11
0.05	0.03	0.03	0.03	0.01	0.01	0.01	0.01	0.02	0.06	0.02	0.04	0.02	0.05	0.02	0.04	0.05	0.05	0.03	0.04	Va12
0.04	0.02	0.01	0.01	0.01	0.01	0.01	0	0.04	0.02	0.01	0.04	0.01	0.04	0.02	0.03	0.04	0.04	0.02	0.02	Va13
0.03	0.01	0.01	0.01	0.01	0.01	0	0.01	0.02	0.01	0.01	0.04	0.01	0.02	0.01	0.01	0.02	0.03	0.01	0.01	Va14
0.04	0.02	0.01	0.01	0.01	0	0.01	0.01	0.03	0.01	0.01	0.04	0.01	0.03	0.02	0.02	0.02	0.03	0.01	0.01	Va15
0.07	0.07	0.06	0.06	0.01	0.02	0.02	0.03	0.05	0.05	0.05	0.06	0.02	0.06	0.04	0.05	0.06	0.06	0.04	0.06	Va16
0.07	0.04	0.06	0.01	0.01	0.02	0.02	0.02	0.05	0.03	0.04	0.05	0.02	0.05	0.03	0.05	0.06	0.06	0.03	0.05	Va17
0.06	0.04	0.02	0.05	0.05	0.02	0.01	0.02	0.03	0.03	0.04	0.04	0.01	0.03	0.03	0.03	0.04	0.04	0.03	0.05	Va18
0.04	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.04	0.03	0.02	0.02	0.02	0.04	0.02	0.04	0.05	0.04	0.02	0.02	V19
0.02	0.03	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.05	0.02	0.04	0.01	0.04	0.03	0.02	0.02	0.02	0.02	0.02	CF

References

1. Kumar, P.; Gupta, S.; Agarwal, M.; Singh, U. Categorization and standardization of accidental risk-criticality levels of human error to develop risk and safety management policy. *Saf. Sci.* **2016**, *85*, 88–98. [CrossRef]
2. Aliabadi, M.M.; Mohammadfam, I.; Soltanian, A.R.; Najafi, K. Human Error Probability Determination in Blasting Process of Ore Mine Using a Hybrid of HEART and Best-Worst Methods. *Saf. Health Work* 2022, *in press*.
3. Permana, H. Risk Assessment as a Strategy to Prevent of Mine Accidents in Indonesian Mining. *Rev. Min. Min. Rev.* **2012**, *18*, 43–49.
4. Onder, S.; Mutlu, M. Analyses of non-fatal accidents in an opencast mine by logistic regression model–a case study. *Int. J. Inj. Control Saf. Promot.* **2017**, *24*, 328–337. [CrossRef]
5. Mojarradi, G.; Rezaei, R.; Ketabi, A. Negative impacts of mine exploitations on rural regions of Tekab Township. *J. Min. Environ.* **2016**, *7*, 57–66.
6. Aliabadi, M.M.; Aghaei, H.; Kalatpour, O.; Soltanian, A.R.; Nikravesh, A. Analysis of human and organizational factors that influence mining accidents based on Bayesian network. *Int. J. Occup. Saf. Ergon.* **2020**, *26*, 670–677. [CrossRef]
7. Floris, L.M.; Carvalho, E.G.; Faustino, B.C.R.; Calegario, C.L.L. Workplace Accidents as a Consequence of Human Error: An Empirical Study in a Gold Mine/Os Acidentes de Trabalho como Consequência dos Erros Humanos: Um Estudo de Caso em uma Mina de Ouro no Brasil. *Rev. FSA Cent. Univ. St. Agostinho* **2021**, *18*, 74–99.
8. Kim, S.; Wallace, K.M. Identifying Design Errors and Human Errors Using Automatic Classifications. In Proceedings of the ICED 2007, the 16th International Conference on Engineering Design, Paris, France, 28–31 July 2007; pp. 439–440.
9. Salvendy, G.; Karwowski, W. *Handbook of Human Factors and Ergonomics*; John Wiley & Sons: Hoboken, NJ, USA, 2021.
10. Liao, P.-C.; Luo, X.; Wang, T.; Su, Y. The mechanism of how design failures cause unsafe behavior: The cognitive reliability and error analysis method (CREAM). *Procedia Eng.* **2016**, *145*, 715–722. [CrossRef]
11. Peansupap, V.; Ly, R. Evaluating the impact level of design errors in structural and other building components in building construction projects in Cambodia. *Procedia Eng.* **2015**, *123*, 370–378. [CrossRef]
12. Lopez, R.; Love, P.E.; Edwards, D.J.; Davis, P.R. Design error classification, causation, and prevention in construction engineering. *J. Perform. Constr. Facil.* **2010**, *24*, 399–408. [CrossRef]
13. Zhefeng, J.; Dayong, D.; Yinbo, Z.; Hua, M. Design and Evaluation Methodology for Cockpit Human Factor of Civil Transport Aircraft. In Proceedings of the International Conference on Applied Human Factors and Ergonomics, Washton, DC, USA, 24–28 July 2019; pp. 269–275.
14. Stevenson, J.D. An estimate and evaluation of design error effects on nuclear power plant design adequacy. In *Structural Engineering in Nuclear Facilities*; Springer: Berlin/Heidelberg, Germany, 1984; Volume 2.
15. Taylor, J.R. *Human Error in Process Plant Design and Operations: A Practitioner's Guide*; CRC Press: Boca Raton, FL, USA, 2016.
16. Danko, G. Quality evaluation and error mitigation for mine climate models. *Calitatea* **2019**, *20*, 123.
17. Lööw, J.; Johansson, B.; Andersson, E. *Designing the Safe and Attractive Mine*; Luleå Tekniska Universitet: Luleå, Sweden, 2016.
18. Stacey, T. The importance of engineering design with regard to safety in mining. In Proceedings of the Hard Rock Safe Safety Conference, Sun City, South Africa, 28 September 2009.
19. Thompson, R. Mine haul road design and management best practices for safe and cost-efficient truck haulage. In Proceedings of the Society for Mining, Metallurgy and Exploration 2010 Conference Proceedings, Lexington, KY, USA, 26–29 April 2010; pp. 1–10.
20. Norouzi Masir, R.; Ataei, M.; Mottahedi, A. Risk assessment of Flyrock in Surface Mines using a FFTA-MCDM Combination. *J. Min. Environ.* **2021**, *12*, 191–203.
21. Reason, J. *Managing the Risks of Organizational Accidents*; Ashgate Publishing: Farnham, UK, 1997.
22. Kustola, K. Mitigating Design Error Root-Causes in Product Development. 2018. Available online: https://publications.lib.chalmers.se/records/fulltext/255252/255252.pdf (accessed on 29 June 2022).
23. Melchers, R. Human error in structural reliability assessments. *Reliab. Eng.* **1984**, *7*, 61–75. [CrossRef]
24. Fang, D.; Jiang, Z.; Zhang, M.; Wang, H. An experimental method to study the effect of fatigue on construction workers' safety performance. *Saf. Sci.* **2015**, *73*, 80–91. [CrossRef]
25. Smidts, C.; Shen, S.; Mosleh, A. The IDA cognitive model for the analysis of nuclear power plant operator response under accident conditions. Part I: Problem solving and decision making model. *Reliab. Eng. Syst. Saf.* **1997**, *55*, 51–71. [CrossRef]
26. Ekanem, N.J.; Mosleh, A.; Shen, S.-H. Phoenix–a model-based human reliability analysis methodology: Qualitative analysis procedure. *Reliab. Eng. Syst. Saf.* **2016**, *145*, 301–315. [CrossRef]
27. Mohammadfam, I.; Aliabadi, M.M.; Soltanian, A.R.; Mahdinia, M. Modeling the causes-effect relationships among major accident predictors based on a fuzzy multi-criteria decision-making method. *Work* **2020**, *67*, 313–321. [CrossRef]
28. Al Hattab, M.; Hamzeh, F. Using social network theory and simulation to compare traditional versus BIM–lean practice for design error management. *Autom. Constr.* **2015**, *52*, 59–69. [CrossRef]
29. Taylor, J.R. Statistics of design error in the process industries. *Saf. Sci.* **2007**, *45*, 61–73. [CrossRef]
30. Zhaorong, W.; Zekavat, P.; Moon, S.; Tang, L.; Sherif, M. Investigating The Root Cause Of Legal Disputes Over Defective Construction In Proceedings of the 43rd AUBEA: Australasian Universities Building Education Association Conference Proceedings, Noosa, QLD, Australia, 6–8 November 2019; RACV Noosa Resort.

31. Islam, R.; Khan, F.; Abbassi, R.; Garaniya, V. Human error assessment during maintenance operations of marine systems–What are the effective environmental factors? *Saf. Sci.* **2018**, *107*, 85–98. [CrossRef]
32. Athar, M.; Shariff, A.A.; Buang, A.; Shaikh, M.S.; Khan, M.I. Review of process industry accidents analysis towards safety system improvement and sustainable process design. *Chem. Eng. Technol.* **2019**, *42*, 524–538. [CrossRef]
33. Wudhikarn, R. Improving the intellectual capital management approach using the hybrid decision method. *J. Intellect. Cap.* **2018**, *19*, 670–691. [CrossRef]
34. Ebrahimnezhad, S.; Gitinavard, H.; Sohrabvandi, S. A new extended analytical hierarchy process technique with incomplete interval-valued information for risk assessment in IT outsourcing. *Int. J. Eng.* **2017**, *30*, 739–748.
35. Wudhikarn, R.; Chakpitak, N.; Neubert, G. Improving the strategic benchmarking of intellectual capital management in logistics service providers. *Sustainability* **2020**, *12*, 10174. [CrossRef]
36. Wudhikarn, R.; Chakpitak, N.; Neubert, G. Use of an analytic network process and Monte Carlo analysis in new product formula selection decisions. *Asia-Pac. J. Oper. Res.* **2015**, *32*, 1550007. [CrossRef]
37. Kumar, A.; Kaviani, M.A.; Bottani, E.; Dash, M.K.; Zavadskas, E.K. Investigating the role of social media in polio prevention in India: A Delphi-DEMATEL approach. *Kybernetes* **2018**, *47*, 1053–1072. [CrossRef]
38. Mohandes, S.R.; Sadeghi, H.; Fazeli, A.; Mahdiyar, A.; Hosseini, M.R.; Arashpour, M.; Zayed, T. Causal analysis of accidents on construction sites: A hybrid fuzzy Delphi and DEMATEL approach. *Saf. Sci.* **2022**, *151*, 105730. [CrossRef]
39. Thakur, V.; Mangla, S.K.; Tiwari, B. Managing healthcare waste for sustainable environmental development: A hybrid decision approach. *Bus. Strategy Environ.* **2021**, *30*, 357–373. [CrossRef]
40. Lu, M.; Wudhikarn, R. Using the best-worst method to develop intellectual capital indicators in financial service company. In Proceedings of the 2022 Joint International Conference on Digital Arts, Media and Technology with ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI DAMT & NCON), Chiang Rai, Thailand, 26–28 January 2022; pp. 81–86.
41. Mohammadfam, I.; Aliabadi, M.M.; Soltanian, A.R.; Tabibzadeh, M.; Mahdinia, M. Investigating interactions among vital variables affecting situation awareness based on Fuzzy DEMATEL method. *Int. J. Ind. Ergon.* **2019**, *74*, 102842. [CrossRef]
42. Kumar, A.; Pal, A.; Vohra, A.; Gupta, S.; Manchanda, S.; Dash, M.K. Construction of capital procurement decision making model to optimize supplier selection using Fuzzy Delphi and AHP-DEMATEL. *Benchmarking Int. J.* **2018**, *25*, 1528–1547. [CrossRef]
43. Quiñones, R.S.; Caladcad, J.A.A.; Himang, C.M.; Quiñones, H.G.; Castro, C.J.; Caballes, S.A.A.; Abellana, D.P.M.; Jabilles, E.M.Y.; Ocampo, L.A. Using Delphi and fuzzy DEMATEL for analyzing the intertwined relationships of the barriers of university technology transfer: Evidence from a developing economy. *Int. J. Innov. Stud.* **2020**, *4*, 85–104. [CrossRef]
44. Singh, P.K.; Sarkar, P. A framework based on fuzzy Delphi and DEMATEL for sustainable product development: A case of Indian automotive industry. *J. Clean. Prod.* **2020**, *246*, 118991. [CrossRef]
45. Häder, M.; Häder, S. Delphi und Kognitionspsychologie: Ein Zugang zur theoretischen Fundierung der Delphi-Methode. *ZUMA Nachr.* **1995**, *19*, 8–34.
46. Azar, A.; Faraji, H. *Fuzzy Management Science*; Institute Mehraban book publisher: Tehran, Iran, 2010.
47. Zhou, Q.; Huang, W.; Zhang, Y. Identifying critical success factors in emergency management using a fuzzy DEMATEL method. *Saf. Sci.* **2011**, *49*, 243–252. [CrossRef]
48. Murray, T.J.; Pipino, L.L.; Van Gigch, J.P. A pilot study of fuzzy set modification of Delphi. *Hum. Syst. Manag.* **1985**, *5*, 76–80. [CrossRef]
49. Kuo, Y.-F.; Chen, P.-C. Constructing performance appraisal indicators for mobility of the service industries using Fuzzy Delphi Method. *Expert Syst. Appl.* **2008**, *35*, 1930–1939. [CrossRef]
50. Bavafa, A.; Mahdiyar, A.; Marsono, A.K. Identifying and assessing the critical factors for effective implementation of safety programs in construction projects. *Saf. Sci.* **2018**, *106*, 47–56. [CrossRef]
51. Cheng, C.-H.; Lin, Y. Evaluating the best main battle tank using fuzzy decision theory with linguistic criteria evaluation. *Eur. J. Oper. Res.* **2002**, *142*, 174–186. [CrossRef]
52. Wang, F. Preference degree of triangular fuzzy numbers and its application to multi-attribute group decision making. *Expert Syst. Appl.* **2021**, *178*, 114982. [CrossRef]
53. Zhang, X.; Ma, W.; Chen, L. New similarity of triangular fuzzy number and its application. *Sci. World J.* **2014**, *2014*, 1–7.
54. Li, R.-J. Fuzzy method in group decision making. *Comput. Math. Appl.* **1999**, *38*, 91–101. [CrossRef]
55. Hsu, Y.-L.; Lee, C.-H.; Kreng, V.B. The application of Fuzzy Delphi Method and Fuzzy AHP in lubricant regenerative technology selection. *Expert Syst. Appl.* **2010**, *37*, 419–425. [CrossRef]
56. Cafiso, S.; Di Graziano, A.; Pappalardo, G. Using the Delphi method to evaluate opinions of public transport managers on bus safety. *Saf. Sci.* **2013**, *57*, 254–263. [CrossRef]
57. Kosmidou, K. The determinants of banks' profits in Greece during the period of EU financial integration. *Manag. Financ.* **2008**, *34*, 146–159.
58. Saraswathi, A. A fuzzy-trapezoidal DEMATEL approach method for solving decision making problems under uncertainty. In Proceedings of the AIP Conference Proceedings, Chennai, India, 8–10 April 2019; p. 020076.
59. Wu, W.-W.; Lee, Y.-T. Developing global managers' competencies using the fuzzy DEMATEL method. *Expert Syst. Appl.* **2007**, *32*, 499–507. [CrossRef]

60. Li, Y.; Hu, Y.; Zhang, X.; Deng, Y.; Mahadevan, S. An evidential DEMATEL method to identify critical success factors in emergency management. *Appl. Soft Comput.* **2014**, *22*, 504–510. [CrossRef]
61. Yazdi, M.; Nedjati, A.; Zarei, E.; Abbassi, R. A novel extension of DEMATEL approach for probabilistic safety analysis in process systems. *Saf. Sci.* **2020**, *121*, 119–136. [CrossRef]
62. Aghaee, M.; Aghaee, R. Selection of logistics personnel by using and hybrid Fuzzy DEMATEL and Fuzzy ANP. *Int. Res. J. Manag. Sci.* **2016**, *4*, 14–22.
63. Akyuz, E.; Celik, E. A fuzzy DEMATEL method to evaluate critical operational hazards during gas freeing process in crude oil tankers. *J. Loss Prev. Process Ind.* **2015**, *38*, 243–253. [CrossRef]
64. Gholamizadeh, K.; Zarei, E.; Omidvar, M.; Yazdi, M. Fuzzy Sets Theory and Human Reliability: Review, Applications, and Contributions. *Linguist. Methods under Fuzzy Inf. Syst. Saf. Reliab. Anal.* **2022**, *414*, 91–137.
65. Omidvar, M.; Zarei, E.; Ramavandi, B.; Yazdi, M. Fuzzy Bow-Tie Analysis: Concepts, Review, and Application. In *Linguistic Methods under Fuzzy Information in System Safety and Reliability Analysis*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 13–51.
66. Lin, R.-J. Using fuzzy DEMATEL to evaluate the green supply chain management practices. *J. Clean. Prod.* **2013**, *40*, 32–39. [CrossRef]
67. Fuadie, D.F.; Rahmawati, Y.; Utomo, C. Factors of Design Errors in Construction Project (A Review). *IPTEK J. Proc. Ser.* **2017**, *3*, 3263. [CrossRef]
68. Hafezi, M.; Hsseinalipour, M.; Ghafoori, S.P. Design Errors in Construction Projects: The Meaning, Reasons, Consequences and Solutions. *Soffeh* **2019**, *29*, 21–34. [CrossRef]
69. Chao, L.P.; Ishii, K. Design process error-proofing: Benchmarking gate and phased review life-cycle models. In Proceedings of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Long Beach, CA, USA, 24–28 September 2005; pp. 301–310.
70. Franciosi, C.; Di Pasquale, V.; Iannone, R.; Miranda, S. A taxonomy of performance shaping factors for human reliability analysis in industrial maintenance. *J. Ind. Eng. Manag.* **2019**, *12*, 115–132. [CrossRef]
71. Mohammadfam, I.; Ghasemi, F.; Kalatpour, O.; Moghimbeigi, A. Constructing a Bayesian network model for improving safety behavior of employees at workplaces. *Appl. Ergon.* **2017**, *58*, 35–47. [CrossRef] [PubMed]
72. Abbassi, R.; Khan, F.; Garaniya, V.; Chai, S.; Chin, C.; Hossain, K.A. An integrated method for human error probability assessment during the maintenance of offshore facilities. *Process Saf. Environ. Prot.* **2015**, *94*, 172–179. [CrossRef]
73. Nkosi, M.; Gupta, K.; Mashinini, M. Causes and impact of human error in maintenance of mechanical systems. In Proceedings of the MATEC Web of Conferences, Palu, Indonesia, 25–27 April 2020; p. 05001.
74. Rollenhagen, C. Can focus on safety culture become an excuse for not rethinking design of technology? *Saf. Sci.* **2010**, *48*, 268–278. [CrossRef]
75. Philemon, E.; Msomba, Z.; Samson, M.; Ramadhan, S.M. Identification of Crucial Risks Categories in Construction Projects in Tanzania. *Int. J. Eng. Res.* **2018**, *7*, 62.
76. Delikhoon, M.; Zarei, E.; Banda, O.V.; Faridan, M.; Habibi, E. Systems Thinking Accident Analysis Models: A Systematic Review for Sustainable Safety Management. *Sustainability* **2022**, *14*, 5869. [CrossRef]
77. Dhillon, B. Human error in maintenance: An investigative study for the factories of the future. In Proceedings of the IOP Conference Series: Materials Science and Engineering, London, UK, 22–24 July 2014; p. 012031.
78. Franciosi, C.; Iung, B.; Miranda, S.; Riemma, S. Maintenance for sustainability in the industry 4.0 context: A scoping literature review. *IFAC-Pap.* **2018**, *51*, 903–908. [CrossRef]
79. Andi, A.; Minato, T. Representing causal mechanism of defective designs: Exploration through case studies. *Constr. Manag. Econ.* **2004**, *22*, 183–192. [CrossRef]
80. Amiri, F.; Zamanian, Z.; Mani, A.; Hasanzadeh, J. Effects of combined exposure to noise, heat and lighting on cognitive performance. *Iran Occup. Health* **2015**, *12*, 10–20.
81. Vatanpour, S.; Hrudey, S.E.; Dinu, I. Can public health risk assessment using risk matrices be misleading? *Int. J. Environ. Res. Public Health* **2015**, *12*, 9575–9588. [CrossRef] [PubMed]
82. Szalma, J.L.; Hancock, P.A. Noise effects on human performance: A meta-analytic synthesis. *Psychol. Bull.* **2011**, *137*, 682. [CrossRef] [PubMed]
83. DiGiovanni, J.; Riffle, T.L.; Lynch, E.E.; Nagaraj, N.K. Noise characteristics and their impact on working memory and listening comprehension performance. *Acoust. Soc. Am.* **2017**, *141*, 050007. [CrossRef]
84. Beyan, A.C.; Demiral, Y.; Cimrin, A.H.; Ergor, A. Call centers and noise-induced hearing loss. *Noise Health* **2016**, *18*, 113. [CrossRef]
85. Hebb, D.O. Drives and the CNS (conceptual nervous system). *Psychol. Rev.* **1955**, *62*, 243. [CrossRef]
86. Jafari, M.J.; Sadeghian, M.; Khavanin, A.; Khodakarim, S.; Jafarpisheh, A.S. Effects of noise on mental performance and annoyance considering task difficulty level and tone components of noise. *J. Environ. Health Sci. Eng.* **2019**, *17*, 353–365. [CrossRef]
87. Asadzadeh, H.; Farokhzadeh, N.; Moghadam, Y.A. The Effect of training materials to help color and light, on the amount of attention and learning Persian language lessons in elementary school girls in the first grade in Sharoud city. *Life Sci. J.* **2013**, *10*, 246–251.
88. Pirmoradi, Z.; Golmohammadi, R.; Motamedzade, M.; Faradmal, J. Assessing lighting and color Temperature in the Office Workplaces and Relationship to Visual Comfort. *Iran Occup. Health J.* **2020**, *17*, 1–10.

89. Künn, S.; Palacios, J.; Pestel, N. Indoor Air Quality and Cognitive Performance. 2019. Available online: https://www.iza.org/publications/dp/12632/indoor-air-quality-and-cognitive-performance (accessed on 29 June 2022).
90. Efficiency, C.P. Design and Documentation Quality Survey Comparison of Designers' and Contractors' Perspectives. 2000. Available online: https://www.researchgate.net/publication/301655224_Design_and_Documentation_Quality_Survey_-_Designers_Perspective_BCE_Doc_00-113 (accessed on 29 June 2022).
91. Saaidin, S.; Endut, I.R.; Samah, A.; Akmar, S.; Ridzuan, A.R.M. Risk Factors for Design and Build Projects in Malaysia-Project Manager's Perception. *Pertanika J. Sci. Technol.* **2017**, *25*, 185–190.
92. Sneddon, A.; Mearns, K.; Flin, R. Stress, fatigue, situation awareness and safety in offshore drilling crews. *Saf. Sci.* **2013**, *56*, 80–88. [CrossRef]
93. Young, M.S.; Brookhuis, K.A.; Wickens, C.D.; Hancock, P.A. State of science: Mental workload in ergonomics. *Ergonomics* **2015**, *58*, 1–17. [CrossRef] [PubMed]
94. Mohamed, S.; Ali, T.H.; Tam, W. National culture and safe work behaviour of construction workers in Pakistan. *Saf. Sci.* **2009**, *47*, 29–35. [CrossRef]
95. Kim, Y.; Park, J. Suggestions of HRA method improvement for the practical assessment of human reliability. *J. Ergon. Soc. Korea* **2018**, *37*, 229–241.
96. Vafadarnikjoo, A.; Mobin, M.; Firouzabadi, S. An intuitionistic fuzzy-based DEMATEL to rank risks of construction projects. In Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management, Detroit, MI, USA, 23–25 September 2016.
97. Seikh, M.; Karmakar, S.; Castillo, O. A novel defuzzification approach of type-2 fuzzy variable to solving matrix games: An application to plastic ban problem. *Iran. J. Fuzzy Syst.* **2021**, *18*, 155–172.
98. Seikh, M.R.; Dutta, S.; Li, D.F. Solution of matrix games with rough interval pay-offs and its application in the telecom market share problem. *Int. J. Intell. Syst.* **2021**, *36*, 6066–6100. [CrossRef]
99. Gao, Y.; Zhang, Z. Consensus reaching with non-cooperative behavior management for personalized individual semantics-based social network group decision making. *J. Oper. Res. Soc.* **2021**, *72*, 1–18. [CrossRef]
100. Zhang, Z.; Li, Z.; Gao, Y. Consensus reaching for group decision making with multi-granular unbalanced linguistic information: A bounded confidence and minimum adjustment-based approach. *Inf. Fusion* **2021**, *74*, 96–110. [CrossRef]