Assessing Human Performance Influencing Factors through LINMAP and Bayesian Belief Networks

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Abstract

This study aims to identify and rank the performance influencing factors (PIFs), which cause errors in human operations, by analyzing the failure weights and ranks of the tasks performed by every operator. Assessing these factors can mitigate human errors and improve safety, efficiency, and job satisfaction. The linear programming techniques for multidimensional analysis of preference (LINMAP) and Bayesian belief networks were employed to analyze an aircraft tire manufacturing industry. In this method, all operators of workshops were evaluated. According to the data analysis, each operator's tasks were weighted, and the potential error rate of each task was determined. PIFs for each workshop were then ranked and prioritized so that the most effective factors could easily be distinguished in order to identify the tasks where the operators had the highest rates of failure. The probability of human error was then obtained. In a predictive model, it is possible to determine when an error occurs and which factors are the most effective in its occurrence. This paper proposes an approach to the easy, inexpensive, and rapid classification of PIFs by determining their correlations through conditional possibilities. The proposed approach is capable of classifying not only PIFs but also the PIF-related tasks with the greatest effects.

Keywords: human error, human reliability analysis, performance shaping factors, linear programming techniques for multidimensional analysis of preference (LINMAP), Bayesian belief networks (BBNs)

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1. Introduction

According to various theories, a major cause of work-related accidents is the unsafe behavior of operators. Defined by various references, a human error is a deviation from the predetermined circumstances that would result in a reduction of accuracy and validity of performance on the part of an operator. The human reliability analysis (HRA) is now in one of the most critical phases of probabilistic risk assessment (PRA) in research and industry. In fact, the HRA consists of two steps: identifying the human error and determining the occurrence probability of that error. If implemented properly, it can enhance the human reliability and reduce the human error probability (HEP). The concept of HEP can be defined as the following formula.

$$HEP = \frac{Number\ of\ times\ an\ error\ has\ occured}{Number\ of\ opportunities\ for\ an\ error\ to\ occur}$$

The HRA aims to predict the possibility of failure to fulfil a task (by the operator), the outputs of which are affected by different factors such as judgments of experts, simulation techniques, and problem-solving processes. The HRA methods are adopted in various fields such as power plants, transportation systems (*e.g.*, trains, ships, aircraft and motor vehicles), medicine factories, nursing tasks, and so many other fields where operators are employed.

Human error is also considered an outcome but not a cause. Errors are formed and provoked by the events occurring at workplaces as well as organizational factors. Humans cannot change circumstances but can change the conditions in which the operators work [1].

Human error (HE) can be related to various factors known and designated as performance shaping factors (PSFs), performance influencing factors (PIFs), influence factors (IFs), performance appraisal factors (PAFs), error producing conditions (EPCs), and common performance conditions (CPCs).

Since 1950, many studies have been conducted on the identification and reduction of human errors and factors affecting the performance of operators.

Hollnagdel [2] indicated that human factors played the most crucial role in industrial accidents by accounting for nearly 60% of accidents occurring as a direct result of human errors. In air transport, this rate reaches 70–90% [3].

There are various methods for identifying, evaluating, and reducing human error (HE) such as THERP, CREAM, SPAR-H, and IDAC. Most of the HRA methods provide an overview of tools and techniques for analysts where the sources of errors are easily discernible. Some scientific papers have adopted the MCDM (multiple-criteria decision-making) method and the AHP–SLIM technique [4]. Paolo and Trucco employed the ANP method [5].

Generally, many methods have been developed to assess human reliability. They are classified as three generations, the first of which includes HRA methods. In this category, an analyst must divide a task into its components. The effects of such factors as pressure (work), time, equipment design, and stress can then be taken into account. Combining these methods, an analyst can determine the nominal potential for human error (HE). The methods of the first generation focus on an operator's skills and activity roles.

The HRA methods of the second generation tend to be conceptual. However, attaining such an objective requires a predictive model having sound theoretical foundations and experimental validations [6].

The methods of the third generation are mainly based on the first generation methods redefined as the third generation methods such as NARA (nuclear action reliability assessment) developed through the HEART (human error assessment and reduction technique) method. Most researchers working on the third generation try to bridge the existing gaps in the previous two categories. Alternative analysis is a new problem including different job spectrums, stability in teamwork, and use of the fuzzy logic to analyze reliability and human error.

Some of the HRA methods discuss the interdependency issues between PIFs, some cases of which are the model of information decision and action in crew (IDAC), the cognitive reliability error analysis method (CREAM) [6], and the standardized plant analysis risk-human reliability analysis (SPAR-H) [7].

A few studies have discussed how PIFs affect each other qualitatively (*e.g.*, CREAM [8]). However, some others have tried to describe the analysis of mental interdependencies between different PIFs in addition to explaining the outcomes in very complex applications requiring excessive efforts by analysts (*e.g.*, IDAC) [9]. Hallbert [10] addressed how experimental data could help determine the strength effects of factors and their interactions; however, they failed to provide analysts with the necessary procedures for guiding their analyses.

There are two groups of challenges to PIFs, the first of which includes the prioritization of PIFs, whereas the second group — known as principal challenges — requires a modelling framework of PIFs in which the quantity and interdependence of factors are represented.

This paper aimed to analyze the challenges related to the categorization of PIFs as well as the correlations between factors. The LINMAP method was then employed to rank the factors based on the opinions of experts and operators. Moreover, BBNs were adopted to propose a model that could to some extent measure the effect of each PIF on other factors as well as the effect of each PIF on the operators. Additionally, the proposed approach consists of no pairwise comparisons as in AHP and ANP methods, which are confusing, tedious, and time-consuming for the operators. In fact, the implementation of the proposed approach requires less time and training. A Bayesian belief network can measure the presence probability of each factor by using conditional probabilities in order to determine which PIFs were the most likely cause of the human error occurrence.

This paper introduces the LINMAP (linear programming technique for multidimensional analysis of preference) for the prioritization of PIFs in conjunction with BBNs to determine the interactions of relevant factors. Section 2 reviews the recent literature on the human error, whereas section 3 presents the LINMAP and BBNs. In fact, the LINMAP is introduced as an MCDM technique in Subsection 3.1. After that, Subsection 3.2 discuses BBNs. The data collection methodology is discussed in Section 4. The PIFs and the research results are then analyzed. Finally, Section 5 draws the research conclusion.

2. Literature Review

Dragana [11] used statistical distributions to analyze the HRA. Employing questionnaires and statistical estimates, Dragana determined the parameters of statistical distribution and divided the human error into into two ergonomic and physical categories through statistical models of Markov, Goel–Okumoto, Jelinski and Jonson.

The HEART is a method of showing that any reliability in task performance might be adjusted as long as EPCs are present. Identifying nine general tasks, this method proposes the nominal values of human unreliability. Moreover, 17 EPCs have been reported to have the greatest effects on an operator's performance. The failure rate is defined as below:

$$P = P_0 \left\{ \prod_i [(EPC_i - 1)Ap_i + 1] \right\}$$

Where P denotes the probability of human error, and P_0 indicates the nominal human unreliability. Furthermore, EPC_i represents the i^{th} error-promoting condition, whereas Ap_i refers to an engineer's assessment of the proportion effect (on a scale of 0 to1) for each i^{th} EPC [12]. Castiglia and Giardina [9] concluded that using the fuzzy concept could improve the results of the HEART.

According to the research literature, the major disadvantage of the HEART is the negligence of correlations between errors. Due to the nature of this study, interpreter might end up calculating a variety of human errors within the context of similar tasks. Unlike the HEART, the IDAC method and the CREAM method seek to evaluate the correlations between errors and factors affecting the performance of operators but require a prolonged period of time for training and implementation.

Chang and Mosleh [13] developed a model called the IDAC (information, decision, and action in the crew context) model to assess the responses given by the nuclear power plant operators. This model includes 50 interactive PIFs. The IDAC factor is classified as two macro categories (*i.e.*, internal PIFs and external PIFs) and 11 hierarchically structured groups. The PIFs within each group are independent; however, the PIFs between groups are dependent. Figure 1 demonstrates the high-level interdependencies of PIF groups in the IDAC [12].

Measuring an HEP estimate, Zhiqiang *et al.* [14] employed the CREAM method, in which the control degrees are presented in four manners. Given the intended field, they are determined by prevailing performance conditions. Zhiqiang then made an estimate between control and HEP ranges and used the method as a base to estimate the HEP points. Next, he collected the method characteristics and observed that the results corresponded to the registered human performance data. In his proposed model, PIFs were replaced by PSFs. Table 1 indicates how PSF groupings might affect each other [11].

The numbers within parentheses indicate the following PIFs. The model expresses that the presence of a specific PSF might adjust the impacts of other PSFs and HEPs. Furthermore, a "+" sign denotes a direct effect (increase–increase and decrease–decrease), whereas a "-" sign denotes an inverse effect (increase–decrease and decrease–increase) [8].

Park and Lee [4] proposed a method called AHP–SLIM to overcome the existing difficulties arising from the judgments of experts on the achievement of an accurate estimate. Their proposed method is a technique of making HEP estimates through the AHP method. Introducing the method in seven steps at 2 levels, the researchers drew a pairwise comparison between ten error factors and five human factors. Finally, nearly 225 pairwise comparisons were made. In the proposed method, Jae in Lee compared two groups of operators with high seniority and low seniority.

Zhou Chong [15] demonstrated that the failure structure might bring about overall failure and consequently human errors. This structure is mainly aimed at analyzing human error. Their method estimated HEA and HEP in a structure close to the AHP method in which they introduced their method called AHP–FLIM to analyze the effects of expert judgments on the failure verification of the index model.

Ambroggi and Trucco [5] evaluated the correlative factors in the aviation industry by analyzing 10 influential factors in an air traffic control tower. Through the ANP, these factors were compared pairwise between the operators working at two airports. The factors were then weighted through the *t*-paired (*t*-student) method. The weights related to the air traffic towers were then tested. In this method, the normalized outputs of each factor weight were considered the HEP points. This study classified the factors to measure the dependent and independent effects. A nearly 95% confidence interval was considered for each factor that facilitated the analysis of results in each control tower.

The methods based on ANP and AHP have their own weaknesses. In fact, they require a wide variety of pairwise comparisons, which are toilsome. This results in deviation from the development of more accurate solutions.

Peng-Cheng [16] employed a fuzzy Bayesian belief network (FBBN) to develop a method for improving the quantification of organizational effects on the HRA. The results indicated that their method was unable to quantify human factors and human reliability. However, it managed to measure human equipment reliability, determine the causes of errors, and prioritize these causes.

BBNs were used in [17] to develop a “6-bubble model”, “9-bubble model”, and a “mixed expert/data model”. These models were developed through the levels and sources of data. The “6-bubble model’’ used the data obtained from an NRC (nuclear regulatory commission) workshop, whereas the “mixed expert/data model” employed a large set of over 30 PSFs. The “9-bubble model” was an intermediate one aimed at identifying the error context.

Trucco [18] proposed a novel method for combining organizational human factors and risk analysis. This method was applied to a case study capable of being developed in other fields. The behavior of the maritime transport system was analyzed by modeling the interactions between different factors through BBNs.

BBNs were also utilized to analyze the population variations of the endangered species. This type of study can develop a model for the habitats and the growth patterns of the species under investigation. The study further included the construction of a causal graph [19].

In a paper called *Human Reliability Modeling for the Next Generation System Code*, Sundaramurthi and Smidts [20] reviewed different methods of human reliability and analyzed the strengths and weaknesses of each technique based on the IDAC model in different scenarios. By modeling the PIFs, they managed to determine the scores of important factors. In the end, they provided an overview of complex factors through BBNs and dealt with the role of human errors in aviation and nuclear accidents. Figure 2 demonstrates a causal graph showing human factors in nuclear accidents [20].

Further details can help develop a complete model which could explain the relationships between different factors. The calculations, however, can become more complicated. The factors of highest importance are frequently identified and placed in the analyzed model.

Kyriakidis *et al.* analyzed humans, their performance, actions, and decisions playing significant roles within a vast range of operations in complex sociotechnical systems. Numerous studies were then conducted to perceive people’s actions and/or inactions within their working environments in addition to identifying the other factors known as performance shaping factors (PSFs), which contribute either positively or negatively to the sociotechnical system performance [21].

Washington *et al.* analyzed challenges to the implementation of system safety assessments in unmanned aircraft systems (UASs). They intended to highlight the main advantages associated with the adoption of a risk-based framework in the system safety performance requirement (SSPR) compliance process, which is capable of considering the uncertainty associated with each of the outputs of the system safety assessment process. In another study, Washington *et al.* also proposed a novel system safety compliance process based on Bayesian methods [22] [23].

In a recent paper, Washington *et al.* analyzed the significant uncertainty regarding the safety of novel or complex aviation systems such as remotely piloted aircraft systems (RPASs). The current aviation safety assessment and compliance processes do not account adequately for uncertainty. They sought to support more objective, transparent, systematic, and consistent regulatory outcomes in relation to the safety assessment of such systems. They aimed to provide the systematic means of accounting for the various uncertainties inherent to any system safety assessment (SSA) processes [24].

Steijn *et al.* implemented the quantification of human factors in a quantitative risk analysis (QRA), which they called the QRA+. The quantitative knowledge concerning the technological parameters was obtained from the officially documented SIL statistics, whereas the standardized plant analysis risk–human reliability analysis (SPAR-H) was employed to quantify the human factors. Beta distributions were then utilized to model the failure probability distributions accounting for the uncertainty inherent in dealing with human reliability. For the seamless integration of existing qualitative knowledge and quantitative knowledge, they utilized a Bayesian belief network. The resultant model provides an integrated and more accurate estimation of failure probabilities for both technological and human factors as well as the uncertainty surrounding such probability estimates [25].

Golestani *et al.* proposed a methodology for quantifying the effects of harsh environmental conditions on the reliability of human actions in performing complex physical operations. According to a review of current human reliability techniques, there is a lack of methodology for quantifying human errors while conducting complex physical operations in extreme environments. The proposed methodology is based on a hierarchical Bayesian network accounting for causal dependencies among environmental factors, human error modes, and scenario-based activities. A novel model was also developed with three reference points (*i.e.*, awareness of situation, system access, and action) to derive human error modes (HEMs) from physiological failure mechanisms and help analysts identify the root causes of human errors [26].

Zhao and Smidts proposed a novel cognitive modeling and simulation environment (CMS-BN) by introducing Bayesian networks to represent the human knowledge and the Monte–Carlo simulation to address uncertainties in the cognitive process. Arguments and responses are modeled by traversing the human knowledge represented as a Bayesian network to retrieve knowledge and update human beliefs and attention distribution accordingly. Uncertainties in the cognitive process are characterized as the Monte–Carlo simulation. The proposed environment also models the interplay between the cognitive process and two PSFs, *i.e.*, stress and fatigue, although additional factors can be further considered. The proposed environment is expected to be beneficial to human reliability analysis and human performance improvement [27].

Zhao and Smidts reported that human operators played a critical role in the operation of complex engineered systems, in particular under abnormal conditions. It is important to assess human performance under the conditions of interest and improve the performance by taking effective measures. They presented the application of a previously developed cognitive modeling and simulation environment to address these two problems. The developed environment simulates how a human operator dynamically interacts with the external system with focus on the operator's cognitive activities. They also demonstrated how the developed environment could be used for human reliability analysis and human performance improvement [28].

Wu *et al.* reviewed the existing human reliability techniques and confirmed that there was a lack of quantitative analysis of human errors in the high-temperature operating environments. They proposed a model to support the human rfieliability analysis of high-temperature operation based on the cognitive reliability and error analysis method (CREAM), the fuzzy logic theory, and a Bayesian network (BN). They employed the fuzzy CREAM to consider uncertainties and adopted a BN to determine the control mode and measure human error probability (HEP) [29].

Greco *et al.* analyzed a model adopted in human reliability analysis (HRA) to characterize personnel tasks and performance conditions through the categories of tasks and effective factors (*e.g.*, task types and PSF) [30].

3. Methods

This section proposes the LINMAP for determining the priority of each operator's tasks and PIFs. After that, BBNs are discussed in order to analyze the interplay between PIFs. The significant correlation coefficients of different factors are also determined.

In the studied industry, the proposed method managed to eliminate the need for many pair comparisons and the long time required for training and implementation. Additionally, the relationships between factors were not ignored in this study. Finally, Bayesian belief networks were utilized to determine the effects of every PIF on human error.

3.1. LINMAP

In this method, *m* denotes the number of PIFs, whereas *n* refers to the number of operator's tasks existing in an *n*-dimensional space. The decision-makers are assumed to select the points which are closest to the ideal point. A decision-maker's subjective judgments on the comparison of paired options are shown as S={(k,l)}, which represents the pairwise comparisons between A_k options and A_l options. Therefore, the decision-maker prefers A_k options. The procedure can define weights (w_j) — j^{th} task weight — and determine the optimal value (x_j^*) —the ideal value of the i^{th} index. The definitions of these vectors (W, X^*) are given based on regular pairs in the S set. The distance of the A_i option from the ideal option is defined as below:

$$t_i = d_i^2 = \sum_{j=1}^{n} w_j \left(x_{ij} - x_j^*\right)^2 \ , \ \ i = 1,2,\dots,m \tag{1}$$

If $t_l \leq t_k$, the solution (W, X^*) to (k,i)∈S is compatible.

The answer to (W, X^*) should be determined in a way that the exceeding condition $t_l \geq t_k$ happens within the least range possible. If $t_l \leq t_k$, then $t_l - t_k$ represents the deviation degree where the intended condition is infringed. Hence, the definition given in Equation (2) can be considered in general.

$$(t_l - t_k)^- = max\{0, (t_l - t_k)\}$$
(2)

Generally, the total incompatibility of whole (P) on the S set is expressed as Equation (3):

$$P = \sum_{(k,l)\in S}(t_l - t_k)^-$$
(3)

Where P (*i.e.*, the incompatibility degree) is not negative because index $(t_l - t_k)^-$ is always non-negative. Therefore, P should be minimized to determine the answer to (W, X^*). Against P, a new value is selected as G (whole compatibility degree) defined through Equation (4).

$$G = \sum_{(k,l)\in S}(t_l - t_k)^+$$
(4)

Where index $(t_l - t_k)^+$ is $max\{0, (t_l - t_k)\}$. Therefore, G should be greater than P. Since index t is the greatest value $\{0, (t_l - t_k)\}$, G>P. It is then possible to write G-P=h, in which h is an arbitrary positive constant value.

$$\begin{cases} G > P \\ G - P = h \end{cases} \tag{5}$$

Since the goal is to minimize the incompatibility degree, the answer to (W, X^*) is obtained by solving a problem in Equation (6).

$$min: P = \sum_{(k,l)\in S}(t_l - t_k)^- = \sum_{(k,l)\in S} max\{0, (t_l - t_k)\}$$

$$s.t \;\; G - P = \sum_{(k,l)\in S}(t_l - t_k) \; = h \tag{6}$$

In light of Equation 5, the mathematical programing model Equation 6 can be converted into a linear programming model depicted in (7).

$$min: \sum_{(k,l)\in S} \alpha_{k,l}$$

$$s.t \;\; \alpha_{k,l} \geq t_k - t_l \quad , \forall (k,l) \in S$$

$$\sum_{(k,l)\in S}(t_l - t_k) \quad = h \tag{7}$$

The equation can also be simplified by $w_j \times x_j^* = \mu_j$ and $t_l - t_k$:

$$t_l - t_k = \sum_{j=1}^{n} w_j \left(x_{ij} - x_j^*\right)^2 - \sum_{j=1}^{n} w_j \left(x_{kj} - x_j^*\right)^2 =$$

$$\sum_{j=1}^{n} w_j \left(x_{ij}^2 - x_{kj}^2\right) - 2\sum_{j=1}^{n} w_j x_j^* \left(x_{ij} - x_{kj}\right) \tag{8}$$

Equation 7 and Equation 8 can be merged and rewritten as follows:

$$min: \sum_{(k,l)\in S} \alpha_{k,l}$$

$$min: \sum_{(k,l)\in S} \alpha_{k,l}$$

$$\sum_{j=1}^{n} w_j \sum_{(k.l)\in S}\left(x_{lj}^2 - x_{kj}^2\right) - 2\sum_{j=l}^{n} u_j \sum_{(k,l)\in S}\left(x_{lj} - x_{kj}\right) = h \tag{9}$$

Where $\alpha_{lk} \geq 0$, $w_j \geq 0$, and u_j are without any signs (unlimited). Equation 9 can be solved in a linear programing form. The optimal value of the target function is related to parameter h; however, it causes no changes in preference prioritization [31].

The linear programming of Equation 9 can be solved to calculate w_j and x^* (*i.e.*, the Euclidean distance of each PIF). Higher weights indicate the possibility of higher errors in each operator's performances. However, T works in a reverse direction. In other words, Euclidean distances that are shorter than the ideal point indicate that PIFs have the greatest effects on each operator's performance. The linear programming problem was solved in MATLAB.

3.2. Bayesian Belief Networks

The term "Bayesian network (BN)" was first used by Judea Pearl in 1985. In fact, a Bayesian belief network (BBN) represents the graphic relationships of a model in which the relationships are shown as variables [32]. In fact, BBNs are similar to a group of graphic models known as the directed acyclic graphs (DAGs). Figure 3 demonstrates the steps taken in creating and applying a model of BBNs. Having specifications for a BBNs allows for the calculation of the next probability distribution for each of the nodes (designated as beliefs).

Selecting a model for the representation of relationships between PSFs largely based on machine learning can most accurately model the causal graph structure. Prospective models include decision trees, artificial neural networks (NNs), support vector machines (SVMs), and BBNs. Decision trees are developed by splitting source data based on some data characteristics. They are used best in instances of attribute-value pairs; therefore, they do not accurately model the causal graph structure [33].

Today, BBNs have found diverse applications in engineering, medicine, aeronautics, computer sciences, geology, education, communication sciences, military strategy, and reliability analysis.

Suppose that E and F are non-dependent or independent events, respectively. If the possibility of E happening is not completely related to the occurrence or non-occurrence of F, E and F are considered independent. Based on probability laws, if E and F are independent, the possibility that both occur simultaneously can be calculated through the following equation:

$$P(E \cap F) = P(E).P(F)$$

However, when E depends on F, the above equation does not apply, and the relevant law changes through the following equation:

$$P(E) = \sum_{i=1}^{n} P(E|F_i)P(F_i) \quad (10)$$

Figure 4 demonstrates the Bayesian network diagram for four nodes, displaying the conditional dependence and independence relationships between nodes A, B, C and D. In this study, MSBNX was employed to solve BBNs and probabilities.

4. Case Study (Data) and Research Procedures

This section discusses the use of the proposed method in the aircraft tire production (ATP) industry. The study was conducted in two categories of operators at two workshops. The first group performed such tasks as Banbury mixer, extruding, calendaring, and beach-off cooling machine (in the first workshop). The second group carried out such tasks as bead assembling, cutting, tire building, and tire curing (in the second workshop). There were four and 11 operators in the first and second workshops, respectively. All the operators were included in a statistical study, where they completed worksheets (questionnaires). The worksheets consisted of two sections, the first of which contained scores within the range of 0–10 for each PIF (0 for the lowest value and 10 for the highest value) (see Figure 5).

Figure 6 depicts the sample worksheets of the ATP industry in which the operators are ranked from zero to ten in vacant cells. The worksheets also include pairwise comparisons (among PIFs) drawn for as many required times as the operator deems fit. Table 2 demonstrates the 32 PIFs analyzed in the current study. The PIFs are determined with respect to the following criteria:

- The literature review of PIFs and pertinent research papers
- The comparison of different PIFs to check any lack of overlaps
- The judgments/opinions of experts

Table 3 gives an overview of the approach to this study. The advantage of the LINMAP over other MADM methods is that it needs a very few number of pairwise comparisons. It is also not time-consuming. Moreover, the LINMAP prioritizes PIFs and tasks simultaneously. The intended frequencies are extracted from the first section of the questionnaires including the tasks common to all operators. The second section of the worksheet is used for each individual operator. Tables 4 and 5 report the results of analyzing tasks. The first column indicates the tasks in each workshop, whereas the second column displays the weight of each task (w_j). The third one indicates the normalized weight of each task where the potential error percentage of each task is represented. Tables 6 and 7 demonstrate the priorities of PIFs having the greatest effects on an operator's performance. The first column displays the ranks of factors arranged on the basis of the highest scores demonstrating which factors have the greatest effects on an operator's performance in each workshop. The second column provides the designations of PIFs sorted according to their average distances from the ideal points (T_i). Moreover, the third column depicts average T_i. As discussed earlier, there are four operators in the first workshop where four values of T_i are obtained. Therefore, their average is reported in this paper. A similar procedure was adopted for the second workshop. There are 11 operators in the second workshop; thus, an average of 11 values of T_i is considered and calculated. The fourth column demonstrates the normalized values of T_i which can measure the effect probability each PIF. Furthermore, the PIFs are ranked to a sensitivity of two decimal digits.

Hence, calendaring task had the highest (w_j) value equal to 0.01667 or 38% indicating that it had the greatest impact on PIFs in the first workshop. The PIFs were also assigned from the highest to lowest on such tasks as extruding (27%), beach-off (18%), and Banbury (17%). In other words, the possibility rates of human error in calendaring, extruding, beach-off, and Banbury were reported at 38%, 37%, 18%, and 17% in the mentioned order. Alternatively interpreted, Table 6 arranged PIFs such as environmental factors, visual impacts on task, inadequate supervision on the task, time-constrained load, obsolete technology, lack of confidence, poor interaction, impact of physical abilities, lack of adequate tools, and inadequate access to tools and equipment in order of priority. They can affect calendaring, extruding, beach-off, and Banbury tasks with the relevant probabilities obtained. For instance, the PIFs having ranking 1 with the value or probability of 13.11% affected the tasks in Workshop 1.

Workshop 2 can be analyzed in the same manner. The highest occurrence probabilities of errors in performance respectively (from the highest to the lowest) belonged to cutting, tire curing, tire building, and bead assembling. Table 5 demonstrates the PIFs arranged in order of priority affecting the tasks in the second workshop. Cutting with a value of 47.2% received the greatest impact from the factors. After that, tire curing with 15.6% and tire building and bead assembling with 18.6% were affected by the stated factors. The factors had identical effects on tire building and bead assembling. Table 7 listed inadequate supervision, workplace cleanliness, time-constrained load, bad planning, improper equipment layout, personal grooming, doing two or more simultaneous tasks, environmental factors, and work complexity in order of importance. They had the greatest effects on the above four tasks in the second workshop.

Figure 7 and Figure 8 demonstrate the Pareto histograms related to the weight (w_j) of Tables 4 and 5, respectively. They also illustrate the plotted curves of cumulative normalized weights.

Figure 9 and Figure 10 separately demonstrate the details of weights for each individual operator in either workshop. In fact, the analyst can detect which operators are prone to error probability in different tasks. For example, Figure 8 indicates that the factors had the greatest effects on extruding (42.1%) and Bannury (31%) for Operator A1. For Operator B1, the factors had the greatest effects on calendaring (70.2%). In addition, extruding for Operator C1 and Banbury for Operator D1 showed the greatest potential of error. The last bar in the histogram displays the average weights of the four operators in Figure 8. Furthermore, Figure 10 indicates that a similar analysis can be provided for the second workshop.

In Figure 10, "Ave" shows the mean weights of operators. Bead assembling for Operator A2 displays a value of 86% (the highest value in second workshop), whereas the same value for "Ave" is the lowest (15.6%). Considering the prioritization of PIFs to mitigate the effects of the latter factors, it is advisable to implement such methods and measures as training operators to compensate for their lack of self-confidence, improving environmental factors (*i.e.*, light, temperature, noise), concentrating on tasks, purchasing new equipment and gears, recruiting new operators to make up for the time-constrained load, designing and locating a new site for the workshop, cleaning or executing 5S at the workplace, and further cooperation among workers.

As discussed earlier, the second phase can be started as follows. In this section, not all factors are utilized to determine the relationships between different PIFs. Although we used significant correlation coefficients between PIFs, the relationships of factors in the IDAC model and the special relationships of factors in the ATP industry were determined through the calculations made by the industry experts. In fact, this model is a simplified version in which the important factors are taken into consideration. Evidently, the factors affect an operator's performance. The numbers next to each arrow in Figure 11 represent the correlation coefficients of two related factors. Also Figure 11 show the factor "fatigue" with a probability of 0.606 affects not only the operator's total performance (human error) but also the input on non-alertness. This factor with a correlation coefficient of 0.49 affects "alertness" and directly impacts an operator's performance (human error). The factors connected to "operator" directly affect an operator's behavior. Moreover, each factor exists in two states: "present" and "non-present", *i.e.*, the factor in question having a specified probability can be "present" or "absent". In this model, the factors having the greatest ability are used with respect to the factors that directly or indirectly affect an operator's performance. The "operator" in this model having a probability of 0.630 is affected by the factors, there is an occurrence possibility of error. With the probability of 0.369, the operator can be error-free, whereas "stress", "non-alertness", and "fatigue" play the most crucial roles in an operator's performance.

Figure 12 demonstrates what share is allotted to each factor in case human errors occur. For example, if the probability of human error is 1, the probability of lack of alertness is 0.747. Moreover, if there is an error or the operator commits an error, this model has the capability of predicting conditional probabilities of each factor. According to the data in Figure 12, the factors related to "lack of confidence, bias, complexity, fatigue, doing two or more simultaneous tasks, lack of alertness, inadequate supervision, and stress" are the ones undergoing the most changes in the form of probability escalation.

5. Conclusion

The LINMAP and BBNs can provide useful information regarding PIF ranking and the occurrence probability of PIFs. As planned, the factors were ranked and the operators' tasks were prioritized. In other words, the error potential percentage of each task was determined. Therefore, it is easy to determine what factors had the greatest effect on the performance of operators (Tables 6 and 7). In addition, Tales 4 and 5 reported the error potential percentages. The method also separately obtained the operators' error percentages in delivering their tasks. The BBNs helped better perceive the relationships between PIFs and the mutual effects of factors. By means of BBNs, a predictive model like that of Figure 12 can be developed. LINMAP and BBNs are used in lieu of ANP or AHP. The latter techniques contain too many pairwise comparisons. This study aimed to provide the rankings of the assigned tasks towards determining the error potential possibilities and prioritizing PIFs. According to the literature, it is essential to prioritize factors and the assigned tasks with the aim of improving operators' performance and developing a more proper layout for instructions and work conditions. Moreover, establishing a relationship between factors and the degrees of their mutual effects can greatly help manage this complex set skillfully.

There was no need for many confusing pairwise comparisons. The methods required short-time training, fast implementation, and observation of the relationships between factors and their mutual effects. Finally, factors and activities were simultaneously ranked.

6. Limitations/Shortcomings and Development of Future Studies

This is the first ever study to employ LINMAP to rank human factors. However, the methods were non-integrated in this study, and it was essential to adopt a BBN to estimate the presence probability of each factor in human error. Henceforth, for the development of future studies, it is necessary to compare this model with other models of human error assessment. It is also desirable to measure and discuss the validity, reliability, and accuracy of this model. PIFs can be classified similarly to the IDAC model, and similar groups can be ranked on the basis of factors. Therefore, overlapping can be prevented.

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Figure 1. The organization of PIF groups and high-level interdependencies within the IDAC

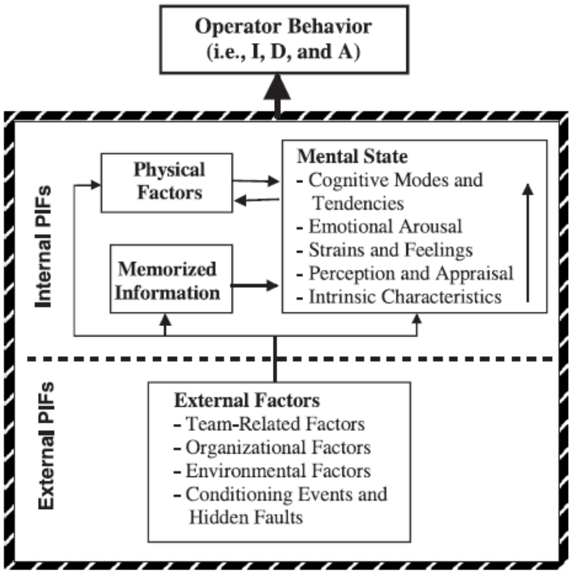

Table 1. Effects between PSFs within CREAM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
(1)										1- Adequacy of organization
(2)	+		+			+	+	+		2- Working conditions
(3)	+									3- Adequacy of MI and operational support
(4)	+									4- Availability of procedures/plans
(5)		-	-	-						5- Number of simultaneous goals
(6)		+	+	+	-		+		+	6- Available time
(7)										7- Time of day
(8)	+									8- Adequacy of training and experience
(9)	+							+		9- Crew collaboration quality

Figure 2. The causal graph for the BBN analysis in

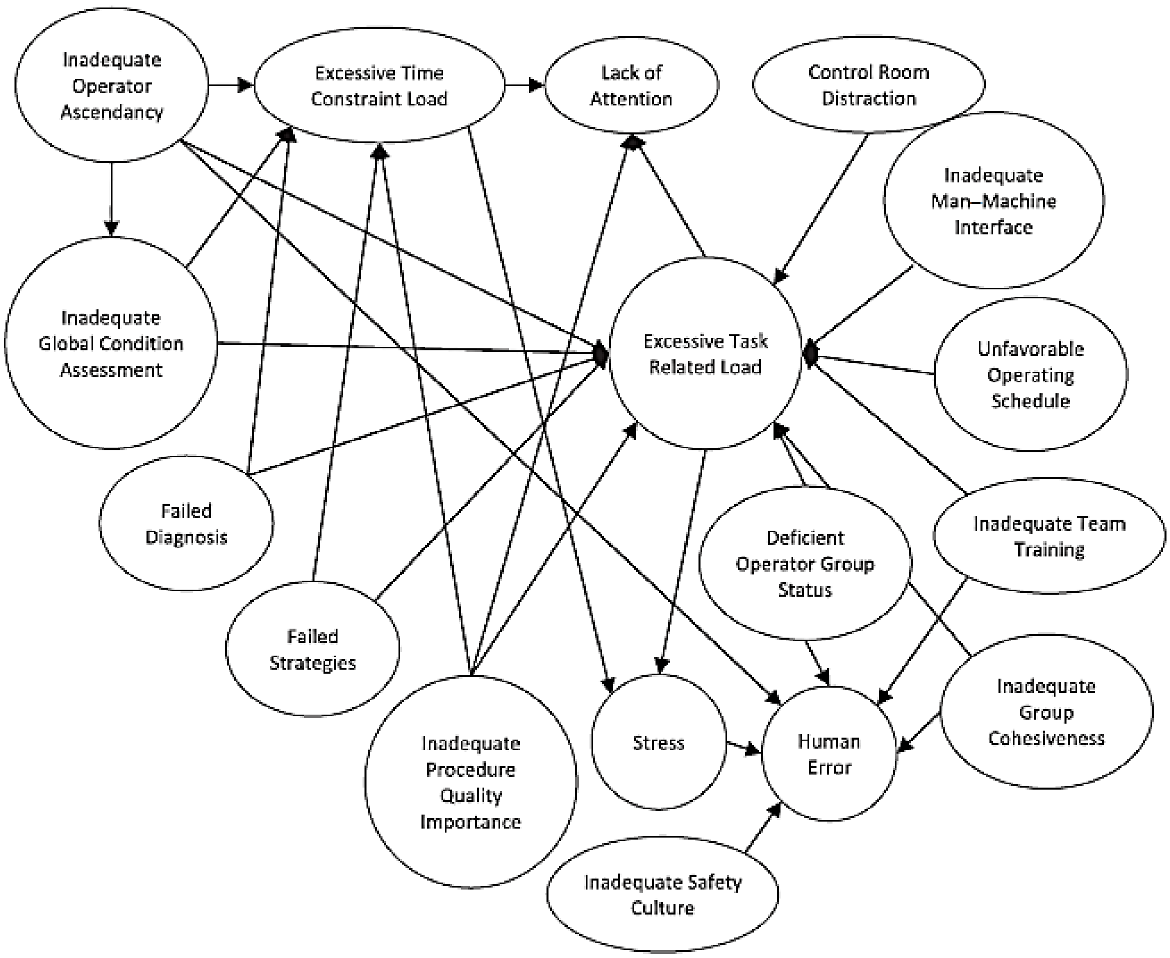

Figure 3. The steps in the BBN development

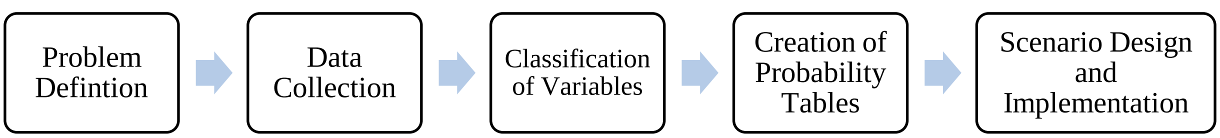

Figure 4. The BBN diagram for four PIFs

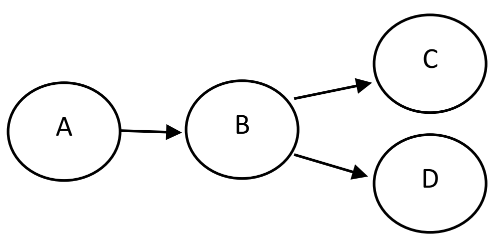

Figure 5. Scores 0 to 10 for PIFs and tasks

10	9	8	7	6	5	4	3	2	1	0
Direct effect	Huge effect		High effect		Moderate effect		Low effect		Very low effect	Ineffective

Figure 6. The worksheet sample

First section of the worksheet

#	Factors	Task 1 : Calendaring	Task 2 : Extruding	Task 3 : Beach-off	Task 4 : Banbury
1	Environmental factors				
2	Organizational Culture				
3	Inadequate supervision on the task				
4	Cleaning workplace				
⋮	⋮	⋮	⋮	⋮	⋮

Second section of the worksheet

1. In general, Factor Number.................. will be more effective than Factor number............. on my performance.
2. In general, Factor Number.................. will be more effective than Factor number............. on my performance.
3. In general, Factor Number.................. will be more effective than Factor number............. on my performance.
4. In general, Factor Number.................. will be more effective than Factor number............. on my performance.

⋮ ⋮ ⋮ ⋮

Table 2. PIFs used in the ATPI

No.	Corresponding PIFs	No.	Corresponding PIFs
1	Environmental factors	17	Bias
2	Organizational Culture	18	Hurry
3	Inadequate supervision on the task	19	Leaving work
4	Cleaning workplace	20	Personal Grooming
5	Complexity	21	Impact of personal protective equipment on the task
6	Lack of adequate tools for tasks	22	Impact of physical abilities on the task
7	Adverse physical conditions (cold, etc.)	23	Visual impact on the task
8	Fatigue	24	Lack of transparency in work guidelines
9	Stress	25	Time-Constrained Load
10	Lack of alertness	26	Workload
11	The possibility of a deliberate error	27	Bad planning production
12	Functional errors (inadvertent error)	28	Doing two or more tasks simultaneously
13	Lack of confidence	29	Inadequate access to tools and equipment at work
14	Lack of training and experience	30	Improper layout equipment
15	Responsibility and commitment to task	31	Improper maintenance of equipment
16	Poor interaction and collaboration with colleagues	32	Obsolete technology

Table 3. The approach to LINMAP and BBNs in an ATP industry

Phase	Step	Description of steps
First phase (Priorities of tasks and PIFs)	1	Defining the problem and reviewing the literature
	2	Identifying 66 PIFs
	3	Selecting PIFs in the ATP industry (32 PIFs selected) in the light of experts' opinions
	4	Identifying task assignments and classifying the individuals performing the same task
	5	Dedicating relevant scores to each factor (first section of worksheet)
	6	Selecting preferences and advantages of factors to others by

Table 3. The approach to LINMAP and BBNs in an ATP industry

Phase	Step	Description of steps
		operators (second section of worksheet)
	7	Loading data into software constructing linear programming
	8	Determining the weight of each task (w_j) and each factor's distance from the ideal point (t_i)
	9	Normalizing data
Second phase (Interplay between PIFs)	10	Determining correlations between PIFs and determining their significance
	11	Reviewing the literature and analyzing results in consultation with industry experts to present a model showing interplay between PIFs
	12	Proposing a predictive BBN model

Table 4. The weights of tasks in the first workshop

Percentage of potential Error (Normal weight)	Weights of tasks (w_j)	Tasks
38%	0.01667	Calendaring
27%	0.011755	Extruding
18%	0.007729	Beach-off
17%	0.007313	Banbury

Table 5. The weights of tasks in the Second workshop

Percentage of potential Error (Normal weight)	Weight of tasks (w_j)	Tasks
47.2%	0.0258	Cutting
18.6%	0.0102	Tire curing
18.6%	0.0102	Tire building
15.6%	0.0085	Bead assembling

Table 6. The priorities of PIFs for Banbury, extruding, calendaring and beach-off tasks

Rank	PIFs	Ave. T_i	Normal Ave. T_i
1	Environmental factors	0.573	0.1311
	Visual impact on the task	0.573	
	Inadequate supervision of task	0.573	
	Time-Constrained Load	0.573	
	Obsolete technology	0.573	
2	Lack of confidence	0.594	0.1264
	Poor interaction	0.594	
	Impact of physical abilities	0.594	
	Lack of adequate tools	0.594	
	Inadequate access to tools	0.594	
3	Responsibility	0.637	0.1177
	Improper layout equipment	0.637	
	Hurry	0.637	
4	workload	0.702	0.1068
	Stress	0.702	
	Leaving work	0.702	
5	Organizational culture	0.788	0.0953
	Bad planning production	0.788	
6	Complexity	0.896	0.0839
	Adverse physical conditions	0.896	
7	Bias	0.901	0.0832
8	Personal protective	1.026	0.0733
	Doing two or more tasks	1.026	
	Improper maintenance	1.026	
9	Cleaning workplace	1.178	0.0637
	Lack of alertness	1.178	
	Functional errors	1.178	
	Lack of training & experience	1.178	
10	deliberate error	1.185	0.0634
11	Fatigue	1.359	0.0553
	Personal Grooming	1.359	
	lack of guidelines	1.359	

Table 7. The priorities of PIFs for bead assembling, cutting, tire building, and tire curing tasks

Rank	PIFs	Ave. T_i	Normal Ave. T_i
1	Inadequate supervision of task	2.510	0.0987
	Cleaning workplace	2.510	
	Time-Constrained load	2.510	
	Bad planning production	2.510	
	Improper layout equipment	2.510	
	Personal Grooming	2.510	
	Doing two or more tasks	2.510	
2	Environmental factors	2.525	0.0981
	Complexity	2.525	
3	Organizational Culture	2.550	0.0972
	Improper maintenance	2.550	
	Obsolete technology	2.550	
4	Lack of alertness	2.563	0.0966
	Lack of confidence	2.563	
5	Responsibility	2.605	0.0951
	workload	2.605	
6	Lack of adequate tools	2.625	0.0945
	Fatigue	2.625	
	Stress	2.625	
	personal protective	2.625	
	Impact of physical abilities	2.625	
	lack of guidelines	2.625	
	Inadequate access to tools	2.625	
7	Adverse physical conditions	2.710	0.0915
	Functional errors	2.710	
	Lack of training & experience	2.710	
	Poor interaction	2.710	
	Leaving work	2.710	
8	Bias	2.818	0.0879
9	Hurry	2.950	0.0840
10	Visual impact on the task	3.059	0.0810
11	deliberate error	3.284	0.0755

Figure 7. The Pareto histogram for the potential error percentage in Workshop 1

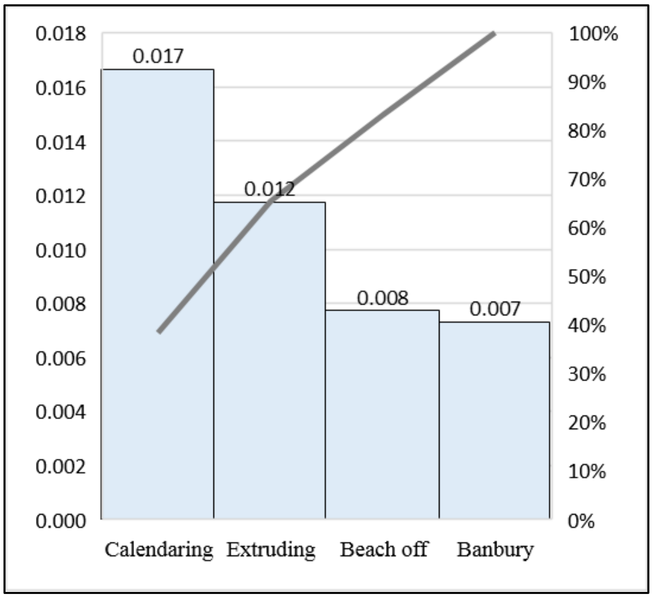

Figure 8. *The Pareto histogram for percentage of potential errors in Workshop 2*

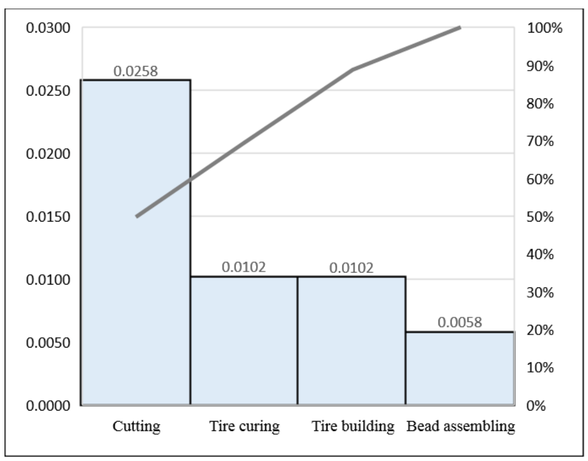

Figure 9. *The analysis of individual operators A, B, C, and D in Workshop 1*

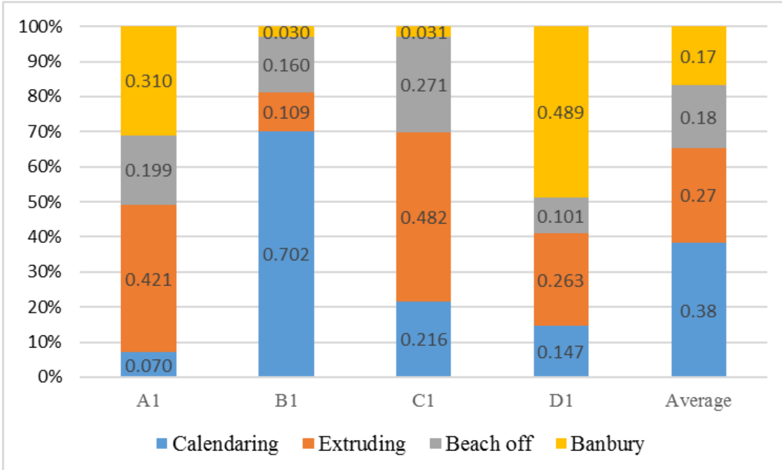

Figure 10. The analysis of individual operators A, B, C, D, E, F, G, H, I, G, and K in Workshop 2

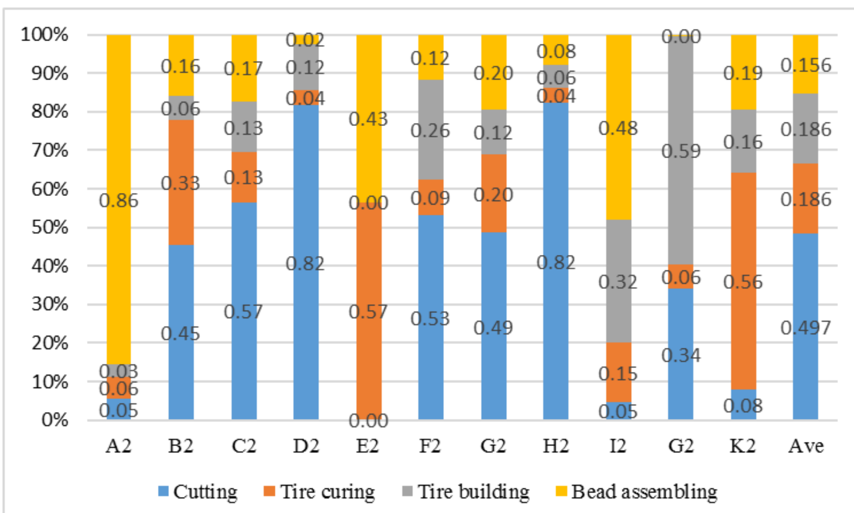

Figure 11. The BBN of PIFs for the ATP industry

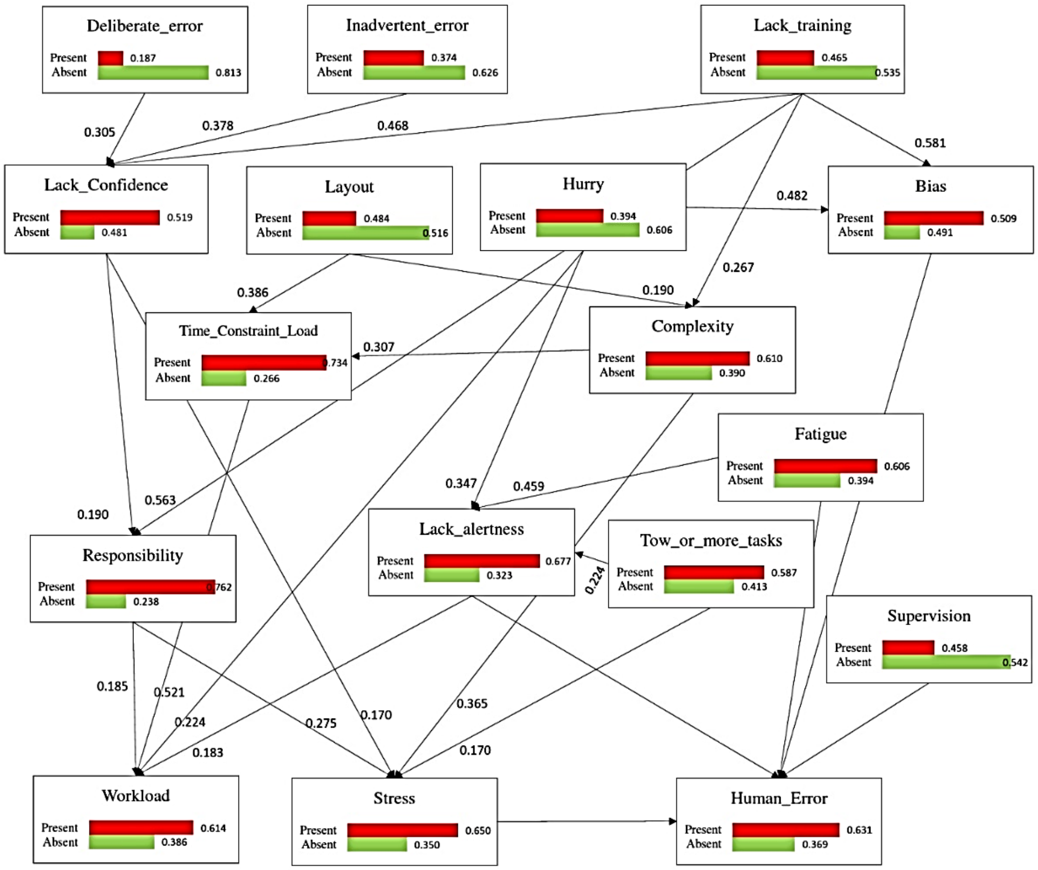

Figure 12. The occurrence probability of PIFs in case of human errors