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BN-SLIM: A Bayesian Network methodology for human reliability assessment based on Success Likelihood Index Method (SLIM)

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ABSTRACT

Success Likelihood Index Model (SLIM) is one of the widely-used deterministic techniques in human reliability assessment especially when data is insufficient. However, this method suffers from epistemic uncertainty as it extremely relies on expert judgment for determining the model parameters such as the rates and weights of the performance shaping factors (PSFs). Besides, given an operation consisting of several tasks, SLIM calculates the human error probability (HEP) by ignoring possible dependencies among the tasks.

The present study is aimed at using Bayesian Network (BN) for improving the performance of SLIM in handling uncertainty arising from experts opinion and lack of data. To this end, SLIM is combined with BN to form the so-called BN-SLIM technique. We demonstrate how BN-SLIM can consider uncertainty associated with the rates of PSFs by using probability distributions. BN-SLIM is also able to provide a better estimation of human error probability by considering conditional dependencies resulting from common PSFs. The probability updating feature of BN-SLIM can be used to identify the PSFs contributing the most to human failure event. The outperformance of BN-SLIM over SLIM is demonstrated via an illustrative example.

1. Introduction

Human factor is one of the main causes of accidents in nuclear power plants, aerospace systems, marine industry, and the oil and gas industry [1]. In the past two decades, human error consequences have led to the environmental damage, major capital loss and noticeable death toll. In March 2005, the BP refinery explosion in Texas City caused 15 deaths and 180 injuries. According to the Chemical Safety and Hazard Investigation Board (CSB) report, human factor deficiencies were to blame for the accident [2]. In August 2006, a fatal runway overrun in Kentucky caused 49 deaths. The final report issued by the national transportation safety board revealed that human errors on the part of the pilots and the air traffic controller were to blame for the crash [3]. Therefore, it is essential to identify potential human errors and estimate their occurrence probability in the operation of complex systems and processes.

Human Reliability Analysis (HRA) is a systematic approach to analyze and identify the causes and consequences of human errors in different human-machine systems. HRA aims to diminish the likelihood and consequences of human error by recognizing and assessing how humans affect system safety [4]. An integral part of HRA is assessing the Performance Shaping Factors (PSFs), i.e., the factors influencing Human Error Probability (HEP). In other words, PSFs are environmental, personal or task-oriented factors with positive or negative effects on human performance in different contexts [5].

During the last decades, a lot of research has been conducted to improve HRA methods, resulting in two main generations of HRA techniques. In the first generation techniques, such as Technique for Human Error Rate Prediction (THERP) [6], Human Cognition Reliability (HRC) [7], and Human Error Assessment and Reduction Technique (HEART) [8], human is considered as a mechanical or electrical component (depending on the context) who inherently has deficiencies [9]. These techniques focus on the characteristics of tasks much more than the effects of the context and the environment in estimating the HEP. The second generation techniques, such as Cognitive Reliability and Error Analysis Methods (CREAM) [10], Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) [11] and Information, Decision and Action in Crew context (IDAC) [12], were developed to improve the first generation techniques. In the second generation techniques, the operator cognition and context are considered as the major contributing factors to the HEP. However, the both generations have some limitations such as being highly subjective, lacking a causal mechanism to link PSFs to the operator performance [13], and not being easily compatible with system safety assessment models [14].

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Nomenclature

Acronym discerption

BN	Bayesian Network
CREAM	Cognitive Reliability and Error Analysis Methods
CPT	Conditional Probability Table
HEART	Human Error Assessment and Reduction Technique
HEP	Human Error Probability
HRA	Human Reliability Analysis
IDAC	Information, Decision and Action in Crew context
MADE	Mean Absolute Discretization Error
MV	Mean Variation
PSF	Performance Shaping Factor
RV	Ratio of Variation
SLI	Success Likelihood Index
SLIM	Success Likelihood Index Model
SPAR-H	Standardized Plant Analysis Risk Human Reliability Analysis
THERP	Technique for Human Error Rate Prediction

List of Symbols

Symbol	Discerption
A_i	Variable *i* in the Bayesian Network
E	Observed evidence
I	Number of nodes in Bayesian Network
J	Number of intervals
M	Number of SLI instances
N	Number of PSFs
P_{PSF}	Probability mass function of a certain PSF
R_i	ith rate of a PSF
R_{PSF}	Set of rates of a PSF
U	Set of all possible variables in Bayesian Network
W_i	Weight of the ith PSF
π	Prior Probability
θ	Posterior probability

Among the HRA methods, Success Likelihood Index Model (SLIM), proposed by Embrey et al. [15], is one of the most flexible and commonly used techniques for estimating HEP under a combined effect of a set of PSFs. SLIM can afford a wide range of PSFs according to the application of interest and thus can be used in different industries [16–19]. On the other hand, SPAR-H and CREAM have been developed based on specific PSFs which may not cover all the details of a performance context [13].

Despite its popularity, SLIM suffers from the foregoing drawbacks of the first and second generations techniques of HRA. One of the important shortcomings, especially in case of data scarcity, is that the parameters of SLIM such as the rates and weights of PSFs should be determined by experts, exposing the assessment of HEP to subjectivity and thus varying degrees of epistemic uncertainty. To mitigate this limitation Musharraf et al. [20] and Akyuz [21] used evidence theory and fuzzy theory, respectively, to combine different degrees of belief about the rates and weights of the PSFs; however, the assignment of prior belief masses to the model parameters has still remained a challenge in these approaches [22]. Another limitation of SLIM, which is also common in other HRA methods, is its inability in considering the dependencies among HEPs in a number of related tasks. HEPs dependencies may arise from the influence of human error of one task on human error of the subsequent tasks [6,11,23] or from the common PSFs involved in HEPs of two or more tasks [24].

Bayesian Network (BN) has been proposed as a promising technique for enhancing the performance and accuracy of HRA techniques such as SPAR-H and CREAM [14,25]. Groth and Swiler [14] transferred SPAR-H to BN and showed how BN framework can be exploited not only for reasoning with perfect, partial or no information on PSFs states but also for considering the PSFs interdependencies. Kim et al. [25] combined CREAM and BN so that the uncertainty associated with the PSFs rates could be modeled using probability distribution functions although the relationships between PSFs and the HEP were still deterministic. Since no major attempts have been made so far to improve the drawbacks of SLIM using BN, in this study we have developed an innovative technique for HEP assessment by mapping SLIM into BN, so-called the BN-SLIM technique.

The proposed BN-SLIM can be used to alleviate the limitations of SLIM and to improve its accuracy and performance. In the conventional SLIM, a large amount of uncertainty is involved in estimating the values of the rates and weights of PSFs. The probabilistic framework of BN enables the analyst to consider the uncertainty via prior probability distributions. It also helps decrease the uncertainty when the updated probabilities are substituted for prior probabilities as more information becomes available, making a priori subjective estimates tend to a posteriori more objective results [26]. BN's probability updating feature can also be exploited by analysts to determine which PSF and which PSF rate have contributed more to the occurrence of human error. We will apply BN-SLIM to an illustrative example to demonstrate how it may outperform SLIM by handling dependencies among tasks with common PSFs and by performing belief updating.

The rest of this paper is organized as follow: Section 2 provides an overview of SLIM and BN techniques. Section 3 is devoted to the development of the BN-SLIM. In Section 4 the application of the BN-SLIM to a case study is illustrated and the obtained results are discussed. Conclusions are given in Section 5.

2. Background

2.1. Success Likelihood Index Model (SLIM)

SLIM is one of the flexible techniques to estimate HEP during a task execution. As a decision-analysis approach, it proposes a degree of preference called Success Likelihood Index (SLI) for each task under the combined effects of PSFs [15,27] . Although this model heavily relies on experts judgment, it is quite practical where data is insufficient about human error.

In conventional SLIM, weights and rates of PSFs define how each PSF contribute to an SLI. For a given task and PSF, the rate of the PSF shows to what extent the PSF is desirable for executing the task while the weight of the PSF shows the relative importance of the PSF to the task. The following steps are taken in the SLIM [27,28]:

1 Determine the set of PSFs that would influence the human error potential in executing the task of interest.The set of PSFs can be identified in association with the task characteristics and environment.
2 Determine the weight of each PSF. Considering that several PSFs may contribute to the same task in a specific scenario, the largest weight (W) is assigned to the most important PSF, and so on; where $\sum_{i=1}^{N} Wi = 1$ and N denotes the number of PSFs.
3 Determine the rate of each PSF. Ri is a deterministic number between 1 and 9 (inclusive), with Ri = 1 for the worst and Ri = 9 for the best conditions of the ith PSF.
4 Calculate the SLI of the task. Once the rates and weights of all the relevant PSFs are determined, Eq. (1) can be employed to calculate the SLI of the task:

$$SLI = \sum_{i=1}^{N} \text{Wi . Ri} \tag{1}$$

5 Estimate the HEP in executing the task. The logarithmic relationship in Eq. (2) can be used to convert the SLI into the corresponding HEP:

$$Log(HEP) = a\ SLI + b \tag{2}$$

where the constants a and b can be determined by two tasks for which the amounts of HEPs and the corresponding SLIs are known.

2.2. Bayesian Network (BN)

BN is a probabilistic graphical model for reasoning under uncertainty. The qualitative part of BN is a directed acyclic graph composed of nodes and arcs. The nodes display random variables with various states, and the arcs represent the causal relationships between the nodes [29].

Conditional Probability Tables (CPTs) are the quantitative part of BN which make it a powerful reasoning tool. CPTs quantify the conditional dependency of a child node given all possible combinations of the states of its parent nodes; instead of CPT, marginal probabilities are assigned to root nodes (i.e., nodes with no parent). Regarding the chain rule, the joint probability distribution of nodes P(U) is calculated as:

$$P(U) = \prod_{i=1}^{I} P(A_i|Pa(A_i)) \tag{3}$$

where U is a set of random variables $U = \{A_1, A_2, ..., A_I\}$, $Pa(A_i)$ is the parent set of node A_i, and P(U) reflects the properties of BN with I variables [30].

Using Bayes' theorem, it is possible to obtain the updated (posterior) probability of events by observing new evidence (E) [31]:

$$P(U|E) = \frac{P(E|U)P(U)}{P(E)} = \frac{P(U, E)}{\sum_U P(U, E)} \tag{4}$$

In the context of HRA, the evidence can be in the form of observation of human error in a task or the occurrence of incidents in an operation, or new information about the performance context. The probability updating characteristic of BN is widely employed in diagnostic reasoning. Besides the unique capability of BN in diagnostic reasoning, it enables to marge data from different resources, considers multi states variables, and models cause-effect relationships between factors [32]. These aspects of BN have received increasing attention in the field of HRA, for instance, in modeling the relationship between PSFs [4,33], assessing human failure events dependencies [24], and extending and improving the available HRA methods [14,25].

3. BN-SLIM

To estimate the HEP in SLIM, the rates and the weights of the PSFs must be determined. In the absence of relevant data, which is usually the case, subjective measuring of rates and weights by experts can increase the uncertainty of the estimated HEP. Moreover, given several tasks in an operation, SLIM estimates the HEP of each task separately, disregarding the dependencies between human failure events in the tasks (e.g., due to common PSFs) which could lead to inaccurate estimation of the total HEP. To alleviate this drawback, we have developed an innovative technique, so-called BN-SLIM, by mapping SLIM into an equivalent BN. The benefit of doing so, is twofold:

(I) An operation may include a number of tasks to be fulfilled in parallel or series. Since tasks may share common PSFs, there would be dependencies among the SLIs of the tasks. Such dependencies, if not taken into account (as is the case in SLIM), can lead to an overestimation or underestimation of the total HEP. BN-SLIM, thanks to the capability of BN in considering dependencies, is expected to address this drawback of SLIM.

(II) BN-SLIM enables experts to express their uncertainty about the rates of PSFs in the form of probability distributions instead of deterministic point estimates. Given new evidence about HEP, the probability distribution of the rates can be updated; this, in turn, can help decrease the uncertainties and provide acumen for a proactive approach for preventing error under different contextual conditions.

In Sections 3.1 and 3.2, through an illustrative example, we will show how the initial results of the SLIM (i.e., the identified PSFs and their respective weights and rates) can be used to develop the BN, which together with the SLIM forms the proposed BN-SLIM methodology.

3.1. Model development

Following the steps of the original SLIM in Section 2.1, it is assumed that a set of N PSFs affecting the execution of a particular task along with their corresponding rates and weights has already been identified by subject matter experts. To develop the BN version of SLIM (i.e., BN-SLIM), the first step is building the structure of the BN, specifying the nodes and the arcs as conditional relationships between the nodes. According to the original SLIM, the effect of different PSFs on the HEP is modeled through the SLI variable (see Eq. (1)). Thus, two functions are needed for estimating the HEP value: One for modeling the relationship between the PSFs and the SLI, and the other for calculating the HEP using the SLI. So a BN with $N + 2$ nodes would be required: N nodes for representing the N PSFs and 2 nodes for representing the SLI and the HEP variables.

To better explain the model development, consider a case where training and experience are the only PSFs affecting the human performance in a task, i.e., $N = 2$. The BN for estimating the HEP given the task and its PSFs is depicted in Fig. 1, generated using AgenaRisk software [34].

Each PSF node would have several states to represent its rates. Since according to Eq. (1) each PSF directly impacts the amount of SLI, causal arcs are drawn from the PSF nodes to SLI node. The number of states of SLI node is equal to the number of possible combinations of the rates (states) of PSFs nodes. For the sake of simplicity, consider only three rates “R1 = 1”, “R5 = 5” and “R9 = 9” as the states of PSF nodes “Experience” and “Training”. The weights of 0.2 and 0.8 are considered for Experience and Training, respectively. As such, $3^2 = 9$ different values can be calculated for the SLI according to Eq. (1) as:

$$\begin{aligned} SLI = {} & 0.2 \times R_{Exprience} + 0.8 \times R_{Training} = 0.2 \times \{1,\ 5,\ 9\} \\ & + 0.8 \times \{1,\ 5,\ 9\} = \{1.0,\ 1.8,\ 2.6,\ 4.2,\ 5.0,\ 5.8,\ 7.4,\ 8.2,\ 9.0\} \end{aligned} \tag{5}$$

Each value of the SLI can be presented as a state of SLI node. Furthermore, according to Eq. (2), SLI node should be the only parent of HEP node. This node has two states, that is, human error occurs (HEP = Yes) and human error does not occur (HEP = No).

Completing the structure of the BN in Fig. 1, CPTs should be assigned to SLI and HEP nodes to quantify the effects of the PSF nodes. The marginal probability distributions assigned to each PSF node encodes the analyst's uncertainty about the rates of the PSF node. For illustrative purposes, assume that the probability distribution of the states of Experience node can be presented as $P_{Experience}$ (R1, R5, R9) = (0.4, 0.4, 0.2). This probability mass function may indicate that during the operation the probability that the task is executed by an operator with no experience (i.e., Experience = R1) is 0.4, with at least 5 years of experience (i.e., Experience = R5) is 0.4, and with more than

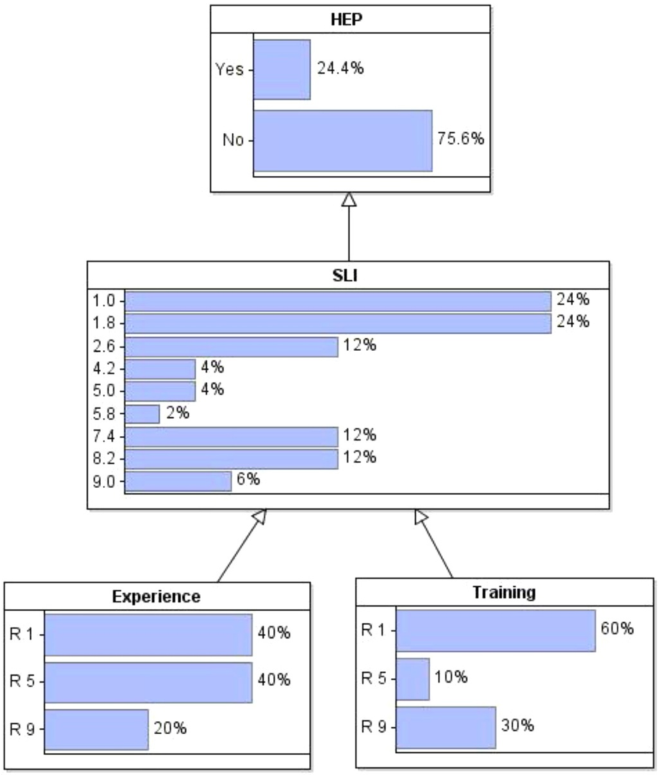

Fig.1. BN-SLIM structure.

10 years of experience (i.e., Experience = R9) is 0.2.

In a similar way, the probability distribution of the states of Training node is assumed as P_{Training} (R1, R5, R9) = (0.6, 0.1, 0.3). The probability distributions of the rates (states) make it possible to consider the uncertainty associated with the rates of PSFs whereas in conventional SLIM only one rate for each PSF should be specified.

The SLI node as an intermediate node in the BN makes a link between the PSFs and the HEP. The CPT of SLI node in Table 1 shows which combination of the rates of Training and Experience results in which state (amount) of the SLI.

To build the CPT of HEP node, the conditional error probability is assigned by direct application of the logarithmic formula in Eq. (2). where $a = -0.348$ and $b = 0.128$ have been calculated assuming that two pairs of corresponding SLIs and HEPs are known for the tasks as (SLI = 1, HEP = 0.6) and (SLI = 9, HEP = 10^{-3}). Having the values of a and b determined, the CPT to estimate the HEPs for possible values of the SLI can be presented in Table 2.

However, it should be noted that since two pairs of corresponding SLIs and HEPs are identified by subject matter experts with respect to

Table 1
CPT of SLI node with 9 states and two PSFs, Experience and Training, as its parents. The weights of 0.2 and 0.8 have been considered, respectively, for Experience and Training.

Training →	R1			R5			R9		
SLI↓ Experience→	R1	R5	R9	R1	R5	R9	R1	R5	R9
1.0	1	0	0	0	0	0	0	0	0
1.8	0	1	0	0	0	0	0	0	0
2.6	0	0	1	0	0	0	0	0	0
4.2	0	0	0	1	0	0	0	0	0
5.0	0	0	0	0	1	0	0	0	0
5.8	0	0	0	0	0	1	0	0	0
7.4	0	0	0	0	0	0	1	0	0
8.2	0	0	0	0	0	0	0	1	0
9.0	0	0	0	0	0	0	0	0	1

Table 2
CPT of HEP node given the states (values) of SLI node.

HEP↓ SLI→	1.0	1.8	2.6	4.2	5	5.8	7.4	8.2	9.0
Yes	0.600	0.317	0.167	0.046	0.024	0.013	0.004	0.002	0.001
No	0.400	0.683	0.833	0.954	0.976	0.987	0.996	0.998	0.999

the error context of interest, they are subjective and could vary from case to case [17,20,21,27]. For example, Kirwan [27] considered (SLI = 4, HEP = 0.5) and (SLI = 6, HEP = 10^{-4}) for identifying a and b while Islam et al. [17] calculated a and b assuming (SLI = 1, HEP = 0.15) and (SLI = 9, HEP = 10^{-5}). It should be noted that the present study is not aimed at resolving the uncertainty arising from such subjectivity, and thus the provided values are merely for demonstration purposes.

This information on the probability distributions of the PSFs rates can be ideally obtained from historical and empirical data or provided by subject matter experts when empirical data is not available or sufficient. Therefore, depending on the available data and expert knowledge, the rates of the PSFs could be identified probabilistically, deterministically, or both [14,25]. Given the previous rates and weights, as can be seen in Fig. 1, P(HEP = Yes) = 0.244. As shown in Fig. 2, the developed BN-SLIM is also capable of estimating the HEP when the rates of Training and Experience are given deterministically (as is the case in conventional SLIM), for instance due to exact knowledge.

It is noteworthy to mention that BN-SLIM can provide a quick estimation of HEP for a variety of cases with no need to perform all calculations needed in SLIM. This capability makes BN-SLIM a suitable alternative for conventional SLIM, especially when it is essential to estimate the HEP instantly, including decision making in the marine operations [17] or in emergency response actions where time is critical.

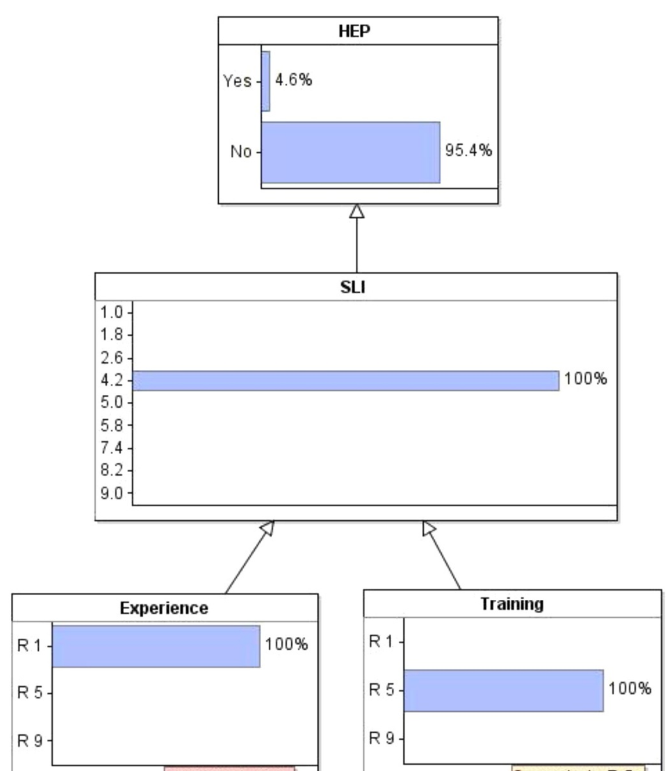

Fig. 2. BN-SLIM with deterministic PSF rates, representing the conventional SLIM.

3.2. Model refinement

To make the BN-SLIM more compatible with the conventional SLIM, the model can be refined so that the rates of PSF nodes could vary from 1 to 9 (see Section 2.1). Having a wider range of PSF rates could lead to a better modeling of uncertainty. Moreover, it would enable the modeler to predict the HEP while considering all possible performance conditions derived from different combinations of PSFs rates.

However, increasing the number of the rates to 9 and having n PSFs as the parents of SLI node would increase the size of the CPT of SLI node to $9^N \times 9^N$ cells to fill in: 9^N rows to present the states (values) of SLI node and 9^N columns to present the combinations of the states of PSF nodes. To handle this complexity, SLI values can be discretized into a limited number of states using equal frequency discretization method [35]. Discretization is a common approach in machine learning to handle the large size of continuous values which otherwise may considerably slow down the inference. Equal frequency discretization technique groups continuous numeric values into discrete intervals so that each interval would contain approximately the same number of values.

To demonstrate the application of equal frequency discretization method, consider 81 SLI values resulted from the combination of nine rates ($1 \leq Ri \leq 9$) of Experience and Training, with identified weights of 0.2 and 0.8 as in Section. 3.1. The suggested number of intervals (J) and also the frequency of numbers in each interval are both equal to $\sqrt{M}$, where M is the number of possible SLI instances [36]. Obviously, the higher the number of intervals the lower the discretization error. Equal frequency discretization technique sorts all SLI instances in an ascending order, and then divides the range into a specified number of intervals, in such a way that every interval contains the equal number of sorted SLI instances.

If several SLI instances happen to have the same value, the first interval can contain more than n_I instances. The following intervals are determined with the same method, so that the last interval may contain less than n_I instances. The last interval will be merged with the preceding interval if its frequency is less than half the mean frequency interval [37]. Each interval of SLI is considered as a state of SLI node. Therefore, considering 81 possible SLI instances (given two PSFs each with 9 rates), the optimal number of states for SLI node would be $\sqrt{81} = 9$; by sorting the SLI values the upper and lower bounds of each state of SLI node can be determined. The allocated SLI instances to each interval are listed in Table 3. As shown in the second row of Table 3, the first interval contains more than 9 instances because two instances has the same value of 2.2.

The CPT of SLI node contains ones and zeros to model the relationship between the combinations of rates and the corresponding SLI states. For instance, the row of state [1.0 − 2.2] in the CPT of SLI node can be populated as:

$$P\Bigg(SLI = [1.0 - 2.2] \mid Expeience = Ri, Training = Rj\Bigg) = \begin{cases} 1 & if\ 1.0 \leq 0.2Ri + 0.8Rj \leq 2.2 \\ 0 & else \end{cases} \tag{6}$$

Where Ri and Rj are the rates of Experience and Training, respectively, for $1 \leq i \leq 9$ and $1 \leq j \leq 9$. Other rows of the CPT are filled in the same way. The CPT of HEP node is populated as explained in Section 3.1 using the average value of each SLI state (interval).

It is worth noting that there are always some discretization errors when continuous data is discretized into intervals. It means that discretization of SLI values may lead to slightly different HEPs in BN-SLIM from those obtained from conventional SLIM. The Mean Absolute Discretization Error (MADE) can thus be computed to find out the expected difference between the results of BN-SLIM and SLIM as:

$$MADE = \frac{\sum_{i=1}^{M} |HEP_i^{SLIM} - HEP_i^{BN-SLIM}|}{M} \tag{7}$$

where HEP_i^{SLIM} and $HEP_i^{BN-SLIM}$ are the calculated HEPs using SLIM and BN-SLIM, respectively, for all M possible values of SLI. Given the foregoing example with two PSFs “Experience” and “Training” each with 9 rates, $M = 9^2 = 81$ is the number of the SLIs that may result from the combination of the PSFS rates; thus the MADE of the proposed discretization is calculated as 0.01 which could be improved by increasing the number of intervals.

Table 3
Discretization of SLI instances into 9 states (intervals) using equal frequency discretization technique.

SLI Interval	SLI instances
[1.0 − 2.2]	1.0, 1.2, 1.4, 1.6, 1.8, 1.8, 2.0, 2.0, 2.2, 2.2
(2.2 − 3.0]	2.4, 2.4, 2.6, 2.6, 2.6, 2.8, 2.8, 3.0, 3.0
(3.0 − 3.8]	3.2, 3.2, 3.4, 3.4, 3.4, 3.6, 3.6, 3.8, 3.8
(3.8 − 4.6]	4.0, 4.0, 4.2, 4.2, 4.2, 4.2, 4.2, 4.6, 4.6
(4.6 − 5.4]	4.8, 4.8, 5.0, 5.0, 5.0, 5.2, 5.2, 5.4, 5.4
(5.4 − 6.2]	5.6, 5.6, 5.8, 5.8, 5.8, 6.0, 6.0, 6.2, 6.2
(6.2 − 7.0]	6.4, 6.4, 6.6,6.6,6.6, 6.8, 6.8, 7.0, 7.0
(7.0 − 7.8]	7.2, 7.2, 7.4, 7.4, 7.4, 7.6, 7.6, 7.8, 7.8
(7.8 − 9.0]	8.0, 8.0, 8.2, 8.2, 8.4, 8.6, 8.8, 9.0

4. Model application

4.1. Case study

Developing the BN-SLIM step-by-step through a simple example of only two PSFs and one task (and one HEP) in the previous section, the model can be applied to a more complicated example consisting of more PSFs and tasks. As such, the application of BN-SLIM to improving the HEP estimation can be demonstrated for cases where various error contexts during carrying out tasks can lead to human errors.

The illustrative example is composed of three sequential tasks. For Task 1 and Task 2, experience and training were considered as the main PSFs influencing the success likelihood of performance while for Task 3, training and fatigue were considered as the main PSFs. The normalized weights of PSFs for each task are listed in Table 4. Besides, based on collected data and experts judgement, the probability mass distributions of the levels (rates) of experience, training, and fatigue of the operators are assumed to nearly follow exponential, uniform, and normal distributions, respectively (the root nodes in Fig. 3). The mean values and standard deviations of the foregoing prior distributions are listed in Table 5.

Fig. 3 depicts the BN-SLIM extended to estimate the HEPs of the three tasks as HEP 1, HEP 2, and HEP 3. According to the methodology described in Section 3 for developing the BN part of BN-SLIM, the probabilities of the states of each HEP can be calculated. Since the tasks should be performed sequentially (in series), OR gate can be used to calculate the Total HEP. The CPT of the nodes were populated

Table 4
Weights of the PSFs for Tasks 1, 2, and 3.

Task	Experience	Training	Fatigue
Task 1	0.55	0.45	–
Task 2	0.2	0.8	–
Task 3	–	0.15	0.85

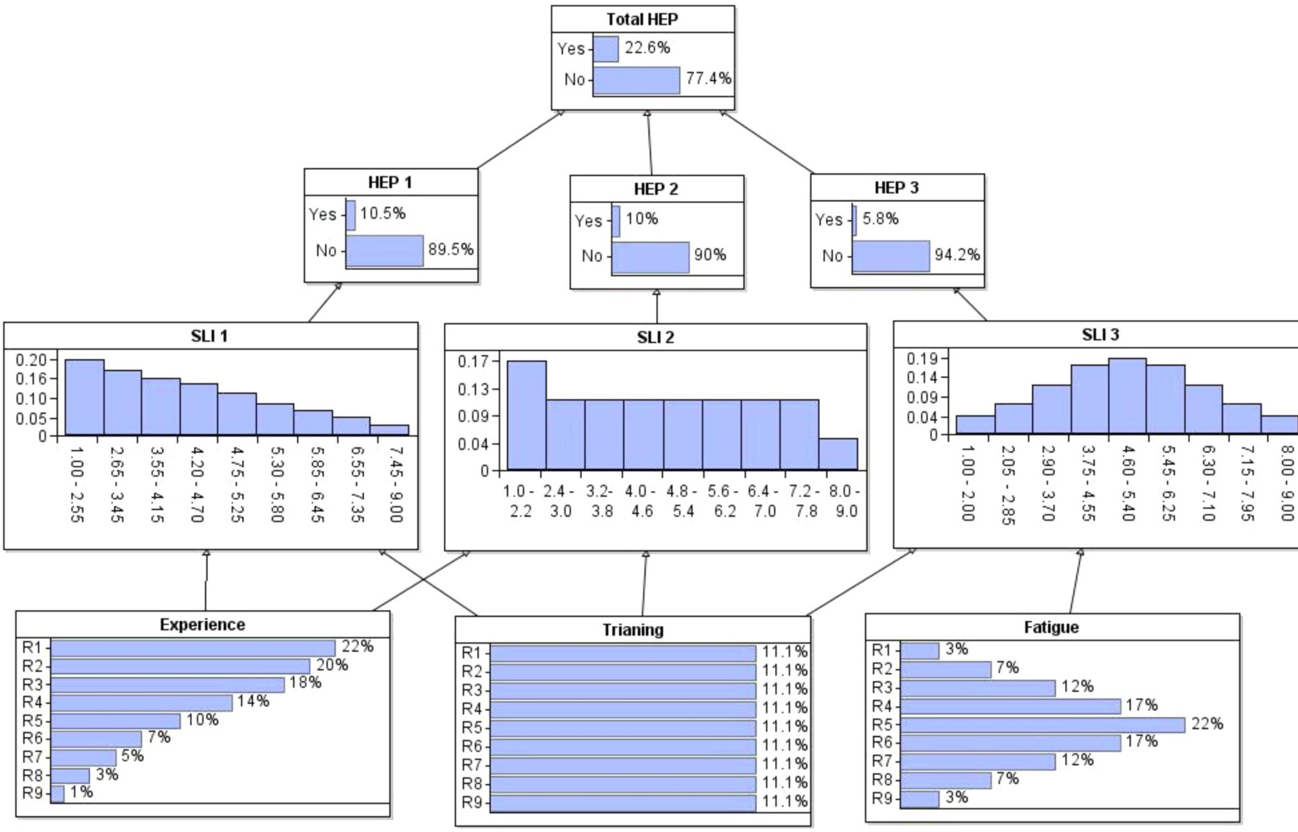

Fig. 3. BN-SLIM for the calculation of individual HEPS and the Total HEP.

Table 5
Parameters of prior and posterior probability distributions of the rates of the three PSFs (root nodes) in Fig. 3. The mean values and standard deviations of the probability distributions are also given for the sake of clarity.

PSF	Prior distribution of rates		Posterior distribution of rates given Total HEP = Yes	
	Mean	Standard deviation	Mean	Standard deviation
Experience	3.32	2.01	2.76	1.76
Training	5.00	2.58	3.06	2.07
Fatigue	5.00	1.88	4.60	1.98

according to the explanations in Sections 3.1 and 3.2. The CPTs of nodes Total HEP and HEP1 and part of the CPT of node SLI1 are given in the appendix.

4.2. Results and discussion

Given a number of related tasks during an operation, SLIM calculates the HEP of each task separately, ignoring the dependencies among the HEPs due to common PSFs. BN-SLIM, on the other hand, can consider such dependencies thanks to the modeling features of BN. As can be seen from Fig. 3, using BN-SLIM the probability of the total human error has been calculated as $P\,(Total\ HEP = yes) = 0.226$. However, ignoring conditional dependencies among the HEPs (which is the case in SLIM) would have resulted in an overestimation of the total HEP as

$$P(Total\ HEP = yes) = 1 - (1 - P(HEP\ 1{=}\text{yes}))(1 - P(HEP\ 2{=}\text{yes}))(1 - P(HEP\ 3{=}\text{yes})) = 1 - (1 - 0.105)(1 - 0.100)(1 - 0.058) = 0.241$$

One of the exclusive abilities of BN-SLIM over SLIM is diagnostic reasoning, aimed at updating the probability distributions of the PSF rates given some evidence. For instance, if it is known that human error has occurred, BN-SLIM can identify both (i) the PSF which has contributed the most to the error and (ii) the most likely rate of each PSF which has been present during the error. Indeed, updating analysis helps HRA practitioners conduct "what-if" scenarios in order to gain better acumen and accordingly take proactive approaches for preventing human errors [14].

To make the discussion more concrete, two "what-if" scenarios are conducted below.

4.2.1. First scenario

In the first scenario, we set $P(Total\ HEP = yes) = 1$ as evidence to determine the most critical PSF contributing to the human error although the source of error is unknown. (It is not known which tasks were executed erroneously). Propagating this evidence throughout the model, the posterior probability distributions of the rates of the PSFs can be calculated (Fig. 4); the posterior mean values and standard deviations are reported in Table 5.

Comparison of posterior and prior probability distributions of PSFs can be used to evaluate and rank order the PSFs based on their

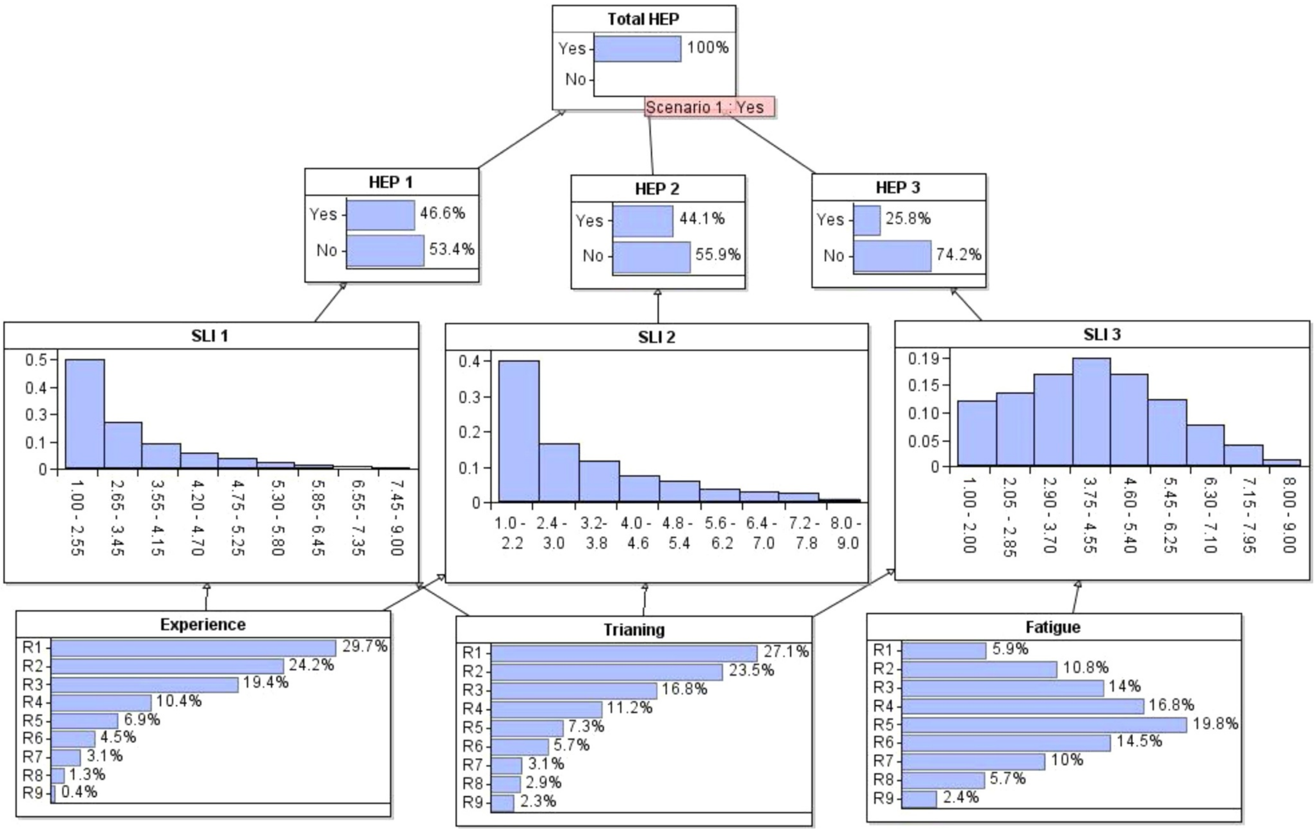

Fig. 4. BN-SLIM for the calculation of posterior probability of the rates given "Total HEP = yes".

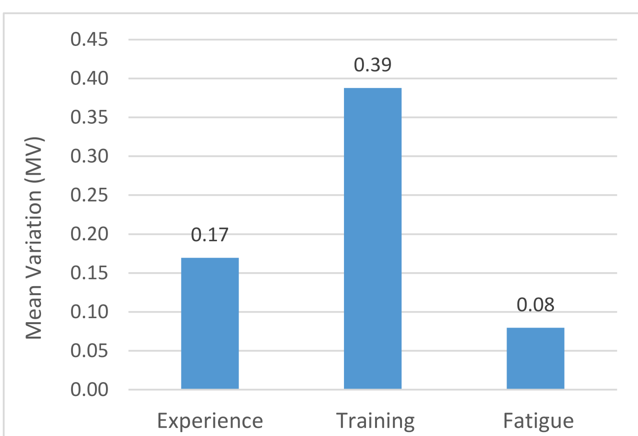

Fig. 5. Mean variation of the probability distributions of the PSFs: the higher the MV the more critical the respective PSF.

contribution to the total human error. One of the criterion for measuring the contribution of a PSF is the Mean Variation (MV) as the difference between the prior and posterior mean values of the rates:

$$MV_{PSF} = \frac{\sum_{i=1}^{9} Ri \times \pi(Ri) \; - \; \sum_{i=1}^{9} Ri \times \theta(Ri)}{\sum_{i=1}^{9} Ri \times \pi(Ri)} \tag{8}$$

where $\pi(Ri)$ and $\theta(Ri)$ are the prior and posterior probabilities, respectively, of the rates. Given the prior and posterior mean values in Table 5, the MVs of the PSFs have been calculated as shown in Fig. 5.

As can be seen from Fig. 5, Training and Experience can be identified as the most and second most critical PSFs, respectively, given a total human error. Among the PSFs, Training might have been expected to have the largest influence on the total human failure due to its contribution to all the three tasks and also its largest total weight of 1.4. However, it could not be so easy to rank order the two other PSFs, i.e., Experience and Fatigue, based on their contribution: Experience is involved in two tasks with a total weight of 0.75 whereas Fatigue is involved only in one task yet with a higher weight of 0.85.

As can be seen in Fig. 5, MV can prioritize PSFs based on their contribution to the overall human error which helps analyst optimally allocate the resources in order to reduce the likelihood of human error.

Moreover, to gain more insight into the performance conditions for this scenario, a comparison between the posterior and prior probabilities of each rate of the PSFs can be conducted. This comparison can help specify which rates are more likely to have contributed to the Total HEP. To this end, the ratio of variation (RV) of each rate can be defined as:

$$RV_{Ri}^{PSF} = \frac{\theta(Ri) - \pi(Ri)}{\pi(Ri)} \tag{9}$$

The RVs of the rates of Training, $RV_{Ri}^{Training}$, as the most critical PSF, have been depicted in Fig. 6; as can be seen, the training rates lower than 4 are more likely to be present in the Total HEP. Therefore, using

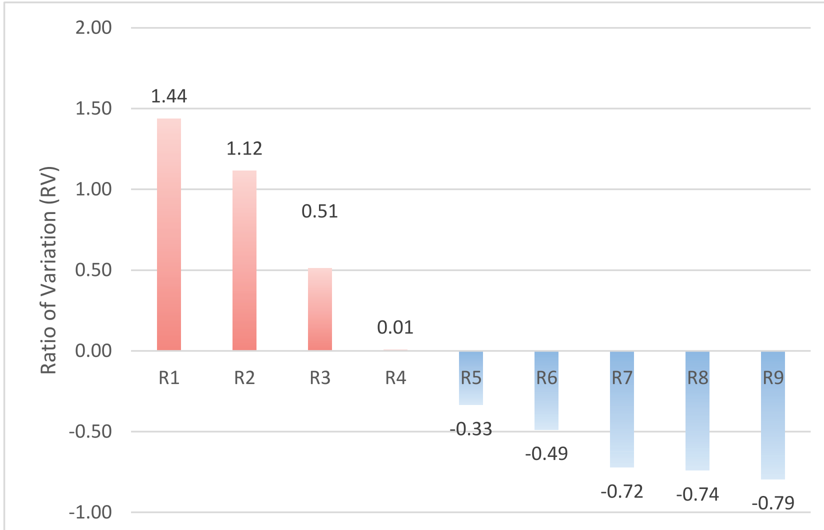

Fig. 6. Ratio of variation of training rates given the total human error (i.e., "Total HEP" = yes).

MV, Training is identified as the most critical PSF while using RV the lower rates of Training (lower than 4) are identified as the most likely conditions of Training with regard to this scenario.

4.2.2. Second scenario

In the second scenario, two pieces of evidence are applied: a human error has occurred, i.e., $P(Total\ HEP = yes) = 1$, and the level of experience of the operator who may have been involved in executing the tasks has been five (e.g., five years), i.e., $P(Expereience = R5) = 1$. Considering the posterior probabilities calculated given this evidence, the RVs of the rates of Training, as an example, have been presented in Fig. 7.

As can be seen, R1, R2 and R3 are, respectively, the rates with the highest RV, indicating that operators with a level of "Experience" of five and levels of "Training" lower than 4 are more likely to have participated in the error in the context of the foregoing three tasks. This outcome demonstrates that RV of PSF rates can be used as an effective diagnostic criterion, reflecting more precisely the likely performance context given a human error.

5. Conclusions

This paper has proposed a new model, so-called BN-SLIM, for improving the performance of SLIM using BN. The BN-SLIM was developed by mapping SLIM in BN so that the causal links between performance shaping factors (PSFs) and human errors as well as the dependencies among human errors could be modeled. We demonstrated that the BN-SLIM can effectively be applied for human error probability (HEP) assessment as it outperforms SLIM with regard to the following modeling aspects:

- Handling uncertainty: BN-SLIM is better able to handle uncertainties by considering probability distributions of PSF rates in contrast to SLIM which only adopts deterministic rates. Indeed, BN-SLIM

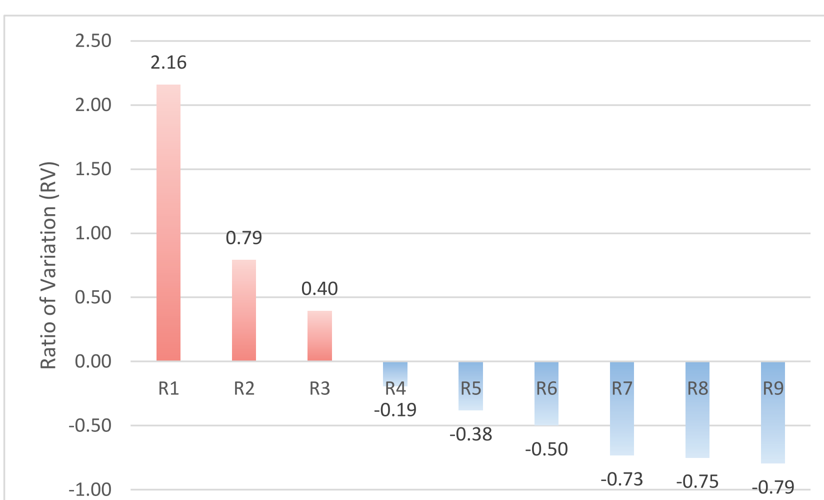

Fig. 7. Ratio of variation of training rates given a human error (i.e., "Total HEP" = yes) by operators with five years of experience (i.e., "Experience" = R5).

enables practitioners to use both expert judgment and empirical data in a probabilistic way, which could be a significant step toward improving the performance of SLIM which relies on the deterministic judgment of experts.
- Considering dependencies: Given an operation consisting of a number of tasks, SLIM estimates the total HEP of the operation as an aggregation of the HEPs of the tasks, ignoring the dependencies among the HEPs due to common PSFs. BN-SLIM, on the other hand, can consider the conditional dependencies among the tasks' HEPs while calculating the operation's total HEP. This capability would result in a more accurate prediction of human performance.
- Diagnostic analysis: Thanks to the capability of BN-SLIM in probability updating, two criticality measures have been defined in the present study. Given a HEP, the mean variation, which is defined as the normalized difference between the mean values of the prior and posterior distributions of PSF rates, can be used to identify the PSF contributing the most to the HEP. Likewise, the ratio of variation, which is defined as the normalized difference between the posterior and prior probabilities of PSF rates, can be used to identify the most likely PSF rate leading to the HEP. This capability could be very effective in proactive risk assessment and management to prevent or reduce the likelihood of human failure events.

Aside from the above-mentioned improvements made to SLIM via BN-SLIM, there is still room to enhance the performance and accuracy of BN-SLIM. For instance, similar to the rates, the weights of PSFs can also be modeled probabilistically to present the experts uncertainty about the importance of PSFs in relation to a certain task. This, however, can significantly increase the size of conditional probability tables and make the modeling too complex and intractable.

Besides, the uncertainty associated with the constant parameters of the logarithmic function used to calculate the HEP, both in SLIM and BN-SLIM, still remains an open question for further research. Nevertheless, according to the added features, we believe that the proposed BN-SLIM is more compatible with probabilistic safety assessment and management methodologies.

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The financial support provided by the EU-H2020 NARSIS project under grant No. 755439 is appreciated.

Appendix

Tables A1, A2, and A3 indicate the CPTs of Total HEP, HEP1, and SLI1 nodes in Fig. 3.

Table A1
The CPT of Total HEP node.

HEP1	Yes				No			
HEP2	Yes		No		Yes		No	
HEP3	Yes	No	Yes	No	Yes	No	Yes	No
Yes	1	1	1	1	1	1	1	0
No	0	0	0	0	0	0	0	1

Table A2
The CPT of HEP1 node.

SLI1 Interval→ HEP1↓	1.00–2.55	2.65–3.45	3.55–4.15	4.20–4.70	4.75–5.25	5.30–5.80	5.85–6.45	6.55–7.35	7.45–9.00
Yes	0.3215	0.1157	0.0609	0.0377	0.0245	0.0156	0.0096	0.0050	0.0019
No	0.6784	0.8842	0.9390	0.9622	0.9754	0.9843	0.9903	0.9949	0.9980

Table A3
Part of the CPT of SLI1 node.

SLI1 Intervals → Experience↓	Training↓	1.00–2.55	2.65–3.45	3.55–4.15	4.20–4.70	4.75–5.25	5.30–5.80	5.85–6.45	6.55–7.35	7.45–9.00
R1	R1	1	0	0	0	0	0	0	0	0
R1	R2	1	0	0	0	0	0	0	0	0
R1	R3	1	0	0	0	0	0	0	0	0
R1	R4	1	0	0	0	0	0	0	0	0
R1	R5	0	1	0	0	0	0	0	0	0
R1	R6	0	1	0	0	0	0	0	0	0
R1	R7	0	0	1	0	0	0	0	0	0
R1	R8	0	0	1	0	0	0	0	0	0
R1	R9	0	0	0	1	0	0	0	0	0
R2	R1	1	0	0	0	0	0	0	0	0
R2	R2	1	0	0	0	0	0	0	0	0
R2	R3	1	0	0	0	0	0	0	0	0
R2	R4	0	1	0	0	0	0	0	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

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