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Research Article

Estimating the Influence of Improper Workplace Environment on Human Error: Posterior Predictive Analysis

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A model for identifying, analyzing, and quantifying the mechanisms for the influence of improper workplace environment on human error in elevator installation is proposed in this study. By combining a modification of a human error model with real-world inspection data collected by an elevator installation company, the influence paths of improper workplace environment on the conditional probability of human error were quantified using a Bayesian network parameter-learning estimation method and posterior predictive simulation. Under the condition of an improper workplace environment, the probability of human error increased by 80% of its original value, a factor much higher than that resulting from improper management. The most probable influence was found to be improper workmanship and changes in the information required by the worker, thus triggering cognitive failure and consequent unsafe actions by workers. The proposed methodology (posterior predictive simulation) provides a new approach in construction studies for quantifying the probabilistic levels of various causal paths, and the results show the key mechanism for the influence of improper workplace environment on human error using real-world mechanical installation data.

1. Introduction

1.1. Importance of Workplace Environment in Effective Elimination of Human Error. From theoretical and empirical studies [1, 2], human error by workers was found to be the most important causal factor in accidents. If human error in the construction industry can be effectively reduced, the occurrences of construction accidents can be minimized [3, 4]. Previous studies revealed that if the factors of facilities, work methods and operations, processes, equipment, tools, products, new technologies, and work organization that lead to human error in the work environment can be eliminated by an effective workplace environment, the probability of human error can be greatly reduced, and the occurrence of accidents can be controlled [5, 6]. "Workplace environment" ordinarily refers to the environment of workplace in a location during the construction itself, that is, structural and product workplace environments. However, with the gradual integration of workplace environments with construction processes, the workplace environment stage needs to be more connected to the construction stage. Thus, the setup of construction methods and processes must also be included in the general category of workplace environment [7]. Therefore, in the present study, the term "workplace environment" includes both the engineering and process workplace environments. Since theoretical and empirical studies of cybernetics have indicated that a safety-oriented workplace environment is one of the most economic and effective means for controlling accidents [8, 9], experienced workers may still resort to unsafe behavior in response to the work environment conditions and the process demands even under conditions in which unsafe behavior is strictly prohibited [2, 10], thus highlighting the importance of the workplace environment in the elimination of human error.

1.2. Lack of Clarity in Current Understanding of Workplace Environment-Human Error Relationship. Although the importance of an effective workplace environment for the minimization of human error has been confirmed in many studies, existing research does not provide sufficient explanation for the mechanism of the influence of workplace

environment on human behavior. This lack is reflected in the following three aspects:

(1) The mechanisms of the influence of workplace environment on human error are asserted on the basis of qualitative (or even scant) explanations, whereas an analytical approach is required to reveal the relative importance of the mechanisms of influence for use as a management reference. Most existing research simply uses statistical correlation as a basis for connecting a structural and/or engineering workplace environment with unsafe behavior. Therefore, the explanation for the mechanism is inadequate. Studies based on workplace environment principles [11], expert opinions [12], or statistical correlation [13] have shown that the probability of occurrence of unsafe worker behavior can be reduced by improvements in the workplace environment [14]. For a type of accident that may occur on a steel structure construction site, Leu and Chang [15] conducted a Bayesian modeling study based on expert opinions and forecasted the probability of various types of accidents by comparisons with actual accident data. Their model covers a wide range of variables, including variables relevant to workplace environment and unsafe human behavior. However, their study focused only on the forecasting of accident probabilities without examining the influence of the variables of workplace environment and human error. In Haslam et al.'s [16] deviation model, the accident path begins with origination influences, is then adjusted by shaping factors, and finally forms the immediate accident circumstances. Though the factors causing accidents were properly abstracted and clustered into groups, the influence of each factor was not quantified. The influence of a factor is shown intuitively by the proportion of accidents in which that factor is involved, which ignores interactions between factors and provides no confidence level for the measurement. Furthermore, these studies do not provide an analytical approach that demonstrates the relative importance of the mechanics of influence for use in the allocation of management resources.

(2) Most data have been collected from questionnaires, expert decisions, and other subjective methods [17–19]. Compared with actual engineering data, this data collection process and use of subjective data are more likely to cause random error and deviation, leading to inaccurate results. Li et al. [20] stated that the lack of an accurate and comprehensive database is the main difficulty in the study of human error. In their study, the fuzzy Bayesian method was introduced to deal with a variable value, but still the basic data were the scores given by experts who estimated the conditional probability for each causal relationship, affecting the reliability of the results. In the study by Leu and Chang [15], actual accident data were used to verify the reliability of the model. However, the accident causation model was still heavily expert-driven, and deviation in the result caused by the subjective data was not eliminated.

(3) Although modeling research studies have been conducted to address the relationship between workplace environment and human error, the existing theoretical models and methods require the incorporation of the psychological states of workers who interact with the work environment in order to discover the drivers of human errors. Jiang et al. [21] assumed that behavior is the product of human cognition on the environment, that is, that the most direct cause of human error is cognitive failure, where cognitive failure depends on individual factors (including physical and psychological conditions) and environmental factors (risk exposure). However, they did not explain how the environment imposes constraints that cause cognitive failure and further result in human error.

As can be seen from the gaps summarized above, the existing research results are not able to clearly explaining the mechanism for the influence of workplace environment on the occurrence of human error. Thus, individual project participants do not have a sound basis for evaluating the importance of a safe workplace environment, and workplace designers and owners lack impetus and motivation to participate in and implement safety programs for the workplace environment, which are the major challenges in promoting error prevention through the workplace environment. By clearly identifying the mechanism of influence between the engineering workplace environment and human error in the construction industry, the concept of error prevention through the workplace environment can be further promoted. Therefore, on the basis of the models proposed by the aforementioned research, the present study uses real-world observation data to analyze and explain the mechanism for the influence of workplace environment on human error.

1.3. Challenges of Human Reliability Analysis in the Construction Industry. Because the construction industry needs a mechanistic model for workplace environments that address unsafe human behavior, an important tool is the human reliability analysis (HRA), which analyzes the probability of success of those activities that must be accomplished in terms of the reliability or availability of the system [22]. However, the HRA method is more often used in industries such as nuclear energy, aviation, and related fields [23–25]. In contrast to these fields, the operation site of a construction project features lower automation, greater personnel mobility, more rapid changes in the construction environment, and more open systems (vulnerable to external factors such as weather) [26]. Therefore, using the HRA method to analyze problems in the construction industry is a great challenge [27]. For example, compared with the construction industry, the nuclear power industry is highly automated, with more machinery and system operations that are carried out by workers. Thus, the cognitive

reliability and error analysis method (CREAM) designed for the nuclear power industry has relatively more descriptive variables [28]. In addition, these factors are not dominant in a construction project. In a construction project, the work environment faced by workers is relatively complicated and varied, which is not well captured by the HRA method [29, 30]. As a result, the probability of human error (HEP) cannot be accurately calculated in order to measure the influence of workplace environment on human error. Therefore, in order to apply the HRA method to a construction project, the variables and their definitions need to be modified to suit the characteristics of a construction project.

Although the CREAM incorporates psychological factors (e.g., inattention and missing observations) in the mechanisms of influence between the workplace environment and human errors, studies show that the application of HRA in various industries also shares common defects [31, 32] as follows:

(1) *Lack of available data*: For HRA, the most serious problem is that the data sources are too broad to be applied to specific industries [33]. Thus, if a particular industry wants to understand its specific problems, it must collect data from scratch [34].

(2) *Over-reliance on expert judgment*: In the existing HRA method, the evaluation of factors that influence human errors (performance-shaping factors (PSFs)) and the probability of occurrence rely mainly on the subjective judgment of experts, which can easily cause a large random error [20, 31, 35, 36].

(3) *Coarse measurement of variables having no clear boundaries*: Although methods such as the existing CREAM backtracking can provide the relationships between different PSFs and most HRA methods that have descriptions for different error types, their level of description is too coarse and there are no detailed assessment indicators. This raises doubts about the accuracy of the HEP values calculated by these methods.

Despite these gaps, Liao et al. [37] had proposed a human error model based on the CREAM that includes more variables that capture the characteristics of construction projects. The mechanisms by which improper workplace environments can cause human error in construction can only be identified when the existing variables and their definitions are further modified according to the characteristics of the construction project and when its data are used as the basis for parameter estimation. Although the influence paths for improper workplace environment and human error were identified, the topology of the model requires revisions based on industrial experience to make the model suitable for parameter estimation, and the results need to be mapped and validated with previous studies to corroborate the legitimacy of the results. This study proposes an analytical approach, posterior predictive simulation, based on real-world observations, to answer the following questions: (1) In terms of conditional probability, how much does improper workplace environment contribute to the rate of occurrence of human error? (2) How can the mechanisms of influence be ranked according to the quantity of human errors resulting from an improper workplace environment?

2. Methodology

The goal of this study was to demonstrate an approach to discover and prioritize the impact of improper workplace environment on the probability of occurrence of human errors. First, an influence model (a Bayesian network) published in a previous study was modified, and then, real data were mapped onto the influence model. Second, parameter estimation was performed using the expectation-maximization algorithm to estimate the levels of influence for improper workplace environment on the probability of occurrence of human errors. Third, by comparisons with the baseline derived from posterior predictive simulation, the influence levels of various paths were quantified. Lastly, the focus was turned to discussions of various paths by which an improper workplace environment can lead to human errors, and the results were compared with those of other studies for validation purposes. Details of the methodology and of its implementation for this study are presented in the sections that follow.

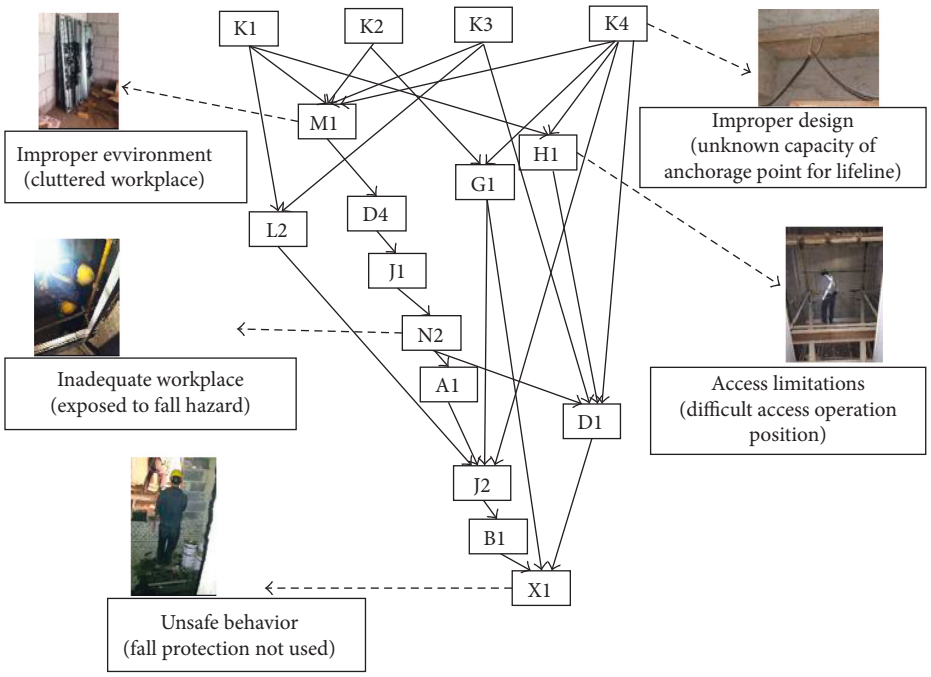
2.1. Modification of the Influence Model: Bayesian Network. First, this study adopted a focused group discussion adaptation of the model proposed by Liao et al. [37] using negative proposition logic. The principle was as follows: as long as two or more members in the focused group raised questions in the model, these questions would be discussed and modified until all members reached an agreement or only one of all members did not support the model, i.e., if the focused group proposed that a certain causal link did not exist or there was not only one variable in the influence path, then the chain of causality would be removed or other possible variables would be considered. The modified Bayesian network (BN) model is shown with the names of the nodes (each of which corresponds to a risk factor, such as faulty diagnosis or inadequate procedure) in Figure 1.

Second, the safety-inspection records collected by an international mechanical installation company were mapped to the model variables according to the following rules:

(1) Is the description of the observational variable a potential danger to the workers themselves? If so, it is deemed to belong to the category of human error. If it only creates an unsafe environment or unsafe condition, then it is identified as one of the PSFs.

(2) By comparing the descriptions of the observational variables with the company safety regulations, the specific object with an error or the environment state is categorized to match the model variables.

For example, a certain observational variable (risk), namely, workers having no protection against falling while working on a ladder at elevations higher than 2 m, would be described by the safety rule as "workers must be protected against falling when working at elevations higher



Node	Content
A1	Observation miss
B1	Faulty diagnosis
D1	Memory failure
D4	Inattention
G1	Inadequate procedure
H1	Access limitations
J1	Communication failure
J2	Missing information
K1	Insufficient maintenance
K2	Inadequate quality control
K3	Improper management
K4	Improper design
L2	Insufficient knowledge
M1	Improper environment
N2	Inadequate workplace
X1	Wrong sequence (unsafe behavior)

Figure 1: Human error model for construction industry using an elevator installation as an example.

than 2 m." This rule focuses on whether fall protection is used while working, which belongs to the description of human behavior. By comparison, this example is found to be consistent with the definition of the model variable "wrong sequence"; that is, one or more operations in an action sequence were skipped. Therefore, this risk item is mapped to this model variable. For instance, the node "wrong sequence" was mapped with the predefined human error "fall protection not used when exposed to a fall hazard."

The expectation-maximization (EM) algorithm was used to estimate the various variables in the model and obtain the conditional probability table (CPT) for each variable. In addition, a posterior predictive simulation was used to set all the root nodes in the network to either zero or one, and the conditional probability of the corresponding unsafe human behavior was calculated according to the CPT. By comparison, the influence of each root node on unsafe human behavior was obtained, and an understanding was gained of the potential influence of the workplace environment on the probability of occurrence of human error that is due to a number of factors.

Finally, the most probable path from workplace environment to human error was selected. The numerical value for the influence of each path was calculated by evaluating the nodes in the path via discussion and identification of the most likely mechanism for the influence of workplace environment on human error.

2.2. Parameter Estimation

2.2.1. Parameter Estimation Approach. Bayesian parameter estimation is a data-learning method that is based on a given BN structure and uses the data to learn the probability distributions of parameters in the networks and nodes. When BN is used to analyze human error, the conditional probability distribution (table) that describes the relationships among nodes can be obtained by parameter estimation. The probability forecasting the final node, that is, unsafe human behavior, can also be studied using the results. By using BN, studies have improved the HRA model by cross adoption of data and expert opinion to increase the credibility of the model. However, because of the high specialization and difficulty of data acquisition in the construction industry, prediction of HEP still relies on the evaluation of experts, which results in low accuracy. Zhou et al. [38] pointed out that the results are often inaccurate when the BN parameter learning only uses pure data calculation, and the method of using expert opinion scores as node probabilities is also inaccurate. With regard to this problem, the combination of expert opinion and data in the parameter learning process is widely believed to effectively improve the accuracy of the probability estimation [39]. Zhou et al. [38] proposed that experts often have difficulty in providing an accurate probability of occurrence of a node but can easily provide a qualitative description. Thus, the reliability of the model could be greatly improved if this type of description can be integrated into it.

BN parameter learning can perform a complete data parameter estimation as well as calculations with missing data. Because the present study performs calculations using actual engineering data, which commonly have missing values, this advantage of BN parameter learning can guarantee the generation of a utilization ratio and thus is very suitable for use as the calculation method in this

study. In addition, because BN was previously developed with a relatively mature algorithm, many types of software that can directly perform the estimation process for the Bayesian parameters are now available. In the present study, the Bayes Net Toolbox (BNT) software for MATLAB 2013a was chosen for the BN parameter learning [40].

2.2.2. Parameter Estimation Logic. This study used actual engineering data for the calculation. Because of the high frequency of missing data values, the typical expectation-maximization algorithm, which uses the Bayesian parameter estimation to deal with the missing data, was adopted. The "expectation" step uses the modified maximum likelihood estimation (MMLE) method to estimate the parameters for the missing data nodes; it then uses these estimated values as the data to fill in the missing values [41]. The "maximization" step estimates the parameters. The specific calculation principles are as follows:

(1) *Step E (expectation)*: For missing data point z, the equation of estimation for its MMLE, $l(\theta)$ is expressed as

$$l(\theta) = \sum_{i=1}^{m} \log\, p\left(x^{(i)},\ \theta\right), \tag{1}$$

where θ is the parameter of the MMLE equation, m is the number of data samples, and $x^{(i)}$ ($i = 1, 2, \ldots, m$) is the sample value. For $z^{(i)}$ ($i = 1, 2, \ldots, m$), if Q_i is the probability density function of $z^{(i)}$, then the equation for the original θ and estimate $l(\theta)$ is expressed as

$$Q_i\left(z^{(i)}\right) = p\left(z^{(i)} \middle| x^{(i)}; \theta\right), \tag{2}$$

where $Q_i(z^{(i)})$ is the largest estimation point for $l(\theta)$.

(2) *Step M (maximization)*: θ' is the updated parameter of the MMLE, expressed as

$$\theta' = \arg\max \sum_{i} \sum_{z^{(i)}} Q_i\left(z^{(i)}\right) \log \frac{p\left(x^{(i)},\ z^{(i)}; \theta\right)}{Q_i\left(z^{(i)}\right)}. \tag{3}$$

Step M calculates the MMLE of the parameter under the Step E hypothesis. The EM algorithm is a process of iterating Steps E and M. As $l(\theta)$ progressively increases, the estimation process ends when the difference between $l(\theta)$ and $l(\theta')$ decreases to a certain range and remains unchanged.

2.3. Quantification of Influence Levels by Path: Posterior Predictive Simulation. Making predictions with Bayesian methods is trivial. To begin, to estimate unknown parameter θ values given observable outcome y and predictors x, the Bayes rule is used:

$$p(\theta|y,\ x) \propto p(\theta)p(y|x,\ \theta). \tag{4}$$

In this study, a Bayesian network model was used to estimate these unknown parameters. Once the θ values are estimated, an unknown observable $\tilde{y}$ can be created or predicted from the same process (model), conditioning on the observed y, x, and θ. Thus, the posterior predictive distribution of $\tilde{y}$ can be estimated:

$$p((\tilde{y})|y,\ x,\ \theta) = \int p(\tilde{y}|\theta,\ y,\ x)p(\theta|y,\ x)d\theta. \tag{5}$$

Following that, the predictive probability differences (x values) of the various unsafe human behaviors, $\Pr(\Delta\tilde{y})$, can be obtained by changing the x values, and since these are all binary, the following is obtained:

$$\Pr(\Delta\tilde{y}) = p\left(\tilde{y}'|y,\ x = 1,\ \theta\right) - p\left(\tilde{y}''|y,\ x = 0,\ \theta\right). \tag{6}$$

2.4. Implementation Details. This study used Python programming to screen and preprocess the data and employed the BNT toolbox in MATLAB as the computation software. The model variable system and network structure were input into the software in the form of a matrix recorded in Excel, and the process was set up to loop 20 times. When the calculation ends, the probability distribution of each node is output. The probability distribution conditions were identified according to the causal relationships among the nodes, and the data were recorded. Then, the CPT for all network nodes was obtained. Part of the CPT is shown in Figure 2.

The CPT describes the probability of occurrence of the child nodes under different parent node states. Because the four root nodes K1, K2, K3, and K4 have no parent root, their probability of occurrence is certain. The analysis and calculations in this study were all based on this CPT.

3. Data

The fundamental data used in this study came from 50,000 records of safety-inspection data of an elevator installation company from 2010 to 2017. Based on the safety risks observed and recorded by the company on a regular basis, it has been deemed one of the most effective programs for safety mitigation [13]. The record for each inspection includes the risk state of various checklist items such as human errors, environment, machinery, and organization. Each record also includes other information such as time, location, inspector, and elevator type. The company checklist contains 81 risk items, which are divided into four categories—fall protection, elevator control, control of energy transfer, and hazardous operations—each containing 12–30 hidden dangers (checklist items). The company policy rule stipulated that any risk found during an inspection should be rectified immediately. The company randomly investigated the safety risks at the site at least eight times per month using the safety audit checklist. By corporate regulation, 3–5 inspections occurred weekly, which could only be carried out by trained inspectors and were immediately logged into the safety-inspection system. When any hazards were found, they were recorded by the safety officer and confirmed by the corresponding supervisor. This double-check process guaranteed the quality of the records. Once the hazards were confirmed, the company policy enforced the elimination of

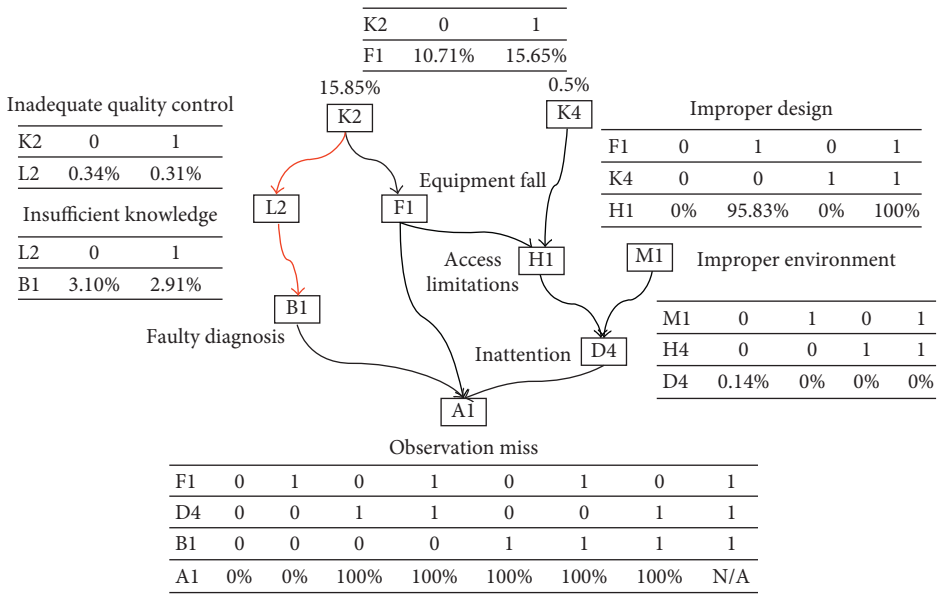


Figure 2: Parameter estimation for CPT (partial BN).

Table 1: Influence (probability increase) of root nodes on unsafe behavior.

PSF	Insufficient maintenance (K1)	Inadequate quality control (K2)	Improper management (K3)	Improper design (K4)
P(X1|PSF = no)	6.08%	3.34%	6.10%	6.07%
P(X1|PSF = yes)	7.08%	16.14%	6.10%	10.91%
PI*	16.4%	383.1%	0.00%	79.6%

*PI (probability increase) = [P(X1|PSF = yes) − P(X1|PSF = no)]/P(X1|PSF = no).

the hazard immediately upon the end of the inspection. In order to use more specifically targeted data, 39,691 records of vertical ladder construction were screened and qualified as the input data for this study.

4. Findings

4.1. Contribution of Improper Workplace Environment to Occurrence of Human Error. Although existing research reports absolute figures for the influence of improper design (root node K4) on human error, quantification of the effects of the other three root nodes (insufficient maintenance, K1; inadequate quality control, K2; and improper management, K3) on human error is necessary so that the existing research can be corroborated. With regard to these node variables, CPT provides the probabilities of parent nodes and those of the subnodes under different conditions, which to some extent are representative of conditions on-site. Therefore, from the assignment of the root nodes, the probabilities of the other nodes can be obtained. For example, when a workplace environment is improper, the root node is assigned as 1 (K4 = 1). The probability of unsafe behavior caused by human under the error sequence class under the assumption of an improper workplace environment can be calculated within a sequence class. Similarly, when the value is assigned as zero, the probability of unsafe human behavior under the assumption of a proper workplace environment can be calculated. Because this calculation is carried out without any change in the on-site work, the probabilistic influence of improper workplace environment on unsafe human behavior can be determined via comparison. When applied to all the root nodes, these calculations can also determine the influence of the other root nodes on human error.

The calculation results obtained for insufficient maintenance (K1), inadequate quality control (K2), improper management (K3), and improper design (K4) are shown in Table 1. Insufficient maintenance refers to poorly maintained equipment; temporary and permanent facilities may be improperly serviced during the initial construction stage, resulting in a disabled and nonfunctioning system. Inadequate quality control refers to defects in entities both tangible (such as devices) and intangible (such as rules), as well as insufficiency of resources and supplies. Improper management means ineffective organizational structure, responsibility allocation, and communication, including that for managing equipment, materials, and subcontractors. Improper workplace environment means defects in the configuration of construction materials and engineering techniques.

Table 1 shows the influence of the four root nodes on the estimated probability of unsafe human behavior, θ. These results show that the probability of human error increases from 6.07% to 10.91%, an increase of 79.6%, when the workplace environment fails. Under insufficient maintenance, on the contrary, the probability increases from 6.08% to 7.08%, an increase of 16.4%. Human error also increases when inadequate quality control exists, increasing from

3.34% to 16.14%, an increase of 383.1%. However, no change due to poor management is detected. These findings are discussed further in Discussion.

According to the results of the parameter estimation in this study, the probability of unsafe human behavior is 3.3% when none of the risks represented by the root nodes are present. In contrast, the probability of unsafe human behavior reaches 20.1% when all four root PSFs are present. Li et al. [20] developed a method for estimating the reliability of humans in construction engineering. In their estimation, the probability of human error was 6.3% when all of the root nodes remained within safe levels and reached 96.3% with all root nodes at unsafe levels. From the perspective of human reliability, the probability of human error is less than 10% in the circumstance of the nonpresence of any root node risks. However, for the case when all four risk conditions are present, the probability of unsafe human behavior found in this study (20%) is much lower than that in Li et al.'s study (96%). In practice, when multiple variables are at an unsafe level, humans will likely take precautions to reduce human errors rather than allowing them to continue out of control.

With the model estimation and CPT calculation, the influence of all nodes on the unsafe human behavior has been quantified. The result shows that the probability of human error within a class of error sequences increases by 79.6% when an improper workplace environment is present, ranking second among the four factors. Overall, workplace environment significantly influences unsafe human behavior both in absolute figures and in relative terms.

4.2. Path Analysis and Roles of Intermediate Nodes. To identify the paths that significantly influence human error, all the paths in the model were tested in terms of the workplace environment against human error and quantified using posterior predictive simulation. First, the intermediate nodes of the intended path were constrained to zero and the root node of interest (K4) was set to 1, and then, the conditional probability of human error was calculated. By comparing the result with the original "wrong sequence" value for the case in which K4 is set to 1 without any other constraints on the nodes, the value of the path's influence could be estimated. Then the paths that most significantly influence human error can be identified. The mechanisms (paths) by which an improper workplace environment invokes human error can thereby be clarified.

As nodes may be affected by many distant nodes, the influence of the paths must be separated from cross effects from outside the path. With regard to this cross-effect, this study also quantified the effects of root nodes other than those in the workplace environment. Once the path that significantly influences human error is identified, it is necessary to confirm whether the other root nodes (K1, K2, and K3) cross this path and to estimate their influence. If other root nodes exist that affect this path (K4), it is important to study the other root nodes to explain the mechanism by which improper workplace environment invokes human error.

Table 2: Probability of nodes in the presence of improper design (K4).

Model variables	Content	Probability (%)
K1	Insufficient maintenance	1.12
K2	Inadequate quality control	21.39
K3	Improper management	1.59
M1	Improper environment	5.18
L2	Insufficient knowledge	1.12
H1	Access limitations	0.07
D4	Inattention	49.75
G1	Inadequate procedure	50.87
J1	Communication failure	73.52
N2	Inadequate workplace layout	2.77
D1	Memory failure	1.43
A1	Observation miss	54.54
J2	Missing information	0.64
B1	Faulty diagnosis	70.02
X1	Wrong sequence (unsafe behavior)	10.90

The probability of each node in the presence of improper design (K4) can be calculated using the parameter estimation results and is given in Table 2. Among the intermediate nodes having a high probability of deficiency are inattention (D4), inadequate procedure (G1), communication failure (J1), and observation miss (A1). Note that not all of the real data were mapped onto nodes of the model; factors of human cognitive functions such as inattention (D4) and absence of observation (A1) were estimated with the data in the parent nodes using (3). The conditional occurrence probability of faulty diagnosis (B1) reaches 70% when the workplace environment fails. However, this result does not account for the entire conditional occurrence probability for improper workplace environment; the cross-effects of workplace environment, quality, maintenance, and management also need to be considered in order to describe the complex mechanism.

The first key finding from the path analysis for the roots is that some important nodes were found to serve as a bridge. For example, all the root risks (K1, K2, K3, and K4) create the condition of "improper environment" (M1). In particular, for each of the four root risks, the path having the greatest negative influence goes through node M1, resulting in differences in the probability of a human error $[\Pr(\Delta\tilde{y})]$ of 5.57%, 23.57%, 6.55%, and 14.78%, respectively. For the problems corresponding to the nodes for insufficient maintenance (K1) and improper management (K3), all possible paths also pass through M1 (improper environment). However, its effect is not obvious, with the human error probability differences of only 5.57% and 6.55%, respectively. Further observation of the path influence for the remaining root nodes through M1 shows weak positive influence, which illustrates that when the workplace environment influence is transferred along the M1-related path, the effect of negative transfer dominates. On the contrary, G1 (inadequate procedure) is interconnected with the path having the greatest influence. The paths having the greatest positive influence that include root nodes K2 (inadequate quality control) and K4 (improper design) both go through

G1; their probability differences for human error are 9.42% and 14.61%, respectively. The other paths through G1 also show strong positive influence, which illustrates that when the influence of the improper workplace environment is transferred along the G1-related path, the effect of positive transfer dominates. The positive and negative relationships are further elaborated in Discussion.

The second key finding, through the crossover analysis of the paths of each of the four roots having the largest positive and negative influence, is that these paths are found to have high repeatability. Specifically, the positive maximum path from the K4 (improper design) node to the final behavior node exactly coincides with that from the K2 (inadequate quality control) node. In other words, all the middle nodes are exactly the same, which means that a strong interaction exists between K4 (improper design) and K2 (inadequate quality control). This result suggests that the influence of quality control should be considered when analyzing the positive mechanism for the influence of the workplace environment on human error. Furthermore, the negative maximum paths of the four root nodes intersect on exactly the same nodes, which indicates that the characteristics of M1 (improper environment) and of all the root nodes should be further elaborated to further demonstrate the influence mechanism.

4.3. Ranking of Mechanisms of Influence Given an Improper Workplace Environment. The failure of a workplace environment (in this case, improper workmanship in the workplace environment) under such a mechanism of influence causes the probability that workers will bypass the use of a safety harness to increase by 9.42%. Among all the paths, this mechanism has the highest probability of occurrence. Supporting the saliency of such a result, Li et al. [20] reported that human errors are mainly the result of workload fatigue due to workplace environment tasks. Although their results are consistent with the finding of this study, this study further demonstrates that insufficient information can also lead to failure of cognitive judgment. From the results of the path analysis, the process of influence of a company's workplace environment on human error may involve the following factors: the company's lack of standard procedures, the installation process, and the installation of lifeline anchorage points (improper design, K4). In addition, during actual installation, sufficient control over the construction method and quality of support points at the site may be lacking, causing the workers to decide for themselves how to perform the installation (inadequate quality control, K2). As a result, the location and structure of the support points may be too casual to allow the builders to determine whether they have sufficient support capacity. Workers performing work that requires a safety harness may find that the support capacity at the anchor point is problematic. If the regulations contain no standard measures instructing the workers on a course of action under such a circumstance (inadequate procedure, G1), the workers cannot obtain the needed information (missing information, J2). Hence, they may think that even if they use a safety harness, these measures would not help (faulty diagnosis, B1); thus, they may bypass the use of the safety harness (wrong sequence, X1). In summary, the human error "fall protection not used" has resulted from cognitive failure arising from information needed by the workers being missing because of incomplete procedures. According to the action-change and action-chain models proposed by Sato [42], failure states of the elements in a system can be transferred as in a chain. In other words, improper workmanship in the workplace environment (made evident as unreliable or unavailable component functionality) creates an environment that causes humans to deviate from predefined standards of performance or workmanship. This deficiency causes the procedure to fail to respond to practical needs by transferring the necessary installation information; thus, the failure state is transferred to the workers, which finally results in human error.

The mode of conduction along the abovementioned paths can be explained by the intuition that an improper workplace environment creates states that limit the working space or accessibility to the site. Most of these states are not normally introduced in the training materials for installation procedures formulated beforehand. The workers will face a completely different situation with no procedures or other information to instruct them regarding the proper way to deal with the new situation. In this case, from interviews with the workers, the authors learned that they are likely to deviate from standard operating procedures, thus risking human error. Although existing research provides little information on the means by which an uncertain process influences human behavior, there has been one study whose conclusion partly confirms this path: Gambatese and Hinze [11] believed that when a workplace environment is formed, construction processes are fundamentally determined. However, if the workplace environment does not transfer the detailed information to the construction stage, the site construction process will not be completely in accordance with the workplace environment expectation, leading to deviation between the plan and the actual states. Thus, the workers will be confronted with a scene different from that described in the standard procedure, causing them to operate arbitrarily and thereby increasing the probability of their choosing human error. This result indicates the necessity of the incorporation of "resilience" into the workplace environment. For instance, Weinstein et al. [43] collected and categorized many workplace environment recommendations from industry experience in which a specific fixed position of an anchor point for a lifeline was stipulated to ensure that protection is available when needed.

5. Discussion

5.1. Negative Correlations and Counterfactual Relationships. The results in the previous section show that all four root risks have the greatest negative influence going through node M1, resulting in differences in the probability of a human error $[\Pr(\Delta\tilde{y})]$ of 5.57%, 23.57%, 6.55%, and 14.78%, respectively. What is the meaning of the negative relationships found in this study, and how should negative relationships among variables be interpreted? A good

explanation should account for the lagging effects among the risks (nodes) that occur. The abovementioned model presenting the mechanisms of influence for a series of risks does not determine whether they occur simultaneously. It is possible that the predecessor risks may create certain limitations, remaining in a given state for a certain amount of time and thereby imposing constraints on the successor risks. In addition, as this research was conducted using a modified theoretical model combined with real data, the analysis given here does not purport to support a predefined causation but rather indicates the notion of a pair in a causal relationship. As such, the analysis explains certain features of causation. Negative correlations exist between the probabilities of some nodes, and improper workplace environment can be explained as the "malfunction of a desired state." Once this state is recorded, the hazard can be eliminated immediately upon discovery, leading to a reduction in the probability of occurrence of succeeding risks. For instance, an area of the workplace may have components with sharp edges (inadequate quality control, K2), materials piled up on the site (improper management, K3), or bare wires resulting from infrequently maintained lines (insufficient maintenance, K1), which can limit workers from performing construction in the area and force them to work near edges from which they may fall (inadequate workplace layout, N2). The relationships in the analysis can thus be interpreted as, "If any of these risks can be eliminated, the probability of succeeding risks can be reduced."

5.2. Role of Management. Numerous studies have been argued that management is a critical factor that can lead to human error. Now that the findings have shown that the influence of an improper workplace environment on human error prevails over that of improper management, the possible reasons can be presented as follows: First, "improper management" in this study refers mainly to defects in organizational management tasks, such as "no registration or control method for jumpers." When quality, maintenance, workplace environment, and other factors interact, the existence of management issues does not greatly influence the probability of occurrence of unsafe human behavior. Previous studies have shown similar findings. In an analysis of the causes of 224 actual accidents, Hecker et al. [44] found that no accident could have been prevented by simply making regulations and rules because most accidents were also related to factors such as workplace environment. Reason [2] proposed that builders are easily forced by changes in the site environment to violate existing rules. Thus, if they do not understand the mechanisms of occurrence and are simply directed by management, the effects are likely to be limited. Second, the result is limited by the scope of the model. Because the model emphasizes multiple factors relevant to human error in individuals, the psychological mechanism for a worker that is affected by the group is rarely mentioned. Meanwhile, Zhang [45] and Jiang [46] emphasized that such interactions can influence human errors. The role of management still has room for expansion. "Management" in this study refers to management of the organization and of the staff of a subcontractor (the elevator installation company) and mainly describes the task assignment, order, and takeover between organizers or inside the organization. However, management interfaces are only a marginal consideration in this study, reflected in behavior feedback and other management factors. Nevertheless, such interactive relationships can have some influence on unsafe human behavior. Because the current study aimed to observe the mechanism of influence of the workplace environment, in consideration of the interactions of other environmental factors with human error and the limitations of this model, the importance of organizational management work should not be overlooked.

6. Conclusion

Using elevator construction work as an example, this study has modified a human error model and conducted Bayesian parameter estimation and maximum likelihood estimation using real-world observational data. By comparing these with conditional probabilities, the influence of improper workplace environment on unsafe human behavior when interacting with other nodes was investigated with the proposed posterior predictive method. A cross-analysis method was adopted to reveal the most probable path for the influence of improper workplace environment on unsafe human behavior. This study has not only revealed a mechanism for the influence of improper workplace environment on human error but also presented an innovative analytical method for combining parameter estimation with a posterior predictive method.

However, this research is restricted by the following items, and thus, the results should be interpreted with caution. First, the study employed the data from a practical project safety check as the basis for computation, under a perfect-data hypothesis that assumes that every data record has perfectly described the occurrence of the various risks at the site. In reality, in a practical inspection, the inspector can make a mistake, may be limited by the staff's level of knowledge, or find ways to hide shortfalls, which can distort the data. Therefore, future studies should incorporate interview techniques or wearable devices to collect such information for more integrated study. Second, after the Bayesian parameter learning performed in this study, the point estimate for each node was calculated according to the output node CPT, but no probability distribution of the nodes was obtained. Thus, only the value differences were compared, and the current study could not compare paths or detect any sharp contrasts between the influences of various nodes. Future studies could utilize bootstrap methods and simulate probability distributions to compare the significance of the influence levels.

Data Availability

The authors worked with a reputable elevator company on a funded research project and thus being accessible to the data. In the agreement of their collaboration, any kinds of data including inspection table, records are owned by the

company and thus being confidential to anybody else. The authors thank the readers for their understanding of the collaboration agreement.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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