American Journal of Multidisciplinary Research and Innovation (AJMRI)

ISSN: 2158-8155 (ONLINE), 2832-4854 (PRINT)

VOLUME 4 ISSUE 1 (2025)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Multidisciplinary Research and Innovation (AJMRI)

Volume 4 Issue 1, Year 2025
ISSN: 2158-8155 (Online), 2832-4854 (Print)
DOI: https://doi.org/10.54536/ajmri.v4i1.3961
https://journals.e-palli.com/home/index.php/ajmri

Study on Human Factor Reliability under the Dynamic Evolution of Intelligent Lifting Construction Accidents

Niu Lixia[1], Wang Jia'ao[1], Muhammad Mansab[1*], Si Wen[1], Xie Fenglian[1]

Article Information

Received: October 18, 2024

Accepted: November 25, 2024

Published: February 04, 2025

Keywords

Dynamic Bayesian Networks (DBN), Fuzzy Theory, Intelligent Lifting, Risk Evolution Analysis, Safety Engineering

ABSTRACT

This research explores human factors involved in intelligent lifting construction operations risks to prevent errors and manage processes affecting risk evolution. The study employs the human factors analysis and classification system with text mining to identify risk-inducing factors from accident reports. An initial hierarchy is created from the data using the ISM technique, which is further developed into a Bayesian network diagram based on Fuzzy Dynamic Bayesian Networks. Using the approach of the fuzzy set and the developed similarity aggregation method, probabilities before or under the conditions of the network nodes are also estimated. The model's performance is carefully verified through forward reasoning based on specific indicators, through an analysis which traces the evolution of the various paths through time, and again through sensitivity analysis. They used the FDBN-based human factor reliability risk model; the results show that the constructed risk prediction and control mechanisms help determine the significant evolutionary risk paths, optimising the management strategies for intelligent lifting construction. It presents new findings regarding outcomes of human reliability engineering applied to intelligent construction systems and presents a set of practical recommendations on safety and operations improvement.

INTRODUCTION

Smart construction has become one of the essential trends of modern architectural construction because the Internet of Things (IoT), artificial intelligence (AI), and big data have shown their applicability in the construction industry. Among these advancements, the construction workers recognise the human-manager-machine interface as a critical intersection by which construction workers connect with smart devices and information systems to enhance safety and efficiency within the construction process. On the other hand, even though such technologies have advanced and are widely used in intelligent hoisting construction, the literature needs more coherent studies focusing on human risks. This gap tends to lead to such occurrences as injuries by robotic arms and mechanical breakdowns that cause severe losses. Research on smart construction sites in China primarily focuses on enterprise digital transformation and construction quality management (Qian *et al.*, 2023; Xu *et al.*, 2022). Traditional safety research in hoisting construction mainly explores the causes of accidents from the perspectives of humans, machines, environment, management, and materials, aiming to identify significant risk factors (Wang *et al.*, 2022). Most international scholars have researched the frontier advancements in human-machine interaction within smart construction sites (Osti *et al.*, 2021; Boateng *et al.*, 2020).

From a construction management perspective, smart hoisting achieves comprehensive digitalisation and visualisation management. By deploying various sensors, cameras, and other IoT devices, real-time data is collected from the construction site and uploaded to cloud platforms for in-depth mining and analysis (Guo *et al.*, 2017). Regarding risk analysis and methods, Forteza *et al.* (2016) introduced a new concept of "site risk," which encompasses risks across the entire construction site and results from the interaction of various individual risk factors. Sadeghi *et al.* (2023) enhanced the safety of hoisting operations by using a fuzzy integrated risk analysis framework (ERAFF) that provides critical causal factors, a comprehensive risk view, and integrated control measures. Zhang *et al.* (2020) employed network analysis methods to systematise the causes of hoisting construction accidents, identifying seven key factors and three critical pathways. Statistical indicators such as degree, strength, and shortest path improved the targeting of accident prevention (Zhang *et al.*, 2020).

The Cloud Bayesian Network (H. Chen *et al.*, 2024) model was proposed to address the challenges of insufficient data, effectively improving risk assessment accuracy. Additionally, various methods such as interpretive structural modelling (Gunduz *et al.*, 2017) and variable weight grey relational models (Zhang *et al.*, 2020) have been applied to assess boosting construction risks. Introducing new interface management tasks in smart hoisting construction significantly increases operators' cognitive and operational load (Muñoz-La Rivera *et al.*, 2021). This raises the risk of human errors and prompts operators to adopt automated strategies to alleviate the burden while performing primary tasks. However, reducing the willingness to verify information may further exacerbate operational risks. The reliability and safety of human-machine interaction systems increasingly depend on human factors (Jeon, 2017).

[1] Liaoning Technical University Institute of Business Administration, Fuxin 123032, China
[*] Corresponding author's e-mail: mansabmalik025@gmail.com

Thus, analysing human reliability has become a crucial area of research. Expert judgment plays a significant role in quantifying human factors in studies of human reliability methods. Expert judgment can assess human behaviour and decision-making, partially compensating for the limitations of statistical analyses and modelling methods (Hamada *et al.*, 2020). In high-risk fields such as aviation and nuclear power plants, expert experience is critical in evaluating operators' skills, load, proficiency, attention, and the effectiveness of safety decisions and interventions (Liu *et al.*, 2020). However, alongside expert judgment, it is essential to use data and modeling methods for comprehensive analysis and assessment to achieve a more accurate and thorough human reliability analysis.

Smart construction sites have become an inevitable trend in the development of the construction industry, and their widespread application has profound significance for advancing the high-quality development of the industry in China. In light of this, this paper constructs an analysis model based on the HFACS theory and fuzzy Bayesian network. It employs text mining techniques to collect word frequency data from accident reports. It applies HFACS theory and interpretive structural modelling to identify the hierarchical relationships of risk factors in smart hoisting construction. The findings are used to develop a fuzzy dynamic Bayesian network model. Additionally, an improved similarity clustering method is introduced to enhance subjective evaluation. The model's rationality and superiority are verified to reduce the likelihood of risk occurrences in smart hoisting construction.

The application of construction technologies such as AI, IoT, and big data is one of the smart technologies in construction. Perhaps the best example of this type of shift, like kinetic interaction, can be observed while considering changes in the construction industry, such as the increasing use of intelligent lifting systems, where the role of the machine is combined with the work performed directly by operators in real-time. Such systems can transform construction work, productivity, and safety (Li *et al.*, 2024). However, sophisticated IT systems in industries today raise concerns over the susceptibility to human errors that can lead to large-scale disasters.

In many regions of the world, intelligent systems are already being implemented in the construction industry as objects of operational use. For instance, large civil engineering projects in Japan and South Korea partially rely on robotics to perform mechanically repetitive or hazardous operations such as hoisting massive structures. Likewise, massive construction megaprojects in Europe integrate AI-progressive systems to regulate flow diagrams. Agnostic breakthroughs have been found to play a significant role in enhancing overall project outcome rates and controlling or occasionally even eradicating work-related accidents. However, one of the biggest problems is still human factors involving operators and technicians who have to control and supervise highly developed mechanisms, often under significant stress (Zhao, 2023).

However, the literature survey shows that more research is needed into human error using intelligent lifting technologies. The prognosis of automation and risk management has been addressed extensively in various industries, including aviation, hospitals, and nuclear industries; however, scanty studies have linked human factors to the utilisation of intelligent lifting systems in construction. These interaction conditions are problematic for bringing human-like operators because they simultaneously control the equipment, observe the performance, and make decisions based on the data. This augments the usability of mental resources and helps raise the probability of making mistakes and, therefore, having accidents (Hamada *et al.*, 2020).

The Human Factors Analysis and Classification System (HFACS) has been instrumental in preventing human errors in numerous industries with the highest risks. Initially designed for the aviation industry, HFACS has since found application in other industries, including healthcare, maritime, and nuclear. However, more needs to be done to use it in intelligent construction systems. This paper, therefore, undertakes to fill the above gap by employing HFACS on intelligent lifting operations to systematically examine the human factors that cause accidents in this area.

In order to enhance the robustness of the findings, the study employs Fuzzy Dynamic Bayesian Networks (FDBN) and Interpretive Structural Modeling (ISM) because the two are powerful tools for modelling risk complexity. FDBNs, more significantly, are well suited for modelling uncertainties and probabilistic dependency; hence, they are best suited for situations where risk quantification involves data that may be scarce or highly uncertain. The study incorporating these intelligent methods with HFACS will help to understand the reliability of human factors in intelligent lifting operations in detail and enable the formulation of suggestions to enhance the reliable safety and functionality of intelligent construction sites. It is clear today that smart construction is not an option, but it is necessary, and smart lifting systems are among the most significant inventions in the given field. In addressing these problems propagating through construction systems, this research can present findings towards making construction environments safer and more efficient across global regions.

MATERIALS AND METHODS

This study first focuses on improving the HFACS method to identify specific accident factors related to unsafe worker behaviour in smart hoisting construction accidents. Then, the ISM method is applied to qualitatively construct a Bayesian network qualitatively, ensuring an accurate depiction of the complex relationships among accident factors. Finally, the model's effectiveness and reliability are further enhanced through quantitative validation of the Bayesian structure. This provides an important reference for safety management in smart hoisting construction. The flowchart is shown in Figure 1.

HFACS Theory

The HFACS (Human Factors Analysis and Classification System) theory is a framework for analysing and classifying human factors. Chen Wei , in his study on human factors contributing to construction safety accidents caused by heavy rainfall, applied the HFACS-CPHRA method and developed a human factors analysis model for such accidents. In the construction industry, risks can arise from government oversight, managerial errors, and other failures in management. After being refined, the HFACS method was optimised into a framework specifically tailored for the construction industry (Wei *et al.*, 2023). By integrating the HFACS model with intelligent lifting operations, accident causes can be divided into four interrelated levels: unsafe acts, preconditions for unsafe acts, unsafe supervision, and organisational influences. Each level contains different categories of human factors that may contribute to unsafe conditions. Through the application of HFACS theory, investigators can systematically explore how risks at different levels accumulate and ultimately lead to accidents, thereby assisting organisations in formulating targeted preventive measures and improvement plans (Wiegmann & Shappell, 2001).

Fuzzy Theory

Fuzzy theory is an effective mathematical tool for handling uncertainty and imprecise information, first proposed by Professor Lotfi Zadeh in 1965 (Zadeh *et al.*, 1996). In subsequent research, Rogulj applied this method to study the difficulties in quantifying the operating status of bridge monitoring equipment (Rogulj *et al.*, 2021). Chen Lu used fuzzy theory to construct a fuzzy power asymmetry conflict analysis model to resolve conflicts under different power structures. The theory mainly addresses fuzzy phenomena and uncertainty that cannot be expressed through traditional precise mathematics. In intelligent lifting operations, where some risk data may be complex to obtain directly, combining fuzzy theory and practical experience becomes particularly important (Chen *et al.*, 2024).

Bayesian Networks

Bayesian Networks (BN) (Bartlett & Cussens, 2017) are probabilistic graphical models for modelling and analysing uncertainties. Chin *et al.* (2009)applied Evaluate key risk factors in new product development using Bayesian network modeling and propose a systematic probability generation method to address uncertainties. A Bayesian network consists of nodes and directed edges, where nodes represent random variables and directed edges represent dependencies between these variables. In the graphical model, CPTs are employed to represent connections between nodes. The CPT defines each node's probability distribution with its parent nodes taking specific values. Thus, the preparation and modelling of the relationships of the variables can be achieved by using Bayesian networks for prediction, diagnosis, and decision-making.

Human Factors Analysis and Classification System (HFACS) Applications

The Human Factors Analysis and Classification System (HFACS) was first developed within an aviation context as it is common for operator errors to have high-risk, troublesome effects. (Shappell & Wiegmann, 2005)structured the framework to analyse incidents hierarchically, identifying contributing factors at four levels: risks, conditions that lead toward risks, appliances that endorse risks, and organisational factors. It provides an incremental approach to analysing human factors that do not lock in individuals' mistakes but look at the general deficiency. In the next few years, the HFACS has been used successfully in other high-risk industries, proving its reliability and adaptability.

In the healthcare industry, HFACS has minimised such surgical mistakes, safeguarded patient lives, and classified underlying conditions that cause human errors. For instance, the system has been extended for operating theatre and intensive care environments involving severe care and accuracy (Catchpole *et al.*, 2008). Comparable adjustments have been made in seaborne markets where HFACS has proved helpful in assessing operator errors due to fatigue, lax training, and communication breakdown (Hetherington *et al.*, 2006). Such adaptations further show that HFACS provides valuable information about human error in any field, thus making the taxonomy all-encompassing as a risk management tool.

In construction, though, using HFACS is a very young science, especially in lift-intelligent operations. Indeed, HFACS has been formulated based on the system approach and complexity of the human-computer interface, especially in these environments; therefore, it is very suitable for analysing human error. The intelligent lifting environment imposes a new set of challenges to the existing framework because it involves the actual performance of the operator, not merely his expertise but also the integration with complex systems and controls. This research aims to further the application of HFACS because this structure will need to accommodate smart construction, which differs from the use of HFACS for an individual operator error where the source of the system failure also includes mechanical elements.

Bayesian Networks and Fuzzy Logic in Risk Assessment

Bayesian Networks (BNs) have emerged recently as powerful techniques for risk analysis and decision-making in the context of risk. BNs offer a visual depiction of the dependency format of various parameters, making it easier for the risk manager to develop a system model with many risks which interrelate dynamically. In construction, BNs have been applied to evaluate risks of equipment failure, the management of safety, and the role of human error. Their capacity to blend qualitative and quantitative data makes them essential in surroundings where information may be ambiguous or approximate (X. Zhang *et al.*, 2020).

Another major drawback of traditional Bayesian networks is that they require accurate point probability estimates for cause-and-effect relationships. This limitation can be overcome by adopting a fuzzy logic approach, incorporating risk experts' judgment while handling variables' linguistic indeterminacy. New, especially for business, is fuzzy logic, stated for the first time by (Zadeh *et al.*, 1996). It expresses the unavoidable uncertainty of decision-making processes by using language in its natural form, such as imprecise language, such as high-risk or low-risk. Fuzzy logic, when extended with the Bayesian Networks as concluded by (Wang *et al.*, 2019), a new structure is achieved that deals well with uncertainty and gives precise risk estimations in delicate environments such as Intelligent Lifting processes.

While ordinary DBNs extend a Static Bayesian Network by adding temporal dynamics, the Fuzzy Dynamic Bayesian Networks (FDBNs) follow the same logic but also consider the temporal consideration. This makes it possible to understand the changes that risks undergo with time, such that FDBNs are especially applicable to construction projects characterised by persistent changes in conditions. For example, an FDBN can demonstrate the dynamic nature in which the probability of human error in intelligent lifting operations varies with the period of the project cycle by incorporating factors such as operator fatigue, equipment deterioration, and adverse climactic conditions.

Interpretive Structural Modeling (ISM)

ISM stands for Interpretive Structural Modeling, a research method applied to define problems/issues lying in specific variables relationship summaries. In risk management, ISM aids in developing a framework for interaction between various risks to produce a transparent model. In construction, ISM has been used to model the interconnections between human error, organisation, and environment to offer an easily understandable depiction of how these ingredients interact to form a risk (Dewi *et al.*, 2023).

Several human and machine interfaces are involved in intelligent lifting operations, and ISM effectively helps to un-complicate these interactions. This study aims to incorporate ISM alongside HFACS and FDBNs to create a model that can identify key risk factors and how these factors make an adverse event more probable.

Risk Indicator Selection for Intelligent Construction Site Lifting Operations

Text Data Mining

As the intelligent construction site lifting technology progresses, various lifting accidents show different characteristics. This has made HFACS, famous for its logistic and sequential design, a valuable tool for describing and identifying the features of accidents in intelligent lifting operations. Using text mining (Shao *et al.*, 2024), this method further investigates the multiple causes of accidents and offers solid evidence for specific early warning and risk mitigation in future. In contrast to conventional facilities used in elevating structures, smart construction sites include systems of observation and early signs of mishappening, and these features have contributed towards a decrease in the number of incidents. Environmental factors can be controlled and eliminated, but preventing an accident is virtually impossible. Consequently, carrying out an analysis of the accident and the summary of things that have been learned should be a significant way of improving the effectiveness of the operation of intelligent lifting.

In order to comprehensively explore the characteristics of lifting accidents in intelligent construction sites, 152 accidents from 2018 to 2023 were retrieved through the State Administration of Work Safety and Crane Engineers website. These reports outline the nature and development of the accidents, their causation and the apportionment of blame, giving data sources for this investigation. Because of the aspects of recording accident data, there is usually the presence of clutter or irrelevant data in the reports that the researchers access. To enhance the decision-making quality, data were preprocessed to filter out data unrelated to the unsafe acts or their root causes, such as the names of the companies involved, suggestions for improvement and a description of the investigation procedure. The accident description, its causes, and the directions of responsibility alone were kept and classified into the essential contents. Then, the cleaned data is analysed and mined using the HFACS method as the next step to determine the causes and conditions for accidents in intelligent lifting operations. This offers a scientific premise for future safety administration and risk management.

Text Data Processing

In the framework of using intelligent technologies and techniques for lifting operations in construction sites based on the accident text corpus, several preprocessing steps were initially applied to the corpus to improve the effectiveness of the next steps. Non-Chinese characters were also excluded since they were deemed noise in the data set's context. At the same time, stop information included in this list are Chinese characters like '的' and '是', which are relatively insignificant and frequently used in Chinese. Initially, all information was categorised by language, and only the Chinese data that referred to lifting accidents were preserved. The text was then divided into meaningful lexical units. In order to increase the precision of identifying the keywords, the inverse document frequency of each term was determined, and the IDF dictionary containing the obtained values was constructed. IDF is a frequent text mining method used to determine the significance of a word in a document set. By performing the IDF value, the focus on the keywords that need to involve lifting safety can be achieved accurately. The TF-IDF algorithm was used to identify keywords from all texts concerning intelligent construction site lifting safety. In this algorithm, both term frequency and inverse document frequency are integrated, guaranteeing the feasibility of the keyword extraction method (Wang *et al.*, 2019). As a result of the extent of text analysis amounting to about 400000 words, a large number of features were extracted using TF-IDF. Indeed, the number of feature words was too large, so the Truncated Singular Value Decomposition (Truncated SVD) method was used to filter feature words and extract 116 representative feature words that contain most of the vital information on the safety of intelligent lifting.

Last, the Complement Naive Bayes (Complement NB) classifier was constructed based on the feature dictionary of the lifting safety in the intelligent construction site domain and then used to match features and extract feature attributes from each lifting accident text. As mentioned in the previous steps, the classifier was fitted and optimised on the training set. The model parameters were given, and further prediction calculations were conducted. The model results were classified as "0" and "1," where "0" represents an error operation that cannot proceed with the experiment, and "1" indicates an accurate model. The results demonstrated that the model had high accuracy, preliminarily showing good precision and generalisation ability on the training set.

Due to the large number of feature words, 51 representative feature values with the highest weight rankings were selected for further analysis. After manually removing words unrelated to lifting safety, such as "construction" and "safety management," the remaining feature values were retained and encoded. As shown in Table 1, the encoding results form the foundation for subsequent comparative analysis and model training.

Text Mining

Using text mining methods is critical in analysing accident reports to discover possible risks and precursors that cause accidents in intelligent lifting activities. This work used rather sophisticated text-mining methods to analyse 152 accident reports obtained from the State Administration of Work Safety and other related bodies to accomplish this. These reports hold essential details on the cause of an accident, the chain of events and the background to the event's occurrence. However, the reports were often numerous and poorly classified in a standard format. Hence, the data required text mining to be cleaned up and put into specific formats for analysis. In the first stage of text mining, data cleaning was mandatory. This was done to filter out information that needs to be more critical, such as the company involved and the procedures it undertakes while investigating an accident or unsafe behaviour. Data cleaning allowed only relevant content – concerning human factors, equipment failure, weather and climate conditions and organisational issues to be retained. This study used the NLP tools of tokenisation and lemmatisation to break down the accident reports into sub-strings of texts that could be processed systematically.

After the text is preprocessed, it is necessary to use the TF-IDF technique to determine the keywords of the accident reports. This method compares the importance of a word in a document determined by the number of times the word is used in the document with the total number of documents. When using the TF-IDF, we could specify the essential terms that capture risks of accidents inherent to intelligent lifting. For example, such terms as "operator fatigue," "misjudgment," and "communication failure" were met rather often during the analysis of the reports and were highlighted for further processing. In the same way, other mechanical and technical terms such as 'malfunction' and 'system failure' formed the basis of an instrumental cause of many of the accidents revealed in the study.

To reduce the high dimensionality of feature space, truncated singular value decomposition was used to identify the most important keywords. This process provided a shortened and more reasonable list of key terms, which usually signify the primary reasons for accidents. The obtained terms were then used to further sort the reports by themes according to the HFACS taxonomy. Each report was classified into one or more of the four levels of human factors identified by HFACS: subcategories such as unsafe acts, conditions for unsafe acts, unsafe supervision and organisational factors.

HFACS Framework Application

To analyse human errors and other factors that contributed to accidents in intelligent lifting operations, the analysed data was subjected to the HFACS framework. As outlined in previous studies, HFACS divides human error into four hierarchical levels: They include

(1) Unsafe Acts,
(2) Preconditions for Unsafe Acts,
(3) Unsafe Supervision, and
(4) Organisational Influences.

Each level has some subcategories that define the kind of mistakes made by humans involving certain levels of operation.

Common immediate causes of accidents in this study include action mistakes like operator misjudgment, inaction mistakes like failure to follow standard operating procedures, and technique mistakes in using tools. Forces that can lead to an unsafe act include lack of proper training, communication shortcomings between the human operator and the automation systems, and unfavourable working environments, including low visibility and poor weather, which were often reported as instigating causes. Several papers also found a need for more safe working supervision associated with failure to provide proper safety control and failure to adopt suitable safety measures. At the organisational level, the common topics entailed safety culture, safety training, and maintenance of lifting equipment.

Inter-Rater Reliability

Due to the nature of intelligent lifting operations and the limitations of the textual data analysis, expert opinion was used to confirm the text mining analysis results. The four experts were selected based on their practical experience in construction safety, experience with intelligent lifting technology, and inclusion of at least two specialists in human factors analysis. The authors separately analysed a subset of the accident reports and coded them with HFACS.

In order to test the reliability of the expert classifications, an inter-rater planned consistency check was conducted. It is a procedure through which the level of unity or consistency between various specialists faced with the task of sorting out the same data is ascertained. A perfect plus/minus one inter-rater reliability means that the implementation of the classification system is accurate; the two raters are equally in agreement with the various risks associated with each classification. Consequently, the inter-rater reliability of this study was 82.02 %, which is very impressive and highly acceptable among the experts. This reliability test gave confidence that the used HFACS classifications reflected the natural causes of the failure of intelligent lifting operations.

Construction of the Fuzzy Dynamic Bayesian Network (FDBN)

The FDBN model was designed to establish the probability of relations between various risk factors applied to intelligent lifting operations. It comprises features of characterising conditional dependencies between variables utilised by the Bayesian networks and the approach of solving problems concerning uncertainty as applied by fuzzy logic. The creation of the FDBN involved transforming the critical sources of risk determined from HFACS and ISM into a BN framework. Every node in the Bayesian network described a particular risk factor, such as 'operator fatigue', 'communication breakdown', or 'unsatisfactory equipment maintenance'. Probabilistic dependencies between these factors were represented with directed edges between the nodes. For instance, night train operator fatigue was associated with unsafe acts such as misjudgment, ineffective equipment maintenance, equipment failure, and unsafe acts. P (B given by all A values) histograms were developed for every node with the help of historical data from the accident reports and experts' estimations.

Due to these varying degrees of uncertainty inherent in the input data, a fuzzy logic system was incorporated into the Bayesian network. What may happen is that fuzzy theory includes linguistic evaluation such as low risk, medium risk, or high risk, which are more realistic, especially when the actual probability is difficult to estimate. Using fuzzy logic, the study integrated the judgment and experience of an expert in the model, making it more reliable. The FDBN was then forward reasoned, which examined the model's capability to predict the probability of accidents due to different risk factors within a given economy and also analysed sensitivity.

Model Construction

Establishing the HFACS Framework

The traditional HFACS framework is only partially applicable to construction projects. The key distinction lies in considering the role of government regulatory agencies in the construction industry (Qi *et al.*, 2024). Regulatory bodies can effectively prevent and control promising construction site safety incidents, such as fires or collapses, through enhanced oversight of project execution processes. Within construction companies, management oversight can manifest in various forms. For example, adequate safety training may lead to secondary accidents, while an unsound safety management system could prevent the entire construction process from becoming disorganised. In specific construction projects, the decisions and actions of company managers are crucial. For instance, if managers intervene directly in production activities by issuing construction directives, decision-making errors could result in significant safety risks. To meet safety analysis needs in intelligent lifting operations in China, a variant of the HFACS model was developed, tailored specifically for analysing the causes of unsafe behaviours in intelligent lifting. This variant was constructed by referencing the HFACS framework, categorising the data obtained from text mining, and fitting the data from interviews with specific construction units and contractors that use digital construction technology. The analysis identified 25 key factors, which were grouped into the following specific levels of the adapted HFACS model, consisting of 4 levels and 15 items, as shown in Table 2.

Data Processing

Reliability Test of the Influencing Factors System

A standard method for verifying the reliability of the HFACS model is to conduct an inter-rater reliability test (Zhao *et al.*, 2022). This method involves having different experts or raters independently apply the HFACS model to the same dataset and then calculate the degree of agreement in their classification results. When the proportion of consistent conclusions among different raters reaches or exceeds 70%, the model can be preliminarily considered to have good consistency and reliability in practical applications. The calculation formula is as follows:

$$IOC = Z/Z+Y \quad (1)$$

Formula IOC (1), the consistency coefficient, represents the number of occurrences of an event and Y Represents the number of non-occurrences of an event.

Four experts with varying backgrounds, including differences in academic degrees, years of experience, and professional titles, were selected for the evaluation, as shown in Table 3. These experts thoroughly understand the mechanisms behind human errors in intelligent construction. Each expert independently analysed 50 items to determine whether they could reach a consensus on judgment under a unified standard.

The inter-rater reliability test results showed that the indicator system's overall reliability reached 82.02%. The reliability of each factor's scores generally stayed within 70%, indicating a relatively high level of reliability.

Establishing the Hierarchical Structure of Risk in Intelligent Lifting Operations

The formation of human error in intelligent lifting accidents is influenced by multiple factors, presenting an interaction and coupling relationship among these factors. After identifying the influencing factors of human error and categorising their levels through the HFACS model, it is necessary to clarify the relationships between these factors and their impact on human error. The internal structure of risks in intelligent tower crane operations and the interrelationships between their elements were analysed using the Interpretive Structural Modeling (ISM) method (Sun *et al.*, 2020). ISM can analyse not only the relationships between adjacent factors but also the relationships between factors at different levels (Sakar *et al.*, 2020)

Let the adjacency matrix be F and a_{ij} Be an element of F.

$$a_{ij} = \begin{cases} 0 & \text{factor i has a direct effect on factor j} \\ 1 & \text{factor i has not a direct effect on factor j} \end{cases} \tag{2}$$

Suppose Matrix (a) is the adjacency matrix F, and Matrix (b) is a reachable matrix. M According to expert judgment, the ISM adjacency matrix is constructed as shown in the following figure:

M is calculated by Boolean algebra rules as follows

$$F_1 = (F+E),\ F_n = (F+E)^n \tag{3}$$

$$F_1 = (F+E) \neq F2 \neq \ldots \neq F_{n-1} = F_n \tag{4}$$

Where F_{n-1} Is the reachable Matrix M, and M It is represented as follows:

$$F = \begin{bmatrix}
0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}$$

(a) Adjacency matrix

$$M = \begin{bmatrix}
1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 \\
0 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}$$

(b) Reachable Matrix

Constructing the DBN Structural Model

After determining the logical relationships between events and clarifying their evolutionary paths through the Interpretive Structural Modeling (ISM) method, each event in the model is mapped onto a Bayesian Network (BN) node, ensuring each event has a specific position within the BN. Primary events, intermediate events, and top events are mapped to the sub-nodes, intermediate nodes, and parent nodes in the Bayesian Network, thereby constructing a hierarchical and logically rigorous network structure, as shown in Figure 2. Since this study focuses on the dynamic evolution of safety risk events in intelligent lifting operations, safety risk events D1, D2, D3, and D4 are set as transition nodes.

Using this structure, the states of each node are meticulously examined and analysed according to real-world conditions. The professional software tool GeNIe is employed to construct a risk model suitable for prefabricated high-rise building construction. Ultimately, the Bayesian Network structure for safety risks is obtained.

Parameter Determination

Expert Evaluation and Fuzzy Language Conversion

This study uses a combination of fuzzy theory and expert scoring methods to determine the conditional probabilities of the intermediate nodes in the model (Besiktepe *et al.*, 2021). This approach mitigates severe biases caused by an over-reliance on historical statistical data while integrating practical engineering insights and expert knowledge to improve the accuracy of the final analysis. To establish the correspondence between experts' linguistic variables and fuzzy numbers, a 7-level linguistic scale is adopted to provide scoring standards for the risk factors in intelligent lifting operations (Peng *et al.*, 2023; Zhou *et al.*, 2024). The fuzzy intervals corresponding to the 7-level linguistic scale are shown in Table 4. To reduce the impact of expert subjectivity, experts whose scores exhibited significant differences in linguistic variables were asked to rescore.

Expert Opinion Aggregation

To integrate expert opinions and ensure a closer approximation to the likelihood of events occurring, this study adopts the improved Similarity Aggregation Method (SAM) (Zhu *et al.*, 2022). This method fully accounts for the influence of experts with different weights on the consistency between two experts, avoiding the increase in subjectivity and error rates caused by ignoring the opinions of lower-weight experts.

Determine Expert Weights

The scoring standards for experts are set based on the criteria of expert title level, working experience, education, and age, as shown in Table 5. According to the scoring levels in Table 5, the weight score for each expert is calculated (Table 6). The calculation method for weights is the ratio of an individual expert's score to the total score of all experts.

Determine the Consistency between Two Experts' Opinions

$$H\left(\tilde{R}_i,\tilde{R}_j\right)=1-\frac{1}{4}\sum_{i=1}^{4}\left|a_m-b_n\right| \quad (5)$$

In Equation (5), $\tilde{R}_i\tilde{R}_j$ if the trapezoidal fuzzy numbers of expert Ei and Ej

$\tilde{R}_i=\left(a_1,a_2,a_3,a_4\right)$ $\tilde{R}_j=\left(b_1,b_2,b_3,b_4\right)$

$H\left(\tilde{R}_i,\tilde{R}_j\right)\in[0,1]$ $H\left(\tilde{R}_i,\tilde{R}_j\right)$

are the same, are there degrees of agreement between the opinions of each expert? A similar degree of opinion between the two experts can be obtained by comparing their values $H\left(\tilde{R}_i,\tilde{R}_j\right)$.

Determine the Weighted Consistency of Expert Opinions

$$A_{\mathrm{W}}\left(E_i\right)=\frac{\sum_{j=1}^{n}W\left(E_j\right)\cdot H\left(\tilde{R}_i,\tilde{R}_j\right)}{\sum_{j=1}^{n}W\left(E_j\right)},i\neq j \quad (6)$$

In Formula (6), and are the weights of experts, respectively, and A_w (E_i) It is the weighted consistency of expert opinions. The improved method considers the importance of expert weights and integrates them into calculating weighted consistency, making the estimated results more accurate.

Determine the Relative Consistency of Expert Opinions

$$A_{\mathrm{R}}\left(E_i\right)=\frac{A_{\mathrm{W}}\left(E_j\right)}{\sum_{i=1}^{n}A_{\mathrm{W}}\left(E_i\right)} \quad (7)$$

Equation (7) A_R (E_i) Represents the relative consistency of expert opinions.

Determine the Consistency Coefficient of Expert Opinions

C_c (E_i)= β.W(E_i) + (1- β). A_R (E_i) (8)

Equation (8) C_c (E_i) represents the consistency coefficient of expert opinions, where β(0 ≤ ≤ 1) is the relaxation factor, which is a critical factor in balancing relative consistency and expert weights. Considering that expert weights have already been calculated, we assume β= 0.5.

Determine the Result of Expert Opinions

$$\tilde{R}=C_{\mathrm{C}}\left(E_1\right)\cdot\tilde{R}_1+C_{\mathrm{C}}\left(E_2\right)\cdot\tilde{R}_2+\cdots+C_{\mathrm{C}}\left(E_n\right)\cdot\tilde{R}_n \quad (9)$$

Equation (9) represents the result of expert opinions.

Determining Node Parameters

After the above processing, the overall fuzzy number of expert opinions can be obtained. Defuzzification is converting the overall fuzzy number into a clear Fuzzy Possibility Score (FPS). In cases of insufficient information, FPS is used as a prior input along with conditional probabilities to measure the relative risk level of each node. This study uses the centroid method for defuzzification, as shown in Equation (10). This Equation S_{FP} Represents the FPS obtained from defuzzification, i.e., the fuzzy possibility value. The expert evaluation scores (FPS) are compared with the integrated results of the IDF values and undergo consistency checks. If consistency requirements are met, further consultation with experts is required until the desired consistency is achieved.

$$S_{\mathrm{FP}}=\frac{\int_a^b\frac{x-a}{b-a}xdx+\int_b^c xdx+\int_c^d\frac{d-x}{d-c}xdx}{\int_a^b\frac{x-a}{b-a}dx+\int_b^c dx+\int_c^d\frac{d-x}{d-c}dx}=\frac{1}{3}\frac{(c+d)^2-cd-(a+b)^2+ab}{c+d-a-b} \quad (10)$$

Determine the probability of a dynamic Bayesian transition node. The probability of the transition node is the risk change relationship between the previous time and the next time, and its expression is shown in Equation (11).

$$\mathbf{P}=\left[p_{ij}\right]=\begin{bmatrix}p_{00} & \cdots & p_{0n}\\ \vdots & \ddots & \vdots\\ P_{n1} & \cdots & p_{nn}\end{bmatrix} \quad (11)$$

Equation (11), P the transition matrix kl represents two adjacent states and p_{kl} the transition probability, where p_{kl} ≥ 0. $\sum_{l\in[0,n]}p_{kl}=1$

Project Overview

A large construction company undertook a project to build a modern high-rise commercial complex in the heart of a city. The project covers a vast area, and the expected building height exceeds 200 meters. To ensure safety and efficiency during the construction process, the company decided to implement intelligent lifting technology.

Determining Model Parameters

The text mining study on 152 accident reports suggested several common themes about human factors and system issues in the intelligent lifting process. Failure on the operator's part was a significant cause of accidents, including misjudgment during critical operations. Operators often misjudged the movements of the lifting equipment or disregarded system warnings, leading to impacts, equipment, or worker harm.

A similar pattern was often reported concerning unsuccessful interaction between human operators and automated systems. Intelligent lifting systems are commonly used, and real-time feedback from the lift sensors, controls, and other control systems is essential. Nevertheless, the reports showed that operators often needed to have understood this information or acted promptly, which resulted in safe acts. These communication breakdowns were worse when there was a high cognitive workload, such as when operators were expected to work with several systems simultaneously.

External conditions were also a significant cause of the accidents in many cases. Another cause of the accidents was that it was so dusty that drivers could not see one another; fog, inadequate lighting, and other bad weather, including gale-force winds and rain, were blamed. These conditions limited the ability of the operators to manage the lifting equipment and raised the probability of mishaps concerning equipment and personnel.

First, six experts from relevant fields were invited to evaluate this project based on factors such as professional titles in the construction and education sectors, different working experience durations, educational background, and age. During the evaluation process, the experts were unaware of each other's involvement to ensure that others did not influence their subjectivity. After data mining and processing, the prior probabilities for the sub-nodes were obtained, as shown in Table 7.

Assuming that each node has only two states—occurred (State = 1) and did not occur (State = 0)—for non-sub-nodes, conditional probabilities were calculated using fuzzy theory combined with expert ratings. For example, in the case of node B2, since its parent node is A1, the occurrence frequency and conditional probability of B2 are shown in Table 8. For node D3, the transition node probability was determined by expert judgment, as shown in Table 9.

Index Analysis

Forward Analysis

After obtaining the relevant factor pathways through ISM and deriving the sub-node probabilities via text mining techniques and expert evaluations to obtain the conditional probabilities, the Bayesian network diagram was generated using GeNIe 2.3 software, as shown in Figure 3. It can be seen from Figure 3 that the risk probabilities of related sub-nodes are relatively high, requiring further analysis of the dynamic evolution paths. The time frame was divided into seven segments, and one construction period was selected for risk analysis. By inputting the probability values of each node into the pre-established DBN model, Figure 4 shows the dynamic probability change curve of sub-node risks after updates. The risk trend increases from low to high and gradually stabilises.

Dynamic Evolution Path Analysis

A Bayesian network model established using GeNIe software can be employed to analyse and simulate how various factors influence unsafe behaviours in prefabricated high-rise building construction. In this model, D1, D2, D3, and D4 serve as four decision nodes, with their states directly linked to the occurrence of unsafe behaviours. When the states of these two nodes are set to "state1 = 100%," the model predicts the occurrence of unsafe behaviours, indicating that D1, D2, D3, and D4 may be critical factors or starting points for the evolution of unsafe behaviour paths. The statistical evolution paths are shown in Table 10.

Through reverse inference, the primary evolution paths leading to risk are identified as follows: compliance issue A1 (41%)—improper equipment installation management B2 (52%)—irrational platform setup C5 (56%)—restricted worker mobility D1 (100%); multiple environmental impacts C3 (56%)—operator misjudgment D2 (100%); lack of supervision mechanism A2 (26%)—lack of safety awareness C2 (69%)—poor workspace planning D3 (100%); lack of supervision mechanism A2 (30%)—inadequate emergency planning and drills B4 (56%)—human error C1 (61%)—machine auxiliary force hazard D4 (100%). The evolution path analysis suggests that the absence of a supervision mechanism significantly impacts intelligent hoisting construction, highlighting the need for enhanced management by governmental and organisational bodies.

By incorporating the FDBN model, it was possible to study how various risk factors combine to enhance the chances of accidents in intelligent lifting operations. In essence, the Bayesian network gave pathways on how these risk factors are linked conditionally to achieve unsafe behaviour and system failure. For example, the data demonstrated that the possibility of an accident doubles when operator fatigue enters alongside a deficiency in the maintenance of lifting equipment. Regarding the causes of accidents, this finding corresponds to the identified pattern that fatigue and equipment failures were common reasons for accidents among workers.

The case study using the FDBN model for the evolutionary path analysis helped us understand how risks change within a construction project throughout its lifecycle. When undertaking large projects, issues like operator fatigue and mechanical component wear become more critical in raising the rates of accidents. Finally, the proposed model demonstrated several LBP phases where the probability of accidents was at its apex so that preventive measures could be implemented.

In these stages, the operators tend to be weary because of their many hours on duty easily, and the machinery is also likely to develop some faults due to constant usage. By recognising these critical periods, it will be possible to ensure that operator fatigue levels are kept to a minimum, primarily through shift rotation, and that machinery is well-checked, especially by using microphones, to ensure that they do not develop faults during critical production times.

Sensitivity Analysis

The sensitivity coefficient is used to quantify the degree of influence one node has on a target node. D1, D2, D3, and D4 were successively set as target nodes, and the sensitivity coefficients of other related nodes were calculated. These sensitivity coefficients reflect each node's sensitivity to the target nodes, as shown in Table 11. From Figure 5, it can be seen that the sensitivity value of operator judgment errors (D2) is generally more significant than that of poor workspace planning (D3), which in turn is greater than that of restricted staff mobility (D1), and the sensitivity value of machine added force threat (D4) is the smallest. Compliance issues are the most sensitive point for poor workspace planning. The lack of a supervision mechanism is the most sensitive point for operator judgment errors.

Therefore, the government should pay more attention to the risks of human error in intelligent lifting construction, strengthen construction safety supervision, and reinforce laws and regulations to prevent unsafe behaviours.

The relative importance of the risk factors was determined through sensitivity analysis on the Bayesian network. This quantitative evaluation determines the sensitivity of the target nodes, which depict unsafe acts, to variations in the parent nodes that depict risk precursors. The findings of the sensitivity analysis indicated that operator judgment and workspace arrangements were the most sensitive factors through which a small change could lead to large fluctuations in accident risk.

For example, a minor advancement in the training of operators or the spatial organisation of the workspace lowered the probability of misjudgment or collisions by an order of magnitude. Pointing to this conclusion, the authors emphasise the need to provide operators with training that involves industry knowledge and dealing with sophisticated equipment, computers, and automation systems. Further, it was evidenced that enhanced planning of the workspace, including the expectations of the line of sight and fewer environmental antipathies, lessened the feasibility of accidents due to poor visibility and area overcrowding.

Another valuable outcome of the sensitivity analysis was the focus on the organisational factors, which comprise training of employees and the safety of equipment to reduce risks. Two significant factors that were considered key factors that could minimise the risk of an accident included safety drills and safety features checks! The breakdown illustrated that even minor enhancements to these areas could significantly reduce the likelihood of unsafe acts, supporting the value of sound safety standards in intelligent lifting operations.

Validation of the FDBN Model

The FDBN model was further tested on historical accident data and fine-tuned with the help of expert opinion on the subject matter. Using forward reasoning, different risk scenarios were constructed, and the model was used to estimate the probability of the accident under different risk factors. These simulations were then run, and the outcomes were compared to the real-life accident results; it was observed that the model provided accurate estimates of the trends in the reports. This validation revealed that the FDBN model proposed in this study can accurately predict accidents in intelligent lifting operations.

Consequently, this study will contribute essential findings to understanding risk factors in intelligent lifting accidents. This paper contributes an integrated research framework by applying HFACS, ISM, and FDBN to develop a nuanced view of the causes and solutions of human errors in smart construction settings. The sensitivity analysis and the evolutionary path analysis offer directly applicable suggestions for enhancing safety management in areas like the training of the operators, the maintenance of the tools and the design of the working environment. The results presented in this paper benefit project managers and safety engineers who want to minimise the probability of accidents in intelligent lifting procedures.

CONCLUSION

The study demonstrates the effective application of the HFACS framework, Fuzzy Dynamic Bayesian Networks (FDBNs), and Interpretative Structural Modelling (ISM) in assessing human error in Intelligent Lifting Construction Operations. By analyzing risk factors and their interrelations, it provides critical insights to enhance safety management. Proper training and fatigue management for operators are emphasized, with the assessment showing that many failures could be avoided through increased operator experience and improved crisis management. Regular equipment checks are also highlighted as vital for preventing breakdowns. Furthermore, the study recommends utilizing real-time data from IoT sensors and AI-based systems to enhance FDBN models, allowing for continuous updates and proactive risk mitigation.

The analysis of 152 intelligent lifting construction accident reports in China identified key accident characteristics, combining ISM and FDBNs to reduce subjectivity, improve model accuracy, and address traditional Bayesian network limitations. The study identified critical evolution paths for human error risks, enabling early prevention of potential issues. Additionally, the importance of strengthened government supervision, updated laws and regulations, and enhanced training and management measures is underscored. Future research should focus on integrating real-time monitoring systems and expanding the analysis to other construction scenarios, such as tunneling or road construction, to deepen the understanding of safety-related human factors.

REFERENCES

Bartlett, M., & Cussens, J. (2017). Integer linear programming for the Bayesian network structure learning problem. *Artificial Intelligence, 244,* 258-271.

Besiktepe, D., Ozbek, M. E., & Atadero, R. A. (2021). Condition assessment framework for facility management based on fuzzy sets theory. *Buildings, 11*(4), 156.

Boateng, E. B., Davis, P., & Pillay, M. (2020). Role of human safety intervention on the impact of safety climate on workers' safety behaviors in construction projects: A conceptual model. In *Advances in safety management and human factors: Proceedings of the AHFE 2019 International Conference on Safety Management and Human Factors, July 24-28, 2019, Washington DC,* *USA* (Vol. 10, pp. 190-200). Springer International Publishing.

Catchpole, K., Giddings, A., Hirst, G., Dale, T., Peek, G., & de Leval, M. R. (2008). A method for measuring threats and errors in surgery. *Cognition, Technology & Work, 10,* 295-304.

Chen, H., Shen, G. Q., Feng, Z., & Yang, S. (2024). Safety risk assessment of shield tunneling under existing tunnels: A hybrid trapezoidal cloud model and Bayesian network approach. *Tunnelling and Underground Space Technology, 152,* 105936.

Chen, L., Pedrycz, W., & Xu, H. (2024). Analysis of power asymmetry conflict based on fuzzy options graph models. *Knowledge-Based Systems, 284,* 111221.

Chin, K.-S., Tang, D.-W., Yang, J.-B., Wong, S. Y., & Wang, H. (2009). Assessing new product development project risk by Bayesian network with a systematic probability generation methodology. *Expert Systems with applications, 36*(6), 9879-9890.

Dewi, C., Chen, R.-C., Christanto, H. J., & Cauteruccio, F. (2023). Multinomial Naïve Bayes classifier for sentiment analysis of internet movie database. *Vietnam Journal of Computer Science, 10*(04), 485-498.

Forteza, F. J., Sesé, A., & Carretero-Gómez, J. M. (2016). CONSRAT. Construction sites risk assessment tool. *Safety science, 89,* 338-354.

Gunduz, M., Birgonul, M. T., & Ozdemir, M. (2017). Fuzzy structural equation model to assess construction site safety performance. *Journal of Construction Engineering and Management, 143*(4), 04016112.

Guo, H., Yu, Y., & Skitmore, M. (2017). Visualization technology-based construction safety management: A review. *Automation in construction, 73,* 135-144.

Hamada, D., Nakayama, M., & Saiki, J. (2020). Wisdom of crowds and collective decision-making in a survival situation with complex information integration. *Cognitive Research: Principles and Implications, 5,* 1-15.

Hetherington, C., Flin, R., & Mearns, K. (2006). Safety in shipping: The human element. *Journal of safety research, 37*(4), 401-411.

Jeon, M. (2017). Emotions and affect in human factors and human–computer interaction: Taxonomy, theories, approaches, and methods. In *Emotions and affect in human factors and human-computer interaction* (pp. 3-26). Springer.

Li, D., Li, S., Tan, Q., Liu, J., Fu, Q., Sun, Y., & Hu, C. (2024). Stability Analysis of Dual-Lifting Vessels under Collaborative Lifting Operation. *Polish Maritime Research, 31*(2), 46-58.

Liu, P., Qiu, Y., Hu, J., Tong, J., Zhao, J., & Li, Z. (2020). Expert judgments for performance shaping Factors' multiplier design in human reliability analysis. *Reliability Engineering & System Safety, 194,* 106343.

Muñoz-La Rivera, F., Mora-Serrano, J., & Oñate, E. (2021). Factors influencing safety on construction projects (FSCPS): Types and categories. *International Journal of Environmental Research and Public Health, 18*(20), 10884.

Osti, F., de Amicis, R., Sanchez, C. A., Tilt, A. B., Prather, E., & Liverani, A. (2021). A VR training system for learning and skills development for construction workers. *Virtual Reality, 25,* 523-538.

Peng, Z., Su, P., & Chen, W. (2023). Indoor Air Quality Assessment of Metro Stations Based on the Optimal Combination Weight and Improved Fuzzy Comprehensive Evaluation. *Journal of Environmental Engineering, 149*(4), 04023001.

Qi, H., Zhou, Z., Irizarry, J., Deng, X., Yang, Y., Li, N., & Zhou, J. (2024). Modification of the HFACS model for path identification of causal factors of collapse accidents in the construction industry. *Engineering, Construction and Architectural Management.* Advance online publication.

Qian, Y., Liu, H., Mao, P., & Zheng, X. (2023). Evaluation of safety management of smart construction sites from the perspective of resilience. *Buildings, 13*(9), 2205.

Rogulj, K., Kilić Pamuković, J., & Jajac, N. (2021). Knowledge-based fuzzy expert system to the condition assessment of historic road bridges. *Applied Sciences, 11*(3), 1021.

Sadeghi, H., Zhang, X., & Mohandes, S. R. (2023). Developing an ensemble risk analysis framework for improving the safety of tower crane operations under coupled Fuzzy-based environment. *Safety Science, 158,* 105957.

Sakar, C., Koseoglu, B., Toz, A. C., & Buber, M. (2020). Analysing the effects of liquefaction on capsizing through integrating interpretive structural modelling (ISM) and fuzzy Bayesian networks (FBN). *Ocean Engineering, 215,* 107917.

Shao, R., Lin, P., & Xu, Z. (2024). Integrated natural language processing method for text mining and visualization of underground engineering text reports. *Automation in Construction, 166,* 105636.

Shappell, S. A., & Wiegmann, D. A. (2005). *Human error and general aviation accidents: A comprehensive, fine-grained analysis using HFACS*. Office of Aerospace Medicine.

Sun, C., Xu, H., & Jiang, S. (2020). Understanding the risk factors of BIM technology implementation in the construction industry: An interpretive structural modeling (ISM) approach. *Engineering, Construction and Architectural Management, 27*(10), 3289–3308.

Wang, J., Guo, F., Song, Y., Liu, Y., Hu, X., & Yuan, C. (2022). Safety risk assessment of prefabricated buildings hoisting construction: Based on IHFACS-ISAM-BN. *Buildings, 12*(6), 811.

Wang, J., Xu, W., Yan, W., & Li, C. (2019). Text similarity calculation method based on a hybrid model of LDA and TF-IDF. In *Proceedings of the 2019 3rd International Conference on Computer Science and Artificial Intelligence.*

Wei, C., Yishuai, T., Weihua, Z., Daoyuan, G., & Zhuoya, Z. (2023). HC-GC human factors analysis model for construction engineering safety accidents caused by heavy rainfall. *China Safety Science Journal, 33*(8), 15.

Wiegmann, D. A., & Shappell, S. A. (2001). *Human error* *analysis of commercial aviation accidents using the human factors analysis and classification system (HFACS).*

Xu, M., Nie, X., Li, H., Cheng, J. C., & Mei, Z. (2022). Smart construction sites: A promising approach to improving on-site HSE management performance. *Journal of Building Engineering, 49,* 104007.

Zadeh, L. A., Klir, G. J., & Yuan, B. (1996). F*uzzy sets, fuzzy logic, and fuzzy systems: Selected papers* (Vol. 6). World Scientific.

Zhang, W., Zhu, S., Zhang, X., & Zhao, T. (2020). Identification of critical causes of construction accidents in China using a model based on system thinking and case analysis. *Safety Science, 121,* 606-618.

Zhang, X., Zhang, W., Jiang, L., & Zhao, T. (2020). Identification of critical causes of tower-crane accidents through system thinking and case analysis. *Journal of Construction Engineering and Management, 146*(7), 04020071.

Zhao, H. (2023). Intelligent management of industrial building energy saving based on artificial intelligence. *Sustainable Energy Technologies and Assessments, 56,* 103087.

Zhao, J., Xie, L., Yang, Y., Hu, X., Ou, C., & Zeng, R. (2022). An ISM-BN based research on navigation risk factors of inland waterway vessels. *China safety science journal (CSSJ), 32*(8), 37-44.

Zhou, Q., Li, H., Zeng, X., Li, L., Cui, S., & Du, Z. (2024). A quantitative safety assessment for offshore equipment evaluation using fuzzy FMECA: A case study of the hydraulic submersible pump system. *Ocean Engineering, 293,* 116611.

Zhu, E., Bai, Z., Zhu, L., & Li, Y. (2022). Research on bridge structure SAM based on real-time monitoring. *Journal of Civil Structural Health Monitoring, 12*(3), 725-742.

APPENDIX

Table 1: Encoding table of characteristic values of influencing factors

Influencing factor	Frequency	Influencing factor	Frequency	Influencing factor	Frequency
Physical state	0.1685	Teamwork	0.0217	Control room temperature	0.0015
Inattention	0.0053	Operating specification	0.0279	Control room humidity	0.0014
Emotional problem	0.0035	Operating system	0.0128	Illumination	0.0028
Safety awareness	0.0069	Rules and regulations	0.0124	Hue	0.0014
Professional skill	0.0861	Reward and punishment system	0.0028	Noise	0.0014
Operational skill	0.0359	Management system	0.0076	Vibration	0.0012
Safety measure	0.01	Job training	0.0318	Crossing condition	0.0014
Protective device	0.0015	Safety Education	0.0341	Construction site	0.0049
Working hours	0.0021	Job management	0.0012	Site obstacle	0.0330
Staffing	0.0023	Technical specification	0.0067	Weather	0.0034
Distribution of responsibilities	0.0423	Work schedule	0.1232	Digital interface display	0.0104
Time pressure	0.0091	Cable worker communication	0.0021	Information transmission	0.0082
Time shortage	0.0334	Signalman	0.0096	Safety sign	0.0440
Emergency plan	0.0032	Untimely signal	0.0055	Display and control page layout	0.0070
Preventive measures	0.0061	Improper command	0.0250	Display and control operation mode	0.0015
Working atmosphere	0.0954	Emergency drill	0.0507	Display and control device density	0.0073
Control room comfort	0.0011	Working space comfort	0.0063	Drive-by-wire reliability	0.0144

Table 2: Analysis of the causes of insecurity

Rank	Integration factor	Concrete performance
Government supervision and policy implementation deficiencies (A)	Compliance issues (A1)	The human-computer interaction system must comply with national and industry safety standards.
	Lack of supervision mechanism (A2)	The risk assessment system and periodic review mechanism need to be revised.

Influencing factors at the organisational level (B)	Control system failure (B1)	Unexpected machine action or system crash
	Device installation and management are not standardised (B2)	The device layout does not meet the design specifications
	Insufficient trust of workers (B3)	Employee training and adaptability should be adequately considered.
	Emergency plans and exercises are inadequate (B4)	Inadequate preparedness at the organisational level to deal with emergencies
A prerequisite for unsafe behaviour (C)	Human error (C1)	Workers fail to use equipment or tools properly
	Lack of safety awareness (C2)	Safety management must be in place, and staff need more risk awareness.
	Multiple environmental impacts (C3)	Harsh weather conditions, dust accumulation, fire hazards, and other environments
	Equipment failure (C4)	Long-term wear and ageing, accidental damage, and other problems
	The platform is not built correctly (C5)	Unstable support structure, improper ground treatment, etc
Unsafe behaviour of construction personnel (D)	Staff mobility is limited (D1)	Affect timely avoidance of danger or efficient completion of tasks
	Operator error judgment (D2)	Motion trajectory prediction error, failure to effectively coordinate the machine
	Workspace planning is not reasonable (D3)	Accidents such as collisions and trips caused by unreasonable planning have increased.
	Machine additional force threat (D4)	Creating additional force while grabbing a dragged object causes danger

Table 3: Expert consistency rating sheet

Hierarchy	Factor	Index consistency						
		All	**1&2**	**1&3**	**1&4**	**2&3**	**2&4**	**3&4**
Deficiencies in government supervision and policy implementation (A)	Compliance issues (A1)	83.33	87	79	85	89	76	84
	Lack of supervision mechanism (A2)	83.33	90	83	92	85	74	76
Influencing factors at the organisational level (B)	Control system failure (B1)	77.83	73	75	85	90	65	79
	Device installation and management are not standardised (B2)	83.50	83	79	89	78	92	80
	Insufficient trust of workers (B3)	83.00	79	85	73	83	93	85
	Emergency plans and exercises are inadequate (B4)	74.00	76	76	81	82	64	65
A prerequisite for unsafe behaviour (C)	Human error (C1)	78.83	89	84	76	78	70	76
	Lack of safety awareness (C2)	82.00	75	85	77	80	83	92
	Multiple environmental impacts (C3)	71.50	66	70	76	72	79	66
	Equipment failure (C4)	80.67	82	93	82	80	75	72
	The platform is not built correctly (C5)	82.50	76	82	80	81	92	84
Unsafe behaviour of construction personnel (D)	Staff mobility is limited (D1)	85.83	96	84	85	85	82	83
	Operator error judgment (D2)	87.17	93	91	83	79	87	90
	Workspace planning is not reasonable (D3)	92.50	89	95	93	92	95	91
	Machine additional force threat (D4)	84.33	81	89	86	75	83	92
	Total	82.02	82.33	83.33	82.87	81.93	80.67	81.00

Table 4: Language variables and corresponding trapezoidal

Linguistic value	Fuzzy interval			
	a	b	c	d
Very low (VL)	0	0	0.1	0.2
Low (L)	0.1	0.2	0.2	0.3
Moderately low (ML)	0.2	0.3	0.4	0.5
Medium (M)	0.4	0.5	0.5	0.6
Moderately high (MH)	0.5	0.6	0.7	0.8
High (H)	0.7	0.8	0.8	0.9
Very high (VH)	0.8	0.9	1	1

Table 5: Expert classification and scoring standard

Standard	Sort	Mark
Professional title grade	Project Manager/Professor	10
	Engineer/Associate Professor	8
	Technician	6
Working hours	≥20Year	10
	15-19 Year	8
	10-14 Year	6
	≤9 Year	4
Educational background	Learned scholar	10
	Master	8
	Bachelor	6
Age	≥50years old	10
	40-49years old	8
	30-39years old	6
	≤29years old	4

Table 6: Expert information and weights

Expert	Professional title grade	Working hours	Educational background	Age	Weight
1	Professor	≥20year	Learned scholar	≥50	0.213
2	Professor	15-19 year	Learned scholar	40-49	0.191
3	Associate professor	10-14 year	Learned scholar	30-39	0.160
4	Associate professor	10-14 year	Master	30-39	0.149
5	Project manager	≥20 year	Master	40-49	0.191
6	Technician	5-9 year	Bachelor	≤29	0.096

Table 7: A table of child node prior probabilities

Node	Influencing factor	State0	State1
D1	Staff mobility is limited	0.692	0.308
D2	Operator error judgment	0.734	0.266
D3	Workspace planning is not reasonable	0.653	0.347
D4	Machine additional force threat	0.681	0.319

Table 8: Conditional probability table of B2 node

A1	State0	State1
State0	0.876	0.212
State1	0.124	0.788

Table 9: Table of probability changes of D3 transfer nodes

A1	**State0**				**State1**			
C2	**State0**		**State1**		**State0**		**State1**	
(T-1)	State0	State1	State0	State1	State0	State1	State0	State1
State0	0.926	0.652	0.677	0.325	0.404	0.752	0.25	0.035
State1	0.074	0.348	0.323	0.675	0.596	0.248	0.75	0.965

Table 10: Statistics of critical evolution paths

Factor	**Induced path**
D1	A1(41%)—B2(52%)—D1 (100%)
	A1(41%)—C5(56%)—D1 (100%)
	A1(41%)—B2(52%)—C5(56%)—D1 (100%)
	A2(37%)—B4 (57%)—D1 (100%)
D2	A2(44%)—D2(100%)
	C3(56%)—D2(100%)
D3	A1(46%)—D3(100%)
	A2(26%)—C2(69%)—D3(100%)
	A2(30%)—B4(56%)—D4(100%)
	A2(30%)—B4(56%)—C1(61%)—D4(100%)
	A2(30%)—C1(61%)—D4(100%)
	A1(30%)—C1(61%)—D4(100%)
	B1(31%)—C4(50%)—D4(100%)

Table 11: Sensitivity coefficient value

	Node	**Sensitivity coefficient**	**Sort**		**Node**	**Sensitivity coefficient**	**Sort**		**Node**	**Sensitivity coefficient**	**Sort**		**Node**	**Sensitivity coefficient**	**Sort**
D1	A1	0.15	1	D2	A2	0.175	2	D3	A1	0.215	1	D4	A1	0.054	4
	A2	0.146	2		C3	0.243	1		A2	0.041	3		A2	0.084	3
	B2	0.085	3						C2	0.113	2		B1	0.108	2
	B4	0.004	6										B3	0.138	1
	C3	0.062	4										B4	0.05	5
	C5	0.018	5										C1	0.009	7
													C4	0.027	6

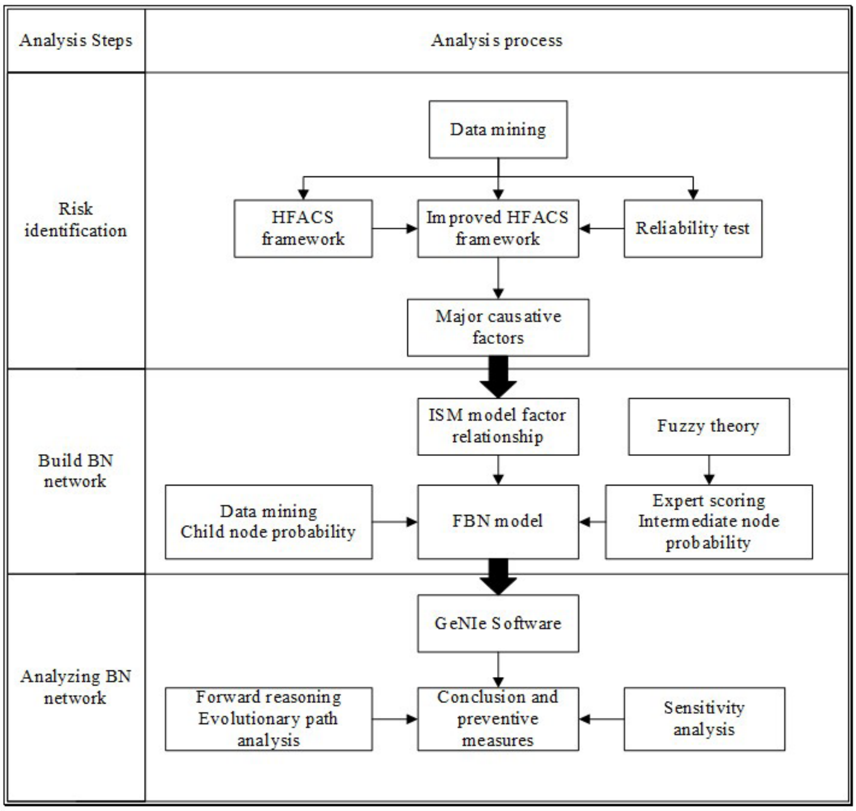

Figure 1: Analysis flow chart

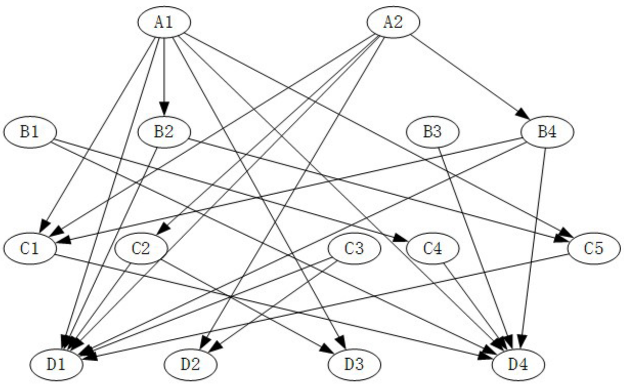

Figure 2: Bayesian network structure

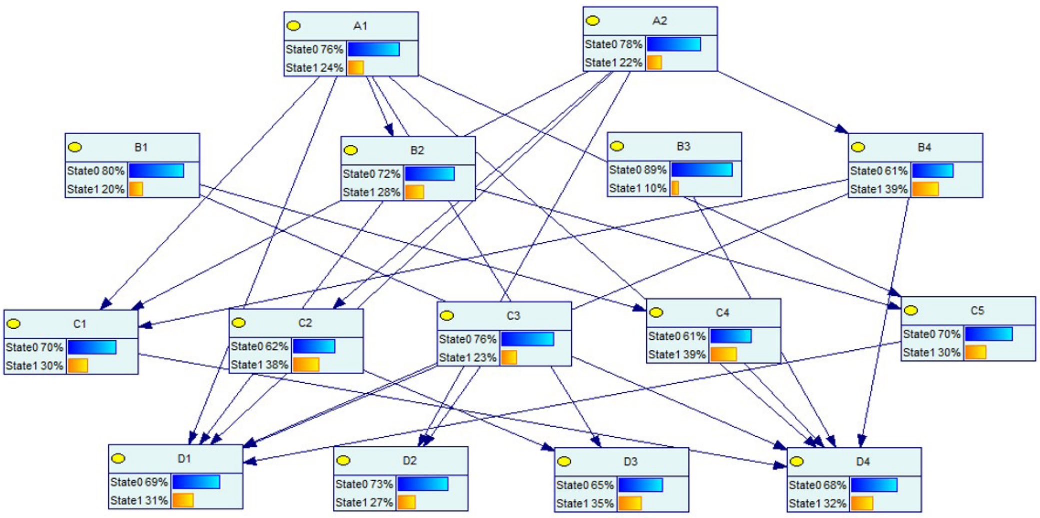

Figure 3: Bayesian network model diagram

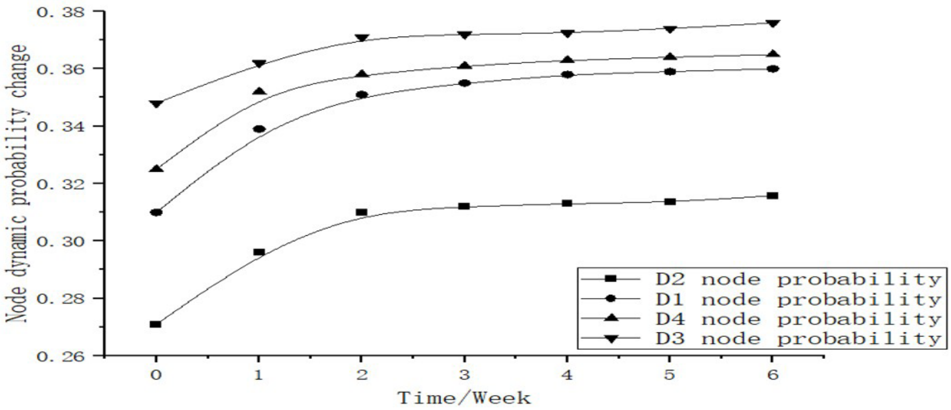

Figure 4: Dynamic probability change curve of child node risk

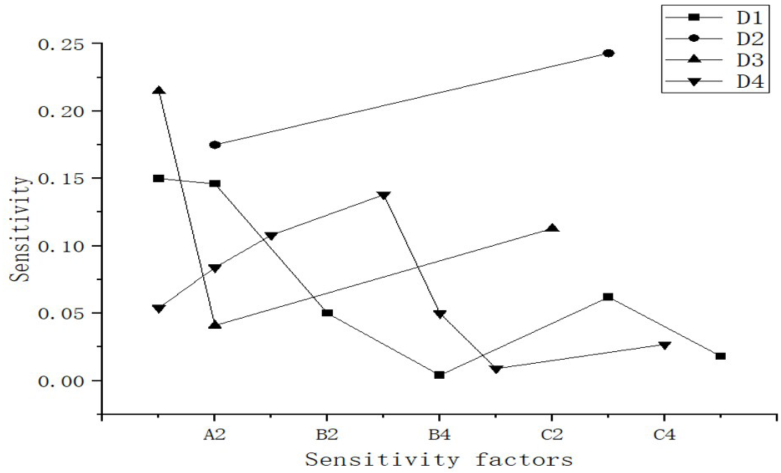

Figure 5: Sensitivity factor analysis