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Prioritization of risk mitigation strategies for contact with sharp object accidents using hybrid bow-tie approach

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A R T I C L E I N F O

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A B S T R A C T

Occupational accidents are still a priority for the construction industry and safety professionals. Appropriate and proactive risk management strategies for complex construction safety management issues are essential to transform the "if-it-breaks-fix-it" approach into "fix-it-so-as-not-to-break." This study introduces a novel hybrid bow-tie (H-BT) model to identify the riskiest causal paths and the most effective protective and preventive strategies. A dataset comprising 829 "contact-with-sharp-object" (CwSO) injury cases collected from 63 projects carried out by three companies is used to define the pairwise relationships among risk factors and define the risk paths using a mutual information matrix. A Delphi analysis is conducted to achieve the final strategies and calculate the risk reduction effect (ΔRR) and cost of each strategy. Finally, protective and preventive strategies are prioritized according to the ΔRR/cost ratio. The findings show that to reduce the number and severity of CwSO accidents, "stop working authority" and "staffing for safety" are the most effective preventative and protective strategies, respectively. Besides, inadequate supervision/management leadership is found to be the originating risk factor in many of the risk paths. This study incorporates mutual information between risk factors, BT, and preventive and protective barriers in the same, easy-to-understand visual model to examine a particular injury type, which is the primary contribution to theory. Overall, the risk assessment model developed is expected to improve the effectiveness of safety management applications in construction sites and eventually contribute to the minimization of incidents in construction projects.

1. Introduction

The construction industry has emerged as one of the riskiest industrial sectors due to its unique, dynamic, and complex nature as well as poor working conditions, the high levels of worker stress, and tight time and cost constraints (Koc et al., 2021). Although occupational accident records have declined over the past decades, construction sites are still among the most dangerous work environments (Ayhan and Tokdemir, 2019a, Ayhan and Tokdemir (2018b)). Globally, a third of all workplace fatalities occur on construction sites, with approximately 100,000 deaths recorded every year (Choi et al., 2020). A report by Eurostat (2022a) shows that over a fifth of all fatal workplace accidents in the EU occur in the construction industry, which has the highest accident rate among industries. In Turkey, over a quarter of all occupational fatalities occur in the construction industry (Social Security Institution, 2021).

One cause of injuries and fatalities on constructions sites involves

Abbreviations: AECOM, Architecture Engineering Construction Operations and Management; BBN, Bayesian belief network; BT, Bow-tie; CV, Coefficient of variation; CwSO, Contact with sharp object; EU, European Union; ETA, Event tree analysis; EW_n, Weight score of the n^{th} expert; FTA, Fault tree analysis; H-BT, Hybrid bow-tie; $H(X,Y)$, Joint entropy of (X, Y); IQR, Interquartile range; IP_{Pn}, Importance of the n^{th} relevant path; $I(X,Y)$, Mutual information shared by X and Y; Md, Median of the strategies rated by the experts; N, Total amount of data; OHS, Occupational health and safety; PPE, Personal protective equipment; P1-P10, Abbreviations of the preventive strategies; R1-R5, Abbreviations of the protective strategies; RF1-RF14, Abbreviations of the risk factors; RS_{Pn-1}, Risk score of the nth path without implementing the strategy; RS_{Pn-2}, Risk score of the nth path after implementing the strategy; 5W1H, Why, What, Where, When, Who, How; μ, Mean scores of the strategies rated by the experts; σ, Standard deviation scores of the strategies rated by the experts; ΔRR, Risk reduction effect.

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contact with a sharp object (CwSO), of which there are two types. First, workers may come into contact with unattended sharp objects scattered throughout construction sites, such as broken materials and items such as cutting tools and nails. The probability of workers experiencing occupational CwSO accidents thus rises due to factors like laziness, haste, time pressures and overconfidence, when, for example, they leave sharp objects in sometimes dangerous places (Aksorn and Hadikusumo, 2007). On the other hand, workers may be engaged with sharp objects while performing a variety of work types, such as iron during formwork installation, formwork tip during concrete casting, façade materials during frame installation, and cable tray during electrical network installation (Nugroho and Sunbara, 2021). In this context, the risk of CwSO accidents increases with imperfect cutting tools, or when workers work in a confined work area, at night, or without adequate personal protective equipment (PPE) (Nugroho and Sunbara, 2021).

In Turkey in 2021, according to Social Security Institution (2021), CwSO accidents accounted for nearly one-third of all the classified occupational accidents. The contact mode of injury classification of Eurostat also shows that CwSO accounts for approximately one-fourth of all accidents in the sector and is the second most frequent contact mode just after "horizontal or vertical impact with or against a stationary object (the victim is in motion)" (Eurostat, 2022b). Given that many CwSO accidents can be prevented through appropriate use of PPE, proper safety staining, and safe work practices with monitor-and-control activities (Fathullah et al., 2021), clearly, an in-depth analysis of CwSO accidents in construction projects is required in order to improve safety performance of the industry.

The development of effective decision-making policies can enable opportunities to better manage construction safety risks and thus facilitate the reduction of occupational incident rates (Alkaissy et al., 2022). An effective occupational health and safety (OHS) risk assessment requires a well-structured model to identify and prioritize risk mitigation measures (Hughes and Ferret, 2007). A framework presenting the most effective strategies can empower decision-makers and safety managers to realize the most and least critical risks and/or strategies (Aminbakhsh et al., 2013). Hence, the most important and urgent measures can be brought to the forefront in the implementation (Xu et al., 2022; Zermane et al., 2022) to improve safety management performance in construction sites in case of limited resources. Therefore, using a prioritization framework as a guideline for identifying the most critical strategies is preferable to conveying random strategies (Zahoor et al., 2017) with regard to planning, budgeting, and managing safety risks. Further, some measures may seem to reduce safety risks more than others, but financial burdens tend to limit their application. Therefore, prioritization should be given not only to risk reduction effect (ΔRR) but also to cost in order to present the most realistic and effective risk mitigation pipeline.

Determining the most adequate risk mitigation measures requires a holistic consideration of the relationships among and interactions of risk factors (Ganbat et al., 2020). In other words, risk paths comprising the fullest extent of relationships among risk factors should be evaluated in detail to develop optimum decision-making processes for OHS risk management (Choe and Leite, 2017; Mohandes et al., 2022). Along with the interactions among risk factors, preventive and protective measures can also be visualized and analyzed by a bow-tie (BT) approach.

According to ISO 31010 standards (2019), BT is a visual representation of risk factors of a top (likely) event and its consequences. The BT approach has been used by many researchers (e.g., Almeida et al., 2023; Alves et al., 2023; Mohd Nizam Ong et al., 2022) since it enables the comprehensive display and analysis within a single model of the potential risk factors and their interactions affecting an event, its possible consequences, measures that can be taken to prevent it, and protective strategies that can be employed to reduce those (Slatnick et al., 2022). In other words, BT analysis reveals the underlying causes of risk events and their consequences while assisting in the development of the most effective measures (Mohd Nizam Ong et al., 2022).

A BT-based visualization approach can also provide practitioners with an easy-to-understand framework to analyze a certain event, helping them to deal with its causes as well as effects more effectively (Tyas et al., 2022). Several studies (Aneziris et al. 2008; Mkrtchyan et al. 2022; Xue et al. 2013; Zhang and Guan 2018) have indicated that the BT method is an effective visualization tool for conducting causal analysis and identifying the most effective barriers to reducing the occurrence and/or effects of risk factors. With a BT-based visualization model, communication among stakeholders can also be enhanced (Slatnick et al., 2022).

Existing studies have mainly proposed risk factors and, eventually, risk mitigation strategies based on prioritization (e.g., Ilbahar et al., 2018; Mete, 2019; Mohandes and Zhang, 2021). A gap still exists in the literature regarding the development of a holistic visualization approach as part of an action or implementation guide based on the pipeline of safety risk factors. Thus, the main objective of the present study is to introduce a systematic framework for the prioritization of risk mitigation strategies by considering their ΔRR and costs with the help of a hybrid BT (H-BT) model as a visualization approach.

The proposed H-BT model integrates a BT approach with mutual information among risk factors captured by real accident reports for identifying risk paths and expert opinions for the assessment of preventive and protective strategies. In order to evaluate the applicability of the proposed model, an examination is made of an accident type, namely, injuries resulting from CwSO events. Overall, it is expected that the proposed H-BT model representing failure paths and a prioritization of risk mitigation strategies based on real injury cases will enable safety professionals to apply more effective OHS management practices.

2. Background

2.1. Risk assessment strategies

Risk management is a process that involves the identification of risk factors threatening business operations and implementation of the necessary measures to prevent them or at least minimize their undesired outcomes (Choudhry et al., 2014). Decision-making and risk management are complementary; decision-making is one of the critical steps of risk management (Fekete, 2022), and risk management is an excellent auxiliary of better decision-making processes (Singh, 2020). In other words, effective decision-making requires the identification of potential risks and detection of the most appropriate measures, while effective risk management requires the development of an applicable decision-making model. Therefore, combining decision-making and risk management processes in a single model in an easily understandable way and presenting it to practitioners by visualizing the model makes both risk management and decision-making more effective and viable. Specifically, the development of a graphical user interface with visualization for risk management and decision-making can help decision-makers examine issues more easily, in greater detail, and to a desired extent (Mkrtchyan et al., 2022).

Many researchers have developed a visually representable decision-making model to deal with, mitigate, or proactively manage risks by adopting a variety of methods, such as Bayesian belief network (BBN) (Mkrtchyan et al., 2022), fault tree analysis (FTA) (Zermane et al., 2022), event tree analysis (ETA) (Hong et al., 2009), and the BT method (de Ruijter and Guldenmund, 2015). In all of these approaches, the central focuses of examination involve overcoming and/or decreasing the complexity of risk management practices with a visual representation.

One of the most widely adopted risk assessment methods applied in a variety of research fields is the BBN algorithm (Islam et al., 2017). Typically, BBN is used to identify probabilistic relationships among interdependent factors (Mohaghegh et al., 2009). Mkrtchyan et al. (2022) made one of many studies that have employed the BBN method for insurability risk assessment of oil refineries. They focused on two critical accident types, fire and vapor cloud explosion, based on expert knowledge and found that none of the included risk factors (e.g., safe work practices, safe work compliance, layout, operational hazards) alone seemed to significantly affect the occurrence of the two risks, highlighting the need to focus on failure paths rather than failure factors. In another study, Wang et al. (2022) developed a BBN model for predicting delay risk in construction projects. According to the modelled reasoning, several risk paths were proposed and the relationship among contractor's service gap, claims, and disputes was found to finally generate a significant risk for construction delay.

Another widely used technique that is supported by visualization is FTA, usually employed for the assessment, identification, and estimation of faults and analysis of the reliability of systems developed (Mahmood et al., 2013). FTA provides an effective mechanism for evaluating the probability of an undesirable event occurring as a result of failure paths by exhibiting them visually and logically (Yazdi et al., 2020). In the risk management literature, several researchers have applied FTA due to its simplicity, efficiency, and ability to identify the root causes of failures (Waghmode and Patil, 2013; Xiao et al., 2023).

For example, Xiao et al. (2022) incorporated FTA into BBN for public safety from unmanned aerial vehicles. FTA was used to derive a fault tree causal mechanism for accidents based on accident reports, following which the proposed fault tree was transformed to BBN model using conversion operations. The researchers found that internal system failures, external environmental factors, and pilot mistakes were the main causes of accidents related to unmanned aerial vehicles. Similarly, Nehal et al. (2022) developed a hybrid FTA-BBN algorithm to model furnace fires. They categorized the causes as operating error, temperature increase, backfire, external, release of dense fumes from chimney, and charge flow. Accumulation of fumes was found to be a critical fault, to which corrosion, overheating, deformation, coke formation, and clogging contributed significantly.

ETA is another risk assessment method leveraging the visualization principle by addressing the occurrence of the probabilistic sequences with the impacts and probabilities of events (Heravi and Charkhakan, 2015). While FTA examines the causes of a top event, ETA analyzes the consequences. The name "event tree" comes from the graphical representation of the analysis, which evokes a tree due to a growth pattern that develops with the increasing numbers of sequenced events (Hong et al., 2009).

One ETA study was conducted by Daas and Innal (2023), who focused on risks related to liquefied petroleum gas. Four emergency conditions were modelled in the ETA model combining local and heavy fires with slight and heavy casualties. The researchers incorporated safety barriers into ETA and found that an automatic fire protection system was the most important emergency safety barrier based on the analytical hierarchy process method. In another study, Chen et al. (2020) implemented an ETA algorithm for chemical process risk assessment, focusing on near misses. The researchers considered three types of consequences, namely, continuous operation, emergency shutdown incidents, and rupture incidents. The probability of emergency shutdown incidents was found to increase significantly after the equipment runs.

The BT algorithm is another method that provides a visualization of the risk assessment process. This method presents the visualization of the risk input and output lifecycles by embodying the dependencies for both the causes and the consequences of an event (de Ruijter and Guldenmund, 2015). Many researchers have used the BT model recently for risk assessment in various research fields as it combines the FTA and ETA (placed at the left and right sides of the graph, respectively), thus providing cause-effect relationships, while focalizing the risk event on the center of the figure (de Ruijter and Guldenmund, 2015; Sharafat et al., 2020). With this methodology, proactive and reactive risk management elements can be analyzed, and the risk event and its management can be visualized and handled systematically (Zhang and Guan, 2018).

BT models can deal with complexity by transforming complex systems into a visual diagram with a logical and coherent expression (de Ruijter and Guldenmund, 2015). For these reasons, and like many past studies, this study centers on the BT algorithm. Among an abundance of research, Sharafat et al. (2020) considered a BT model for analyzing risks related to tunnel boring machine use in difficult ground conditions. Unanticipated ground conditions, rock support system issues, excavation procedure, tunnel boring machine, and mucking system incapabilities, excessive abrasion, and insufficient thrust force in addition to poor management and insufficient logistics support were used as major gates in the FTA. The five initiating events in the ETA analysis were ground deformation, rock bursting, low advance rate of machine, delays in the rock support installation, and decrease in cuttability of cutters.

In another study, Mohd Nizam Ong et al. (2022) developed a BT model for photovoltaic fire loss event. They considered direct current arc fault, ground fault, hot spot effect of photovoltaics, and overheating as threats, with respiratory poisons, electrical shock, fall from heights, asset damage, and propagation of fire being the consequences. Electrical shock was found to cause significant risks for people in the vicinity. The following section mainly reviews related studies using a BT algorithm for OHS risk assessment in the construction industry, and elicits the gaps in the literature.

2.2. Critical studies on visual safety risk assessment in construction

Safety risk assessment in the construction management research domain has been used to improve the OHS conditions of construction sites and well-being of construction workers (Hallowell and Gambatese, 2009). Much research has also employed the visualization methodologies adopted in the present research (ETA, FTA, and BT) to help safety professionals and project managers cope with safety risks more systematically, again proposing a visual representation of the highlighted issues.

For instance, Zermane et al. (2022) assessed the risk of working at height using FTA. The authors utilized actual falling-from-height accident data to explore the probability of each incident in case of the occurrence of the related root cause event. The findings showed that failure to use PPE and lack of safety supervision contributed to the most fatal fall accidents. In another study, Chen and Wang (2017) developed a hybrid FTA-BBN model for fall risk assessment in bridge construction projects. In the FTA part of the study, the researchers found poor work on supporting steel, poor construction of bridge deck, and inadequate lifting operations as the initial causes of fall accidents.

According to comprehensive literature review using the keywords "safety" and "risk" and "construction" and "bow-tie" in the Scopus and Google Scholar search engines, only four studies have adopted the BT model for safety risk assessment in construction projects. Aneziris et al. (2008) used the BT method to assess the risk of injury as a result of falling from height. BT was used for the identification of the whole scenario of the falls (fall from ladder, from scaffold, and from roof, etc.). Applying necessary procedures and performing critical task observation were found to contribute significantly to reducing the risk of falling from a ladder.

Aneziris et al. (2012) proposed a novel risk assessment model incorporating 63 different risk scenarios into a BT model to explore the probability of diverse accident types, such as falls from height, being struck by a moving vehicle, and contact by moving or falling objects. The model was validated by calculating the likelihood of these risk events for a variety of occupational job roles, and the jobs were ranked with respect to their risk level. The probability of fatality among workers erecting timber (including scaffold) was found to be higher than for other workers and activity types.

Zhang and Guan (2018) developed a model integrating the BT and fuzzy optimization methods to determine risk response strategies for improving safety management applications. The BT diagram was first analyzed with linguistic terms that were then converted to corresponding fuzzy membership functions, and the model was validated using a subway station construction project. The results showed that employing skilled welders and the periodic performance testing of mud were the most effective preventive measures; these mitigated, respectively, the nonapplication of correct procedures for constructing reinforcement cages, irrational mud proportions and feature risk factors.

In the last of the four studies identified, Abdolkhaninezhad et al. (2022) integrated fuzzy multi-criteria decision-making with a BT model for safety risk assessment of landfill in construction projects. Health and safety risks were categorized in four major categories: injuries, slight damages, skin allergies and respiratory problems, and increase in pathogenic microorganisms. Non-use of PPE in the landfill was found to be the most critical OHS risk in the construction phase.

An extensive literature review shows that only limited research has developed a BT model for visualizing causalities of occupational accidents in construction projects. No previous studies have established a BT model based on the interrelationships among risk factors identified through real site data and mutual information for construction accidents. By combining the BT model with mutual information, real accident data, and expert opinions, it is intended, a generic safety risk management model in construction can be recommended. This study further integrates preventive and protective safety barriers into a H-BT model to identify and evaluate strategies based on the identified risk paths, which is an additional novelty of the current study. Another point that differs it from past research is the type of accident focused on, namely, CwSO. As mentioned, the exploration of the dynamics of CwSO accident type and proposal of the most effective preventive and protective measures is of critical importance for the industry. These gaps constitute the motivations of this study.

3. Research methodology

The research steps adopted in this study are shown in Fig. 1. The methodology comprised two major steps: first, developing the H-BT model, and second, the prioritization of risk mitigation strategies. In the first step, the H-BT model was constructed to identify risk paths corresponding to the identified risk factors. The mutual information between each risk factor was calculated to quantify the interdependencies among the risk factors and create risk paths correspondingly. In the second step, possible mitigation strategies (both preventive and protective) were determined through a literature review, followed by a Delphi analysis with industry professionals to simplify and verify the proposed list of the strategies. Finally, the risk score for each risk path was estimated for the prioritization of strategies regarding the tradeoff between ΔRR value (the risk reduction effect of each strategy) and cost. The procedures adopted to perform the above-mentioned steps are summarized in the following sub-sections.

3.1. Data preprocessing and mutual information

The procedures applied in this study and the captured dataset are based on a graduate thesis conducted by the first author of this paper. In order to generate the mutual information matrix, the most relevant and widely observed risk factors were extracted from the literature (Table 1).

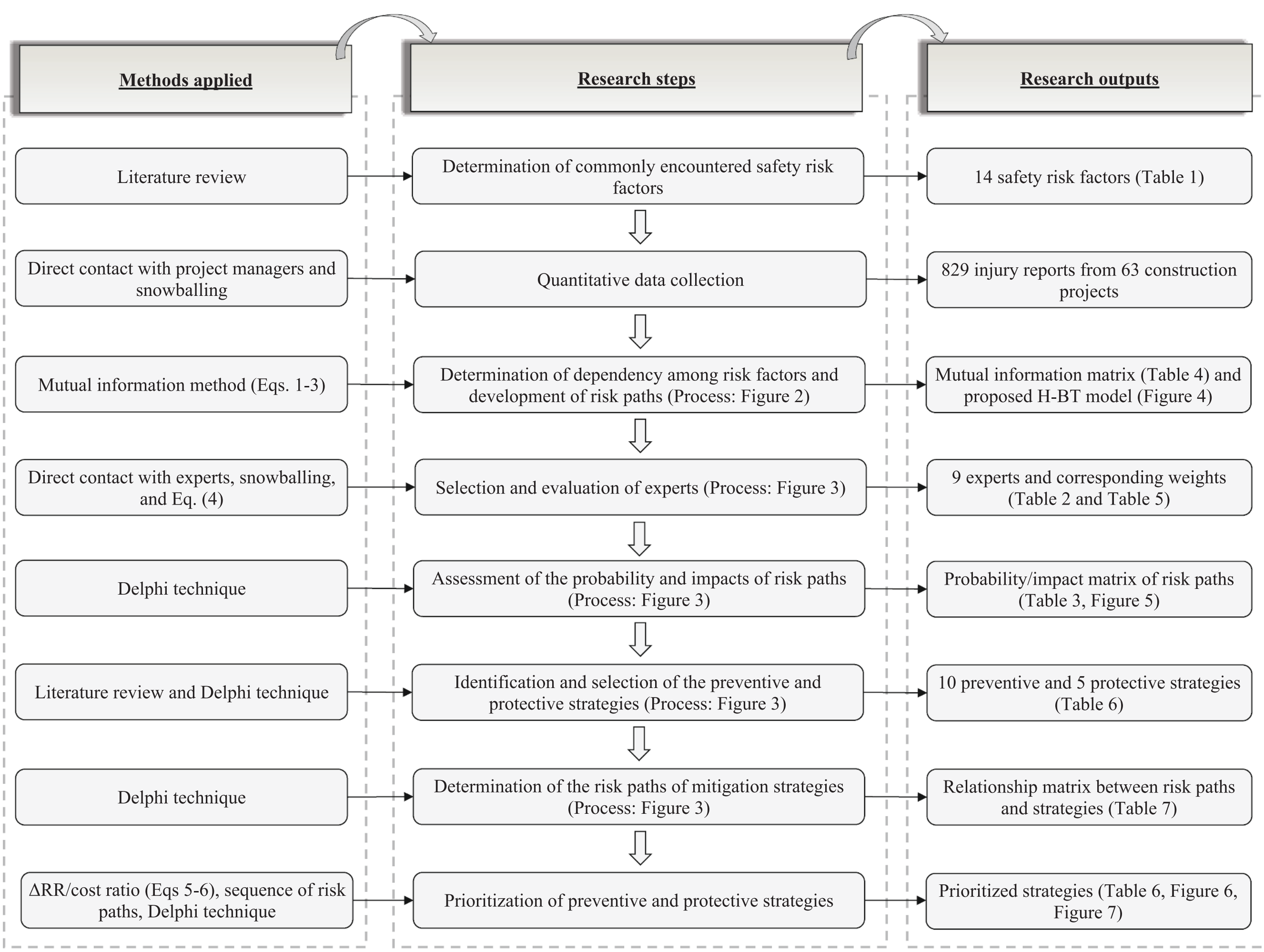

Fig. 1. Research methodology.

Table 1
Commonly encountered safety risk factors on construction sites.

Risk ID	Risk factors	Frequency	Reference
RF-1	Incomplete or inadequate supervision/management leadership	23.88%	Gunduz and Abu-Hijleh (2020)
RF-2	Insufficient control supervision and monitoring	24.49%	Durdyev et al. (2018)
RF-3	Misuse of security system	25.33%	Li et al. (2017)
RF-4	Improper protection system	26.54%	Wong et al. (2009)
RF-5	Unfavourable work environment	56.21%	Satapathy (2022)
RF-6	Unbalanced workload	47.53%	Yang et al. (2019)
RF-7	Failure to assess risk/unawareness of existing hazards	76.60%	Awwad et al. (2016)
RF-8	Insufficient accident analysis system	37.15%	Zahoor et al. (2017)
RF-9	Insufficient communication system	17.49%	Tam and Fung (2011)
RF-10	Rushing/cutting corners	33.90%	Karimi and Taghaddos (2020)
RF-11	Faulty physical movements	31.12%	Haslam et al. (2005)
RF-12	Safe operation violation	43.67%	Soltanzadeh et al. (2017)
RF-13	Shortcomings in OHS/working method training	8.32%	Winge et al. (2019)
RF-14	Educational problems	20.63%	Gibb et al. (2014)

A dataset consisting of 829 construction injury reports related to CwSO was collected from 63 construction projects carried out by three companies to generate a mutual information matrix (Kuzucuoğlu, 2019). The data regarding risk factors that appeared in these reports were converted into binary format (1 = Yes, 0 = No observation) to calculate mutual information values. The frequency of occurrence of risk factors is provided in Table 1. Failure to assess risk and unawareness of hazard (RF-7) was the most frequently faced risk factor in the CwSO accidents, observed in 76.60% of the 829 incidents; the least common was shortcomings in OHS training, reported in only 8.32% of them.

The process of mutual information matrix generation is illustrated in Fig. 2. Mutual information is a method utilized to measure dependency between variables. Mutual information associated with entropy is the central concept of information theory, which is proposed to quantify information (Steuer et al., 2002). If this definition is extended to pairs of variables, the joint entropy of (X, Y) can be calculated as follows:

$$H(X,Y) = -\sum_{x\epsilon X}\sum_{x\epsilon X} p(x,y)\log p(x,y) \tag{1}$$

If this is then converted to mathematical operations, mutual information can be expressed thus:

$$I(X,Y) = \sum_{x\epsilon X}\sum_{x\epsilon X} P(x,y)\log\frac{P(x,y)}{P(x)P(y)} \tag{2}$$

where *I(X, Y)* represents mutual information shared by X and Y, and the average amount of information about X is obtained by observing Y. The relationship between each pair of independent variables is calculated by considering their joint probabilities and the frequency of the observed samples. Mutual information can be directly interpreted as the amount of information shared by two datasets in the unit of bits. Mutual information shared by two variables can be calculated by Eq. (3):

$$I(X,Y) = \frac{N_{11}}{N}log_2\frac{NN_{11}}{N_{1.}N_{.1}} + \frac{N_{01}}{N}log_2\frac{NN_{01}}{N_{0.}N_{.1}} + \frac{N_{10}}{N}log_2\frac{NN_{10}}{N_{1.}N_{.0}} + \frac{N_{00}}{N}log_2\frac{NN_{00}}{N_{0.}N_{.0}} \tag{3}$$

where $P(X=1, Y=1) = \frac{N11}{N}$, and N indicates $N_{11} + N_{10} + N_{01} + N_{00}$, which is the total amount of data.

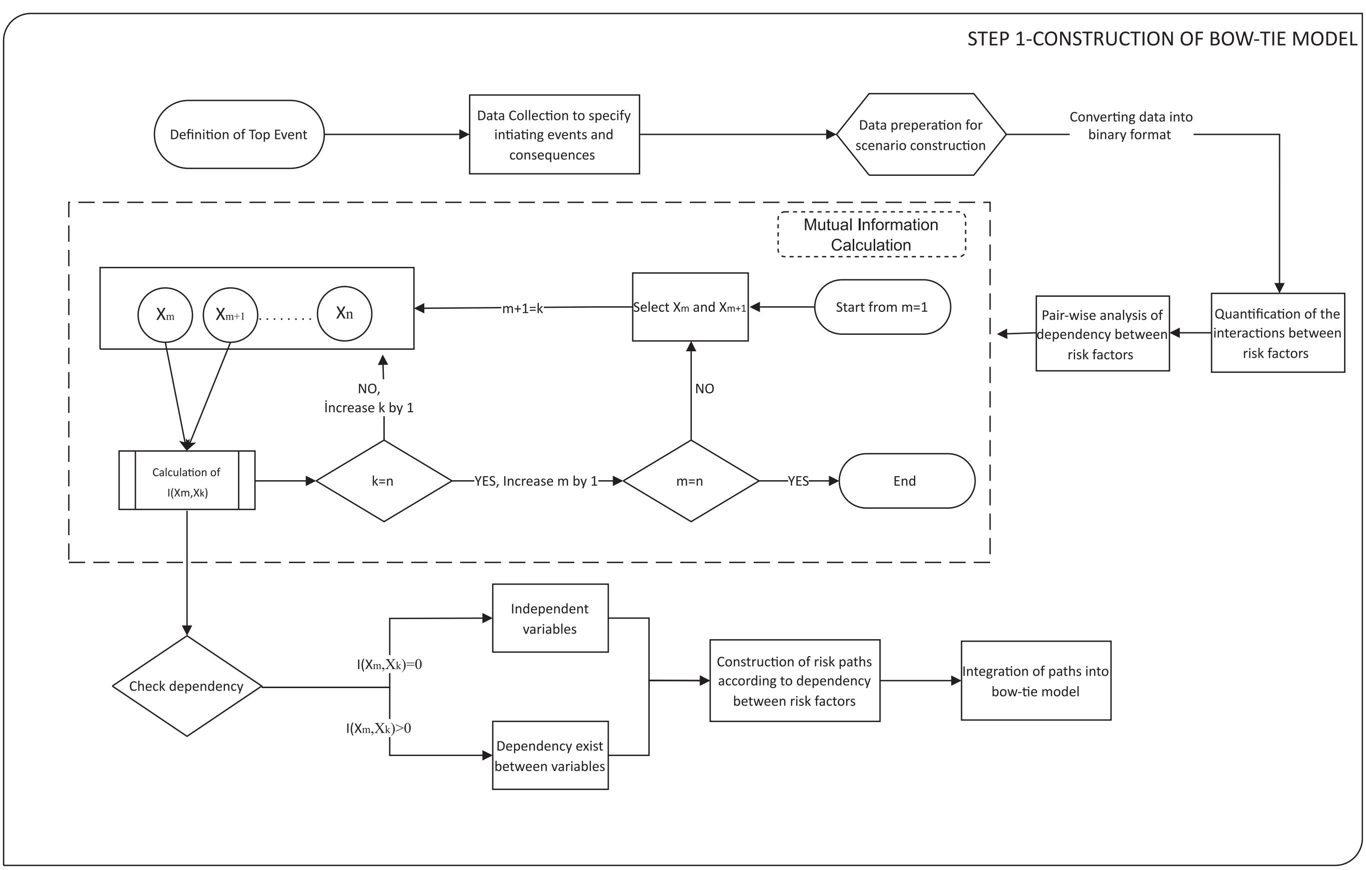

Fig. 2. Procedures of the BT model.

After checking the dependency between variables (i.e., risk factors), risk paths were defined according to the mutual information values. All these paths were calculated and integrated into the H-BT model to sequence the most important risk mitigation strategies (Kuzucuoğlu, 2019).

3.2. Construction of H-BT model

The H-BT model establishes a link between, on the one hand, the causes and consequences of the top event and, on the other, the possible barriers that can reduce either the probability of the occurrence of the event (preventative) or the impacts of the consequences (protective). In other words, preventative barriers facilitate the prevention of initiating events, whereas protective barriers are mainly adopted to minimize the severity of outcomes of the initiating events. The H-BT model consists of FTA, represented on the left side of the model, and ETA, located on the right side of the model. Here, the initiating events were first defined based on 14 risk factors and logically linked with one another (with mutual information values) based on the cause-effect diagram.

In this study, 0.01 was considered as a threshold value (Zhao et al., 2016) for the significant dependency to create relationships between risk factors and eventually constitute risk paths. Then, the top event, CwSO, was used to establish the ETA model. While preventive barriers were integrated into the FTA part of the H-BT model, protective barriers were introduced into the ETA part of the model.

The outcomes of the construction injuries were divided into five categories: near-miss injuries, first aid injuries without time loss, first aid injuries with time loss, medical case injuries without permanent disability, and medical case injuries with permanent disability or death (Ayhan and Tokdemir, 2019b). According to the classification developed by Ayhan and Tokdemir (2019b), the outcomes were integrated into the Bernoulli type of ETA in the H-BT model.

3.3. Prioritization of risk mitigation strategies

The adequacy of risk mitigation strategies was assessed by experts currently working in the construction industry. Three major expert selection criteria were applied: (1) having at least a B.Sc. degree in civil engineering or architecture or working in the safety department of a construction company, (2) having at least ten years of experience in the industry, and (3) having responsibility for dealing with safety incidents on construction sites. Fig. 3 illustrates the expert and most appropriate strategy selection procedure.

In order to determine the risk scores of risk paths on the basis of the risk matrix, 18 preventive and 10 protective strategies were obtained from the literature review and provided to the experts to select the most suitable ones. During the prioritization, the weights of the experts were also considered (Eq. (4); these were calculated based their experience, age, and education level (Table 2).

$$ExpertX^{'}sscore = sumofallscoresineachcategory$$

Table 2
Weighting parameters of experts.

Parameter	Category	Score
Experience in the construction industry (years)	>40	4
	30–40	3
	20–30	2
	<20	1
Education	Ph.D.	3
	M.Sc.	2
	B.Sc.	1
Age (years)	>60	3
	40–60	2
	<40	1

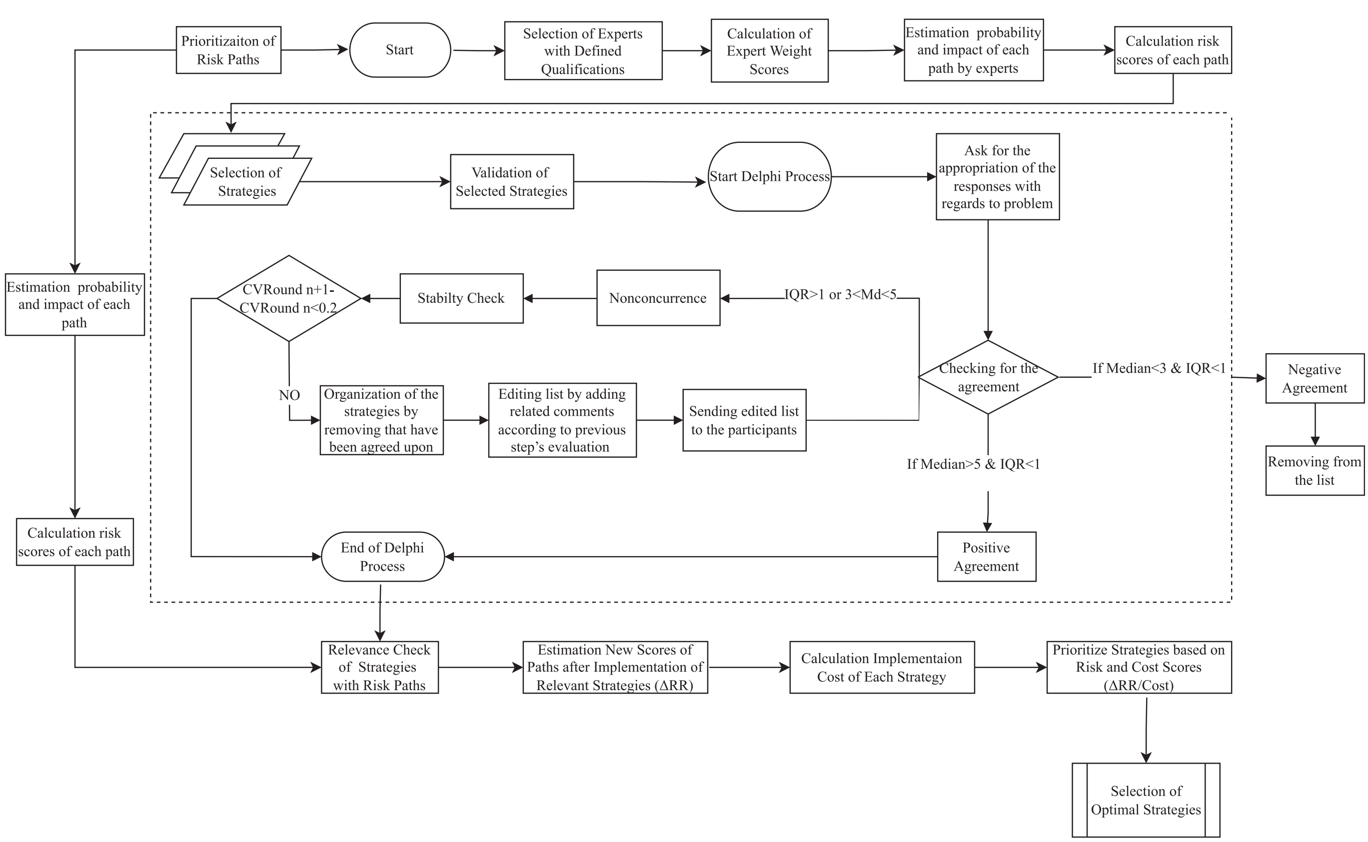

Fig. 3. Evaluation process for risk mitigation strategies.

$$Expert X^{'} s weight = \frac{Expert X^{'} s score}{Sum of all experts^{'} scores} \tag{4}$$

For the prioritization of risk mitigation strategies, a grouping of the risk paths was also required. Weights for each risk path were assigned on the basis of their risk scores. The experts estimated the probability of events and their expected impacts in the case of an occurrence of that risk path. Since making these estimations with mathematical expressions was challenging, linguistic variables were preferred, and corresponding crisp values were used for quantitative analysis (Table 3). The risk score of each risk path was then calculated by multiplying the probability and impact of the corresponding paths.

In the next step, the Delphi method was conducted to achieve a final list of risk mitigation strategies. For this, a seven-point Likert scale was used (1 = least important, 7 = most important), and median and interquartile range (IQR) values were calculated. IQR is used as a consensus criterion in the Delphi method (Ramos et al., 2016). It is calculated by measuring the difference between the first and third quartile, where 50% of the core values can be presented. In the Delphi analysis, stable (i.e., low IQR) values indicate a high level of agreement (Becker and Roberts, 2009). Also, the coefficient of variation (CV), which shows and incorporates the importance and stability of independent variables, was adopted to identify the most important preventive and protective strategies. In order to evaluate whether or not the variable was of importance, the acceptable datum line for the CV was set at 0.2 (Reed et al., 2002).

After the Delphi analysis, a relevance check was employed with the risk mitigation strategies determined. The risk score of each path was calculated once again, with both the sequence of risk paths and experts' scores considered when evaluating the ΔRR of the mitigation strategies. ΔRR was calculated by Eq. (5):

$$\Delta RR = \frac{\frac{RS_{P1-2} - RS_{P1-1}}{RS_{P1-1}} * IP_{P1} + \frac{RS_{P2-2} - RS_{P2-1}}{RS_{P2-1}} * IP_{P2} + \cdots \frac{RS_{Pn-2} - RS_{Pn-1}}{RS_{Pn-1}} * IP_{Pn}}{IP_{P1} + IP_{P2} + \cdots IP_{Pn}} \tag{5}$$

where $RS_{P1\text{-}1}$ is the risk score of the first relevant path for the first case and $RS_{P1\text{-}2}$ is the risk score of the first relevant path after implementing a mitigation strategy; IP_{P1} shows the importance of the first relevant path, and $RS_{Pn\text{-}1}$ represents the risk score of the n^{th} relevant path without implementing the mitigation strategy; and $RS_{Pn\text{-}2}$ illustrates the risk score of the n^{th} relevant path after the implementation of the strategy, with IP_{Pn} being the importance of the n^{th} relevant path. Expert weights were also integrated to calculate the final ΔRR value by using Eq. (6):

$$\Delta RR_{EW} = \Delta RR * EW_1 + \Delta RR * EW_2 + \cdots .. \Delta RR * EW_n \tag{6}$$

where EW_n is the n^{th} expert's weight score.

Finding an optimal strategy also requires consideration of the cost of strategies such that the optimum strategy is the one with the highest ΔRR/cost ratio. Therefore, the experts were also asked about the implementation cost of preventive and protective strategies, again using a five-point Likert scale (1 = very low, 5 = very high). After identifying the ΔRR and cost values of each strategy, strategies were prioritized according to the ΔRR/cost ratio calculation.

Table 3
Crisp equivalences of linguistic variables.

Probability	Impact/consequence	Corresponding number
Improbable	Near miss injuries	1
Remote	First aid injuries without time loss	2
Occasional	First aid injuries with time loss	3
Probable	Medical case injuries without permanent disability	4
Frequent	Medical case injuries with permanent disability or death	5

4. Results

Relationships between risk factors were calculated based on the mutual information matrix, as shown in Table 4. The H-BT model was then constructed according to the significant relationships in the matrix (Fig. 4). As a result, seven risk paths were attained, as illustrated in Fig. 4. The risk paths go from the very beginning of the proposed model to the CwSO node at the center of the model (Fig. 4). For instance, the first risk path follows RF-1, RF-2, RF-3, and RF-5. RF-1 (i.e., incomplete or inadequate supervision/management leadership) was found to be the initiating risk factor in six of the risk paths; the initiating risk factor for the remaining path (Path 7) was RF-9 (insufficient communication system).

In order to locate paths in the risk matrix, profile and weights of the experts (Table 5) were used. Fig. 5 represents the position of the risk paths in the risk matrix. The colors light green, light yellow, and light red in Fig. 5 represent the low-, medium-, and high-risk scores, respectively. Analysis of the results shows that Path 5 (RF-1, RF-6, RF-11, RF-12), Path 6 (RF-1, RF-10, RF-11, RF-12), and Path 7 (RF-9, RF-11, RF-12) were the riskiest.

In order to prevent the occurrence of CwSO and minimize their severe consequences, preventive and protective strategies were proposed and prioritized. By the end of the Delphi process, ten preventive (P1–P10) and five protective (R1– R5) strategies were identified (Table 6). P1 (education and training) had the highest mean, lowest standard deviation, and lowest IQR values ($\sigma = 0.31$, $\mu=6.89$, IQR = 0) among the preventive strategies, while R1 (staffing for safety) had the highest mean, lowest standard deviation, and lowest IQR values ($\sigma = 0$, $\mu=7$, IQR = 0).

Each mitigation strategy was associated with the related risk paths as shown in Table 7. The results show that P2 (authority to remove workers who have demonstrated unsafe behavior), P5 (increasing the number of supervisors), and P7 (audits and certifications) were associated with the majority of the risk paths regarding preventive strategies, while R1 (staffing for safety) and R2 (warning signs) were associated with multiple risk paths with regard to the protective strategies (Table 7).

As the final step of the analysis, the ΔRR/cost values of the strategies were calculated. The ΔRR/cost ratios provided by each expert regarding each strategy are illustrated in Fig. 6, while Fig. 7 shows the overall assessment scheme. The results show that all the experts provided a high ΔRR/cost rate for P10 (stop working authority), emphasizing the effectiveness of this strategy in decreasing the probability of construction injuries due to CwSO (Fig. 6). The overall assessment scheme shows that P10 (stop working authority) and P2 (authority to remove workers who demonstrate unsafe behaviors), and R1 (staffing for safety) and R4 (standardization) were the most effective preventative and protective strategies, respectively.

5. Discussion

5.1. Comparison of this study with past research

This study presents both similarities and differences from past research (Table 8). Several researchers have examined the causal relationship among risk factors leading to occupational accidents in construction projects. For example, Winge et al. (2019) examined the interactions between the causal factors of occupational accidents in construction projects by adopting the construction accident causation (ConAC) framework, finding that risk management, immediate supervision, and workers actions were the key causal factors and significantly correlated. Risk management influenced immediate supervision and worker actions while also immediate supervision influenced worker actions. Many findings of this study are in line with the findings of the study of Winge et al. (2019) regarding causal relationships between risk factors.

We found that RF-1 (inadequate supervision/management

Table 4
Mutual information matrix.

	RF-1	RF-2	RF-3	RF-4	RF-5	RF-6	RF-7	RF-8	RF-9	RF-10	RF-11	RF-12	RF-13	RF-14
RF-1	–	**0.028***	0.009	0.001	0.008	**0.043***	0.009	**0.048***	0.001	**0.037***	0.005	**0.015***	**0.011***	0.005
RF-2	**0.028***	–	**0.062***	**0.014***	**0.093***	0.000	**0.015***	**0.030***	0.004	0.008	0.001	**0.069***	**0.013***	**0.012***
RF-3	0.009	**0.062***	–	**0.030***	**0.011***	0.001	0.001	0.000	0.005	0.001	0.008	0.002	0.002	0.005
RF-4	0.001	**0.014***	**0.030***	–	**0.099***	0.000	0.005	0.000	0.007	0.000	0.000	0.001	0.004	0.008
RF-5	0.008	**0.093***	**0.011***	**0.099***	–	0.000	0.005	0.007	0.003	0.001	0.002	0.008	0.000	0.000
RF-6	**0.043***	0.000	0.001	0.000	0.000	–	0.001	0.000	0.000	**0.054***	**0.025***	0.009	0.000	0.008
RF-7	0.009	**0.015***	0.001	0.005	0.005	0.001	–	**0.031***	0.002	0.005	0.000	0.000	0.000	0.000
RF-8	**0.048***	**0.030***	0.000	0.000	0.007	0.000	**0.031***	–	0.002	0.001	0.000	**0.091***	0.007	0.009
RF-9	0.001	0.004	0.005	0.007	0.003	0.000	0.002	0.002	–	0.000	**0.039***	**0.021***	0.004	0.000
RF-10	**0.037***	0.008	0.001	0.000	0.001	**0.054***	0.005	0.001	0.000	–	**0.011***	**0.022***	0.000	0.002
RF-11	0.005	0.001	0.008	0.000	0.002	**0.025***	0.000	0.000	**0.039***	**0.011***	–	**0.029***	0.000	0.005
RF-12	**0.015***	**0.069***	0.002	0.001	0.008	0.009	0.000	**0.091***	**0.021***	**0.022***	**0.029***	–	0.009	**0.014***
RF-13	**0.011***	**0.013***	0.002	0.004	0.000	0.000	0.000	0.007	0.004	0.000	0.000	0.009	–	**0.037***
RF-14	0.005	**0.012***	0.005	0.008	0.000	0.008	0.000	0.009	0.000	0.002	0.005	**0.014***	**0.037***	–

* Significant mutual relationship.

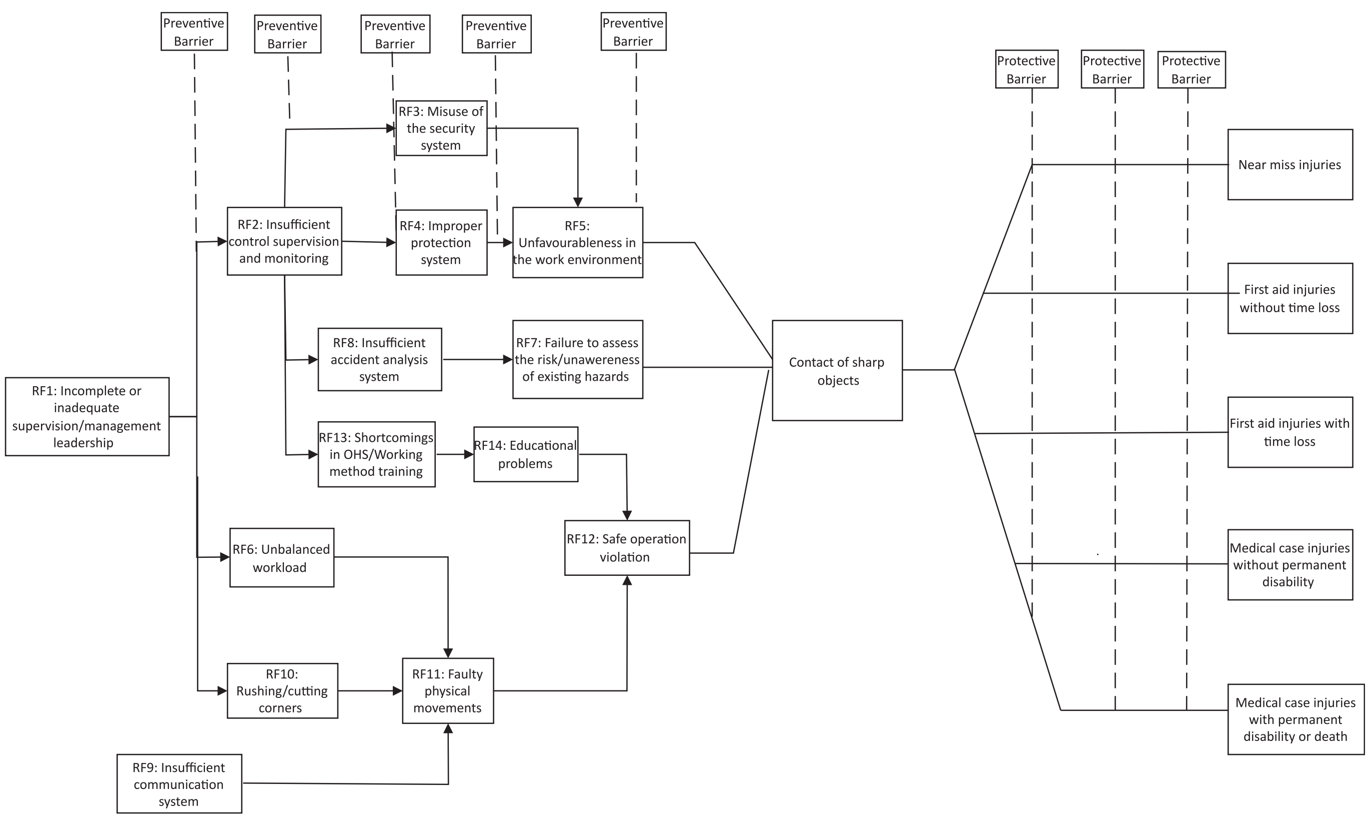

Fig. 4. Proposed H-BT model.

Table 5
Profile and weights of experts.

Expert	Age (yrs)	Experience (yrs)	Education level	Expert's weight (w)
Expert 1	63	33	Ph.D.	0.173
Expert 2	42	13	M.Sc.	0.096
Expert 3	59	38	B.Sc.	0.115
Expert 4	52	27	B.Sc.	0.096
Expert 5	57	29	B.Sc.	0.096
Expert 6	45	20	B.Sc.	0.096
Expert 7	59	31	M.Sc.	0.135
Expert 8	48	23	B.Sc.	0.096
Expert 9	42	15	M.Sc.	0.096

leadership) was the originating cause factor in six of the risk paths. Additionally, RF-1 formed four of the seven risk paths through insufficient supervision and monitoring (RF-2) (Fig. 4). Besides, some risk factors that can be associated with worker actions, such as RF-12 (safe operation violation) and RF-7 (failure to assess the risk/unawareness of existing hazards), appeared at the downstream of risk paths, highlighting similar causal relationships to those found by Winge et al. (2019). The most distinct finding of this study was that insufficient communication (RF-9) was found to be the originating cause factor for the last risk path, while Winge et al. (2019) found communication as one of the immediate factors. As recommended by Winge et al. (2019), this study further incorporated measures into the proposed visual H-BT model.

Another causal analysis study on construction accidents was conducted by Mohandes et al. (2022). These researchers categorized six causes of accidents on construction sites—governmental,

Prob/Impact	1	2	3	4	5
1					
2					
3		Path 1, Path 2, Path 3	Path 4		
4				Path 5, Path 7	
5				Path 6	

Fig. 5. Risk matrix.

Table 6
Preventive and protective strategies.

ID	Preventive strategies	Reference	σ	μ	CV	Md.	IQR
P1	Education & training	Hallowell and Gambatese, 2009; Vitharana et al., 2015	0.31	6.89	0.05	7	0
P2	Authority to remove workers who have demonstrated unsafe behavior	National Safety Council, 2020	0.67	6.33	0.11	6	1
P3	Toolbox meetings	Hinze et al. 2013	0.67	6.33	0.11	6	1
P4	Orientation programs	Hallowell and Gambatese, 2009	0.63	6.22	0.10	6	1
P5	Increasing the number of supervisors	Kheni et al., 2010	0.57	6.11	0.09	6	1
P6	Management commitment	Aksorn and Hadikusumo, 2008; Mohammadfam et al., 2016	0.82	5.33	0.15	5	1
P7	Audits and certifications	Aksorn and Hadikusumo, 2008; Alarcón et al., 2016	0.67	5.33	0.13	5	1
P8	Safety incentives and rewards	Alarcón et al., 2016; Vitharana et al., 2015	0.83	5.56	0.15	6	1
P9	Safety planning	Hallowell and Gambatese, 2009	0.83	5.56	0.15	6	1
P10	Stop working authority	Karakhan et al., 2018	0.57	6.11	0.09	6	1
ID	**Protective Strategies**	**Literature Support**	**σ**	**μ**	**CV**	**Md.**	**IQR**
R1	Staffing for safety	Alruqi and Hallowell, 2019	0	7	0	7	0
R2	Warning signs (Andon)	Celebi and Yilmaz, 2015	0.83	5.44	0.15	5	1
R3	Proper equipment (poka-yoke)	Bajjou et al., 2017	0.83	5.56	0.15	6	1
R4	Standardization	Antillón et al., 2011	0.67	5.33	0.13	5	1
R5	Record keeping and accident analysis	Hallowell and Gambatese, 2009	0.63	6.22	0.10	6	1

Table 7
Risk matrix results of preventive and protective strategies.

Strategies/ Paths	Path 1	Path 2	Path 3	Path 4	Path 5	Path 6	Path 7
Preventive strategies							
P1				x		x	
P2	x	x	x	x		x	
P3					x	x	x
P4				x		x	x
P5	x	x	x	x	x		
P6	x	x	x		x		
P7			x	x	x	x	x
P8				x		x	x
P9	x	x	x				
P10					x	x	x
Protective strategies							
R1	x	x	x	x	x		
R2	x	x	x			x	x
R3	x	x	x				
R4		x	x				
R5			x				x

organizational, workplace, human, materials, and external—and examined the root causes in each category. While we used real accident reports to derive causal relationship between factors, Mohandes et al. (2022) employed a fuzzy decision-making trial-and-evaluation laboratory (DEMATEL) analysis based on expert judgment.

In line with the findings of this study, they also identified poor communication as the most causal factor in the organizational category. The other main causal factors identified (lack of safety knowledge, improper use of materials, and poor safety warning systems) mainly appeared as shaping factors (between the cause and effect factors) in this study. Mohandes et al. (2022) did not identify proper supervision as one of the causal factors, as opposed to this study and Winge et al. (2019). This discrepancy can be explained by the fact that they assessed the causality of factors per category separately. However, some factors in one category may influence the factors in other categories, which can restrict the extraction of hidden relationships.

Taking a different methodological approach, Tong et al. (2021) developed a fishbone diagram to examine accident causation for highway construction projects. Similar to Mohandes et al. (2022), these researchers grouped causes into categories, namely, human, environment, material, and management. They found the root causes to be lack of factors related to decision makers and managers, which can be associated with the main causal factor identified in this study (R1: inadequate supervision/management leadership). Furthermore, similar to this study, worker-related factors (e.g., unsafe acts) were determined by Tong et al. (2021) to be the direct cause of accidents. While they focused on project type and examined accident reports recorded in highway construction projects, we focused on accident type (CwSO) and collected accident reports from a variety of project types.

Like this study, some researchers have adopted a BT model as a generic visualization approach. One of the preliminary studies introducing a BT model was conducted by Aneziris et al. (2008), who focused on the fall-from-height accident type. The consequences of accidents considered were lethal injuries, permanent disabilities, and recoverable injuries, similar to this study. However, they developed BT models for each fall type separately, and the identified factors were related to

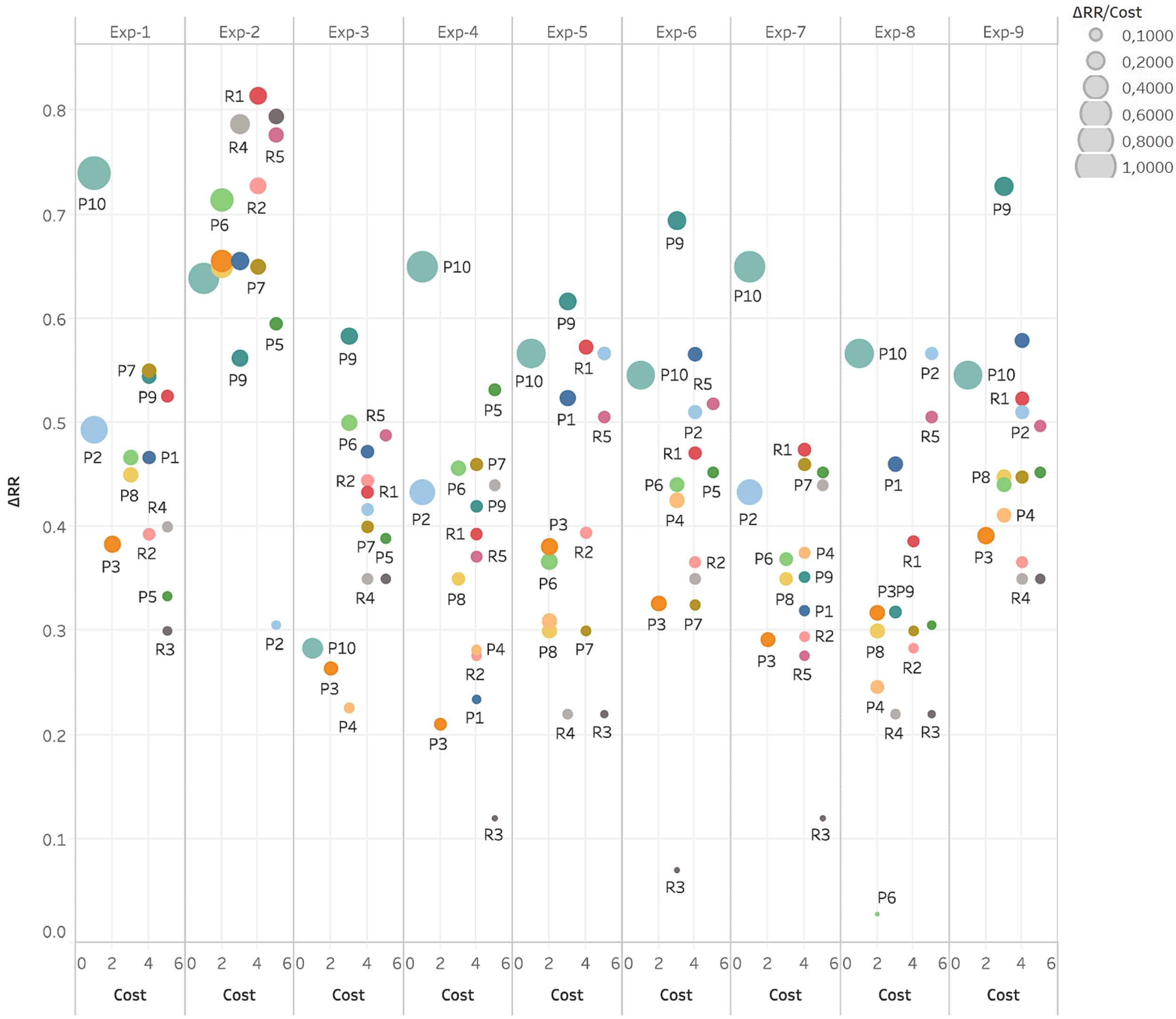

Fig. 6. Expert opinions on ΔRR/cost ratio of preventive and protective strategies.

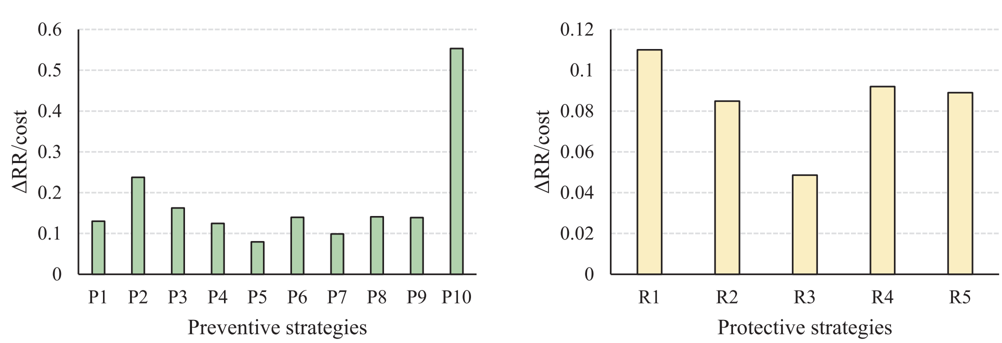

Fig. 7. Effectiveness of strategies.

conditions (type of ladder, workers' ability, floor condition, etc.) rather than risk factors. According to their survey results, Aneziris et al. (2008) identified more general measures—applying necessary procedures and performing critical task observation—as the most effective strategies. Here, however, as mentioned, "stop working authority" (P10) and "staffing for safety" (R1) were identified as the most effective preventive and protective strategies. In another study, Aneziris et al. (2012) concentrated on 63 BT models for a variety of accident types (e.g., fall from height, contact with object, fire, contact with electricity). However, the researchers did not visually present the BT models, evaluating the probability of occurrence of the events, instead.

A similar research question to that asked here (regarding prioritization of preventive and protective strategies) was raised by Zhang and Guan (2018), who focused on subway construction projects. Consequences were divided into four categories—near-less, minor damage, surrounding soil settlement, and foundation pit collapse—while the identified risk factors were mainly related to the works performed (e.g., errors in excavation and wrong joint type) rather than safety related

Table 8
Comparison of this study with similar research.

Reference	Project type	Accident type	Causal analysis	Method for causal analysis	Risk paths	BT model (ETA part)	Strategies integrated with BT	Major Limitations
Winge et al., 2019	Not focused	Not focused	Yes	ConAC	No	No	N/A	A generic BT model can be developed based on the causal relationships between factors.
Mohandes et al. 2022	Not focused	Not focused	Yes	DEMATEL	No	No	N/A	A generic BT model can be developed based on the causal relationships between factors.
Tong et al., 2021	Highway	Tunnel collapse accident	Yes	Fishbone	No	No	N/A	A generic BT model can be developed based on the causal relationships between factors.
Aneziris et al., 2008	Not focused	Fall from height	No	N/A	No	Yes	Yes	Investigated factors were mainly related to conditions rather than risk factors.
Aneziris et al., 2012	Not focused	Not focused	No	N/A	No	Yes	No	BT models were not visually presented.
Zhang and Guan, 2018	Subway	Not focused	No	N/A	No	Yes	Yes	Risk factors were mainly related to works performed rather than OHS risks.
Abdolkhaninezhad et al., 2022	Landfill	Not focused	No	N/A	No	Yes	Yes	Causal relationships between risk factors were not considered in the BT model.
This study	Not focused	CwSO	Yes	Mutual information theory	Yes	Yes	Yes	The H-BT model was developed by CwSO data collected from a variety of project types.

risks. Therefore, the most effective strategies identified in that study (e.g., periodic performance testing of mud) were largely different from those recommended here (P10 and R1). Similar to this study, Zhang and Guan (2018) also evaluated the effectiveness of strategies by considering ΔRR and cost. Another study that visualized OHS risk management with a BT model was performed by Abdolkhaninezhad et al. (2022), who examined OHS risks in landfill sites. The researchers, however, did not explore the causal relationships among the risk factors identified (excavation and embankment, collision, malfunctioning of recirculation pumps, and lack of safety equipment).

Compared to past research, the most significant theoretical contribution of this study to the causal analysis literature on construction accidents is the use of mutual information theory. Accordingly, a set of risk paths is proposed, while previous research has mainly focused on placing factors according to their causal roles, such as originating, shaping, and immediate factors and cause or effect factors (Mohandes et al., 2022; Winge et al., 2019). The risk paths identified here have been further evaluated in terms of their probability and impact, and the most critical risk paths have been highlighted.

Along with causal analysis of risk factors, this study has further identified four outcomes of accidents and constructed an H-BT model. In this way, both preventive and protective measures have been integrated in the model. Although there are some studies that have developed a BT model for safety risk management in construction projects (Abdolkhaninezhad et al., 2022; Aneziris et al., 2008, 2012; Zhang and Guan, 2018), they have mainly focused on project types and not (thoroughly) addressed the relationships among risk factors.

Overall, based on the risk paths formed by incorporating mutual information among risk factors, a single and easily comprehensible model is proposed to identify the most effective preventive and protective measures. Such a comprehensive approach to safety risk management in construction projects has not been documented previously.

5.2. Assessment of the most effective strategies

Among the preventive strategies, “stop working authority” was found as the most effective strategy. This preventive strategy empowers workers to cease activities in case of an unsafe condition that may cause occupational injuries or fatalities. It was found particularly essential to actualize this measure by removing workers who were observed to perform unsafe practices and/or do not follow the OHS procedures. This was also highlighted by Rajendran and Gambatese (2009) as one of the top three substantial practices to improve the safety performance of construction projects.

The zero incident philosophy of Bechtel (2022), an internationally renowned construction company, centers on giving all employees the authority to stop work. This zero-incident philosophy considers all incidents preventable if the employees are able to stop work in case of a risky situation. By following this rule, Bechtel achieved zero lost time from accidents on 90% of their projects, which improved not only the company’s safety performance but also productivity of projects by reducing the time loss that might have occurred as a result of injuries (Zou, 2011). Although stopping work might seem to reduce productivity on construction sites in the short term, it has a significant beneficial impact on the overall productivity in the long run through minimizing cases of work lost, minor injuries, and fatalities.

As shown in Fig. 7, the authority to remove workers who demonstrate unsafe behaviors was the second most effective preventive strategy. This underlines the importance of creating a well-disciplined atmosphere in the workplace in terms of safety regulations that are expressed for the whole process, starting from the training given and lasting to the end of work on site (National Safety Council, 2020). In this era of data supported by technological revolutions, workers who pose risky behaviors can be detected using computer vision-based applications (e.g., Ding et al., 2017; Khan et al., 2022; Yu et al., 2017), and as such, can be moved away from the construction site.

Regarding protective strategies, staffing for safety was found to directly reduce the impact of injuries in most cases. If the likely occurrence of an accident is not well predicted and thus prevented, the most effective protective strategy to reduce its severity is staffing for safety. This involves increasing the number of safety professionals on site to control and monitor workers, unsafe behaviors, and unsafe/dangerous conditions (Alruqi and Hallowell, 2019).

According to a report by Architecture Engineering Construction Operations and Management (AECOM) (2017), budgeting and staffing for safety is one of the most effective best practices to improve safety performance. However, some researchers (e.g., Heng et al., 2016; Xue et al., 2022) have stated that staffing for safety for inspection is a labor-intensive and time-consuming process whose effectiveness greatly depends on the knowledge and experience of the safety staff. This discrepancy can be explained by the fact that the present research only considered *ΔRR* and cost of strategies, while other factors, such as time, effort, and ease of implementation, can also impact the effectiveness of strategies.

In our study, standardization was identified as the second most prominent protective strategy. The strategy can reduce the severity of accidents through the employment of stable and regular techniques and increasing the control of workers with predefined rules (Antillón et al., 2011). It should be emphasized that standardization points to structured and professional management for construction projects. This finding corroborates the results of past research.

For instance, Edwin et al. (2021) compared the safety procedures in the petroleum and construction industries to explore the reasons for high fatality rates in the construction industry. They reported that rules, operations, and procedures are more standardized in the petroleum industry than the construction industry, which may be one of the reasons for high fatality rates in this sector. Many researchers have even proposed safety management approaches with the aim of achieving more standardized safety management applications, such as building information modelling (Sidani et al., 2022), data-driven machine learning (Tixier et al., 2017), and a dimension extraction model (Alruqi et al., 2018).

5.3. Assessment of the risk paths

The identified riskiest paths (Paths 5, 6, and 7) indicate that lack of supervision/management leadership (RF1) causes several issues, and if combined with unbalanced workload (RF-6) and rushing/cutting corners (RF-10), it poses the most significant risk for CwSO. Along with RF-6 and RF-10, communication (RF-9) problems commonly cause faulty physical movements (RF-11). Thus, if safe operations are violated (RF-12), a CwSO accident becomes more probable and severe (Fig. 4). This is quite remarkable, as these paths anatomize the occurrence of severe and frequent CwSO accidents.

Workers are sometimes in a hurry to complete required tasks quickly, which can increase the risk of CwSO (Aksorn and Hadikusumo, 2007), particularly if they are overloaded, pressured, and there is insufficient communication on site. High workload is widely considered a critical cause of occupational accidents through unsafe acts due to several factors (e.g., mental and/or physical fatigue, stress, rushing) (Alexander et al., 2017; Chan et al., 2020; Leung et al., 2010). In this case, workers may sometimes feel they do not have enough time to follow OHS protocols and may leave sharp objects in locations that are easily accessed (Aksorn and Hadikusumo, 2007). This is a prevalent issue in the construction sector in many countries where construction workers often seek work whenever it is offered (Goldenhar et al., 2003), leading to them working up to 60 h a week in some projects or companies. Therefore, workers should be encouraged to report their safety concerns and request rest if they feel overloaded, particularly in delayed projects.

The relationship between communication and faulty physical movement also requires special attention. Insufficient communication is one of the causes of faulty physical movement as workers may not perform the required tasks safely due to their not being informed about the requirements of tasks and essential OHS protocols. If communication problems are combined with pressures on workers, they may tend to take shortcuts or perform cutting activities quickly (leading to sharp edges) without receiving feedback on the safety requirements.

Nonetheless, these factors are not sufficient alone to cause CwSO incidents, unless safe operation is violated. This highlights that many CwSO accidents can be prevented with a careful monitoring of workers' unsafe behaviors, either with traditional site inspection (Zermane et al., 2022) or vision-based detection (e.g., Son et al., 2019), depending on the available resources. This requires both proper supervision/management (through RF6-RF11-RF12 and RF10-RF11-RF12) and participative communication (through RF11-RF12) playing the originating roles for the occurrence of the remaining factors.

Effective supervision, management, and leadership can enforce safety protocols and guarantee the adequacy of safety training. Therefore, it is essential to implement training programs not only for workers but also for managers in order to foster a safety-oriented workplace and improve safety culture in an organization (Tafvelin et al., 2019). Improved supervision and management with rigorous training can help professionals realize where extra safety training and focus are needed. The leadership skills of project and safety managers also impact the acquisition of the information provided by workers and thereby influences their safety behaviors (Zheng et al., 2021). Information generated can be more useful with effective communication between managers and workers, bridging the gap between the information provided and the work performed.

5.4. Practical utilization plan

In project planning, answers to 5W1H questions play a critical role for practical utilization. Fig. 8 shows the answers to 5W1H questions for practitioners who aim to minimize CwSO accidents (or other accident types). For a deeper insight, a practical utilization plan for safety managers is also presented in Fig. 9.

First, based on the accident records in a project (*Project A*), a safety manager can identify a risky event (*Event A*) for in-depth analysis to reduce the frequency of occurrence and severity (Step 1). In this study, *Event A* is referred to as CwSO. In the next step, the manager can examine *Event A* and identify common risk factors that may impact the occurrence and severity of the event as well as the event's possible consequences (Step 2). Then, past accident reports on *Event A* from *Project A* can be obtained, and the same reports can be requested from other similar projects as a data collection step to increase the sample size for more reliable analysis (Step 3). The identified risk factors can therefore be extracted from the reports (manually or using natural language processing) and a mutual information matrix can be generated using Eqs. (1)–(3) (Step 4).

Based on the captured mutual information matrix, a BT model can be visualized, enabling risk paths to be identified. In Step 5, the manager can select the expert team or consider all the staff in the safety management department in the project to evaluate risk paths using the five-point Likert scale (Step 6). The team can further identify both preventive and protective strategies (Step 7). In Step 8, the team can evaluate the effectiveness of each strategy by calculating Δ*RR* using Eqs. (4)–(6) by considering the cost of each strategy (using the five-point Likert scale). As the final step, the manager can prioritize preventive and protective strategies based on Δ*RR*/cost ratio to identify the most effective strategies.

5.5. Contributions of the study

A major contribution of this study to society lies in its visualization of the causal mechanism that leads to CwSO accidents; focusing on the riskiest causal paths is expected to reduce the number and severity of these accidents. Given that CwSO accidents can cause significant permanent disabilities (such as lost fingers and limbs, lost incomes), introduction of the proposed causal model can minimize the probability of construction workers incurring bodily harm or seeing their earning capacity reduced. A significant managerial implication of the research is that the proposed and visualized H-BT model can be easily understood by project stakeholders, which is expected to broaden the extent of the decision-making and enhance communication between stakeholders for improved risk management. Other novel contributions of the study can be summarized as follows:

- Previous research mainly focused on other accident types such as falls from height (Aneziris et al., 2008) or all accident types (Winge et al., 2019), while this study has investigated the causation of and measures against CwSO. Noting that the effectiveness of measures

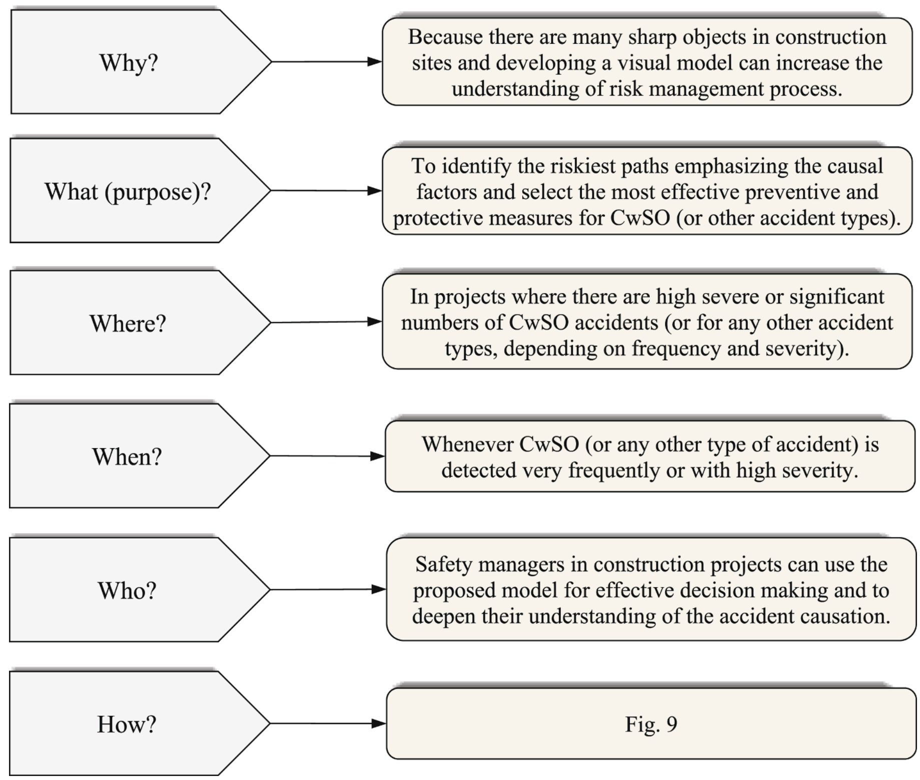

Fig. 8. 5W1H questions and answers from this study.

can vary by type of accident, the most effective measures identified in this study are recommended only for projects that have high CwSO accident rate. Safety managers are advised to adopt the recommended procedures (as shown in Fig. 9) for other accident types.

- Examination of the causal relationships between the factors considered has shown that inadequate supervision was the most prevalent causal factor, while factors related to worker actions appeared at the end of the causal paths, similar to the findings of Winge et al. (2019). However, unlike past research, this study has found “insufficient communication system” to be a significant causal factor of faulty physical movements and safe operation violation. Therefore, developing a robust communication system on construction sites should be considered carefully during the safety planning process.
- “Stop working authority” and “staffing for safety” were identified as, respectively, the most effective preventive and protective strategies for CwSO accidents. These measures have not been highlighted in previous research prioritizing protection and/or prevention measures. Therefore, in order to reduce the frequency of CwSO type of accidents, all the safety staff and site supervisors should be given the authority to stop work. Similarly, in order to reduce the severity of CwSO accidents, safety staff should perform patrol inspections for sharp objects/edges and/or workers using these. Since patrol inspection is considered a time-consuming practice by some scholars, deep learning algorithms trained with site images can also be used to detect dangerous sharp objects (e.g., left on the ground) or sharp edges (e.g., due to imperfect cutting of materials).
- One of the features that distinguishes this study from its counterparts is the use of mutual information theory for determining causal relationship between the risk factors that form risk paths. For the first time in the literature, a probability/impact evaluation of risk paths presents the riskiest paths. In this case, three paths (5, 6, and 7) were determined to be the riskiest in the occurrence of CwSO incidents. In all of these paths, faulty physical movement and safe operation violation are common risk factors. With reference to the statement of Winge et al. (2019) that no failure factors alone cause occupational accidents, it has been found here that the combined effects of these two factors cause CwSO accidents. Therefore, safety staff should be careful about activities that require movement. It is acknowledged that image-based solutions usually focus on detecting “unsafe acts.” Hence, this study further underlines the necessity for the interest of both scholars and practitioners in detecting unsafe or faulty movements.

6. Concluding remarks

Compared to other sectors, the construction industry is exposed worldwide to a high number of occupational injuries and fatalities. Construction workers, in particular, use and/or are in contact with sharp objects scattered in construction sites while performing work activities. Therefore, developing a risk management model that visualizes the occurrence of CwSO accidents and integrates mitigation measures will be highly beneficial; a successful risk management process requires the detailed identification of risk factors, well-structured risk paths, and implementation of the corresponding mitigation measures.

Easily comprehensible BT models can be effective in analyzing the risk paths through which an accident occurs as well as in applying the most suitable risk mitigation measures. Previous studies have neither developed an H-BT model that integrates risk factors, their relationships, consequences, and preventive/protective measures nor proposed a solution for CwSO accidents using real site data.

The primary aim of this study was to develop an H-BT model that visualizes the dynamics of CwSO accidents and offers the most effective preventive and protective strategies. By quantifying the relationships among risk factors through mutual information theory and constituting corresponding risk paths, project managers and safety professionals will be able to use the proposed model to identify the riskiest conditions for CwSO incidents and determine the most effective strategies to deal with them. Since the optimal strategy should correspond to maximum risk reduction with minimum cost, protective and preventive strategies were ranked according to their ΔRR/cost ratio. This study is one of the first

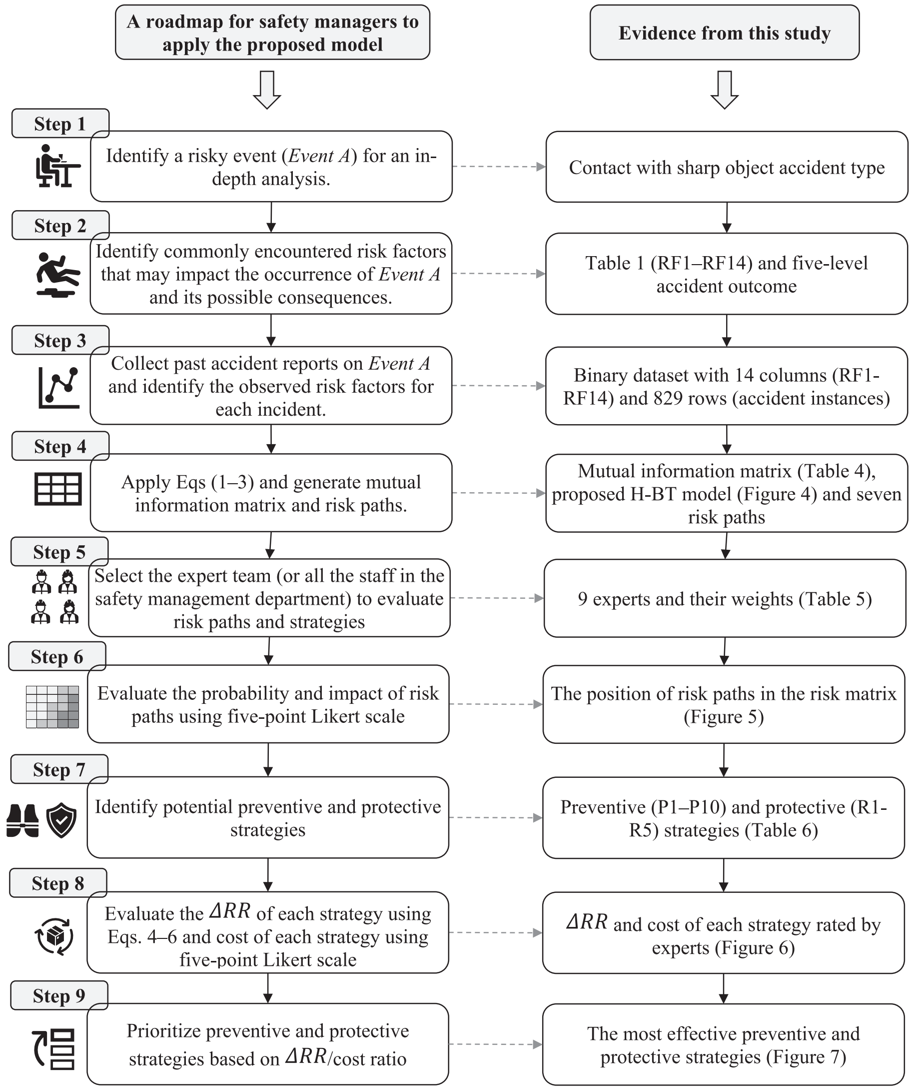

Fig. 9. A routemap for safety managers to apply the proposed model.

attempts to convert risk factors into risk management strategies. A structured and easy-to-implement risk management route that can be practiced in construction sites was therefore proposed for the CwSO accident type.

There are several limitations of the study that should be considered by safety professionals and researchers in the field. First, although the causal relationships between risk factors were elicited by accident reports, the calculation of ΔRR and prioritization of strategies were based on the knowledge of experts. Therefore, a dynamic risk monitoring and management framework that automizes the procedures and minimizes subjective judgments requires further effort.

Another limitation of the study concerns the generalizability of the recommended measures. Since the proposed measures are accident-specific (for CwSO), a more in-depth analysis of other accident types, such as those involving workers falling from height or falling objects, is needed. A model that generates an H-BT model for different accident types simultaneously would therefore be a promising research direction. Similarly, the proposed model can also be extended vertically through incorporating more criteria, such as time, ease of implementation, the need for external support, and traceability into the model, along with risk reduction effect and cost.

Finally, data was only collected for the CwSO accident type from 69 projects carried out by three companies. Increasing the size and dimensions of the dataset by incorporating accidents recorded in other companies involving different accident types for a greater variety of risk factors can increase the reliability and generalizability of the proposed solutions. Nevertheless, the application of the visual-based H-BT approach is expected to make it easier for safety professionals on construction projects to deal not only with CwSO accidents but also with other accident types.

CRediT authorship contribution statement

Dilşen Kuzucuoğlu: Conceptualization, Data curation, Methodology, Visualization, Writing – original draft. **Kerim Koc:** Investigation, Visualization, Writing – original draft, Writing – review & editing. **Gokhan Kazar:** Writing – review & editing. **Onur Behzat Tokdemir:** Conceptualization, Resources, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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