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BUILDING SAFE ORGANISATIONS: USING MACHINE LEARNING TO DECODE SAFETY HABITS OF BLUE-COLLAR WORKERS IN THE CONSTRUCTION INDUSTRY

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ABSTRACT
This study aims to provide a framework for categorising safety behaviours of construction workers, recognising the importance of employee safety in the competitive business environment. Employee safety is crucial to overall efficiency, productivity, and well-being, and the study seeks to contribute to understanding and managing workplace safety in the construction industry.
This study utilises machine learning (ML) algorithms, like logistic regression, support vector machine, and decision trees, to develop a categorisation framework for the safety behaviours of construction workers. The framework is validated using frequent safety behaviours observed in a random sample of construction professionals.
The study finds that workplace safety behaviours (WSB) are primarily influenced by supervisor support, reckless habits, and safety motivation. Limiting workplace accidents, enforcing safety laws, properly documenting safety processes, and organising sessions to educate staff are identified as critical sub-factors. Advancements in technology have resulted in significant improvements across construction organisations in allied domains. Additional considerations include education, pre-empting the possibility of accidents in different workplace situations, and enforcing strong disciplinary measures.
The framework proposed can serve as a valuable tool for organisations to tailor safety interventions. By recognising the diverse influences on safety behaviours, companies can implement targeted measures to address specific root causes of unsafe practices. The practical implications of these findings for safety management in the construction industry are noteworthy.

KEY WORDS
occupational health, safety, workplace, machine learning (ML), construction industry

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INTRODUCTION

Occupational health and safety (OHS) is a critical concern in the construction industry due to its high-risk nature (Karthick et al., 2022). Unsafe behaviour is a prominent cause of accidents at construction sites, leading to severe consequences for workers (Moosa & Oriet, 2022). Different types of accidents are associated with different sets of unsafe behaviours. Despite existing OHS regulations, fatal accidents continue to occur, resulting in loss of lives and high costs for organisations. Fall from heights, electric shocks, heavy equipment accidents, and repetitive motion injuries

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are common dangers faced by construction workers (Liang et al., 2022). Safety behaviour can be classified into safety compliance, which is task-related, and safety participation, which is voluntary and initiated by employees (Guo et al., 2022). Addressing unsafe behaviours and promoting safety compliance and participation are crucial for improving OHS in the construction industry (Segbenya & Yeboah, 2022).

Participation in safety can be divided into proactive and affiliative behaviours. While proactive behaviours require taking the initiative to increase workplace safety, affiliative behaviours involve supporting and cooperative acts (Wu et al., 2022). Accident risk is increased by unsafe behaviour on construction sites, such as failing to adhere to safety regulations. Such accidents result in falls, electrical mishaps, and other dangerous scenarios (Ahamad et al., 2022; Turgay & Özyurt, 2025). The consequences of risky behaviour in the workplace can result in significant injuries, property loss, and even death (Mohajeri et al., 2022; Mohammadi et al., 2025). To limit the likelihood of accidents and the consequences of risky behaviour, construction organisations must develop a safety culture (Fang et al., 2023), provide training on safe work practices (Ahamed & Mariappan, 2023), and enforce safety rules (Oni et al., 2023). Some real-life incidents reported from construction sites affirm the influence of unsafe behaviour in causing accidents. Failure to use personal protective equipment (PPE), such as hard helmets, safety glasses, or gloves, can increase the risk of harm in the case of an accident. It is observed that failure to adhere to safety measures on construction sites can result in fatal accidents. Such behaviour includes failure to wear proper safety gear, such as a hard helmet, or using equipment, such as ladders, incorrectly. Such incidents have been reported in the past, with workers suffering from head injuries or falling from heights and losing their lives. Therefore, it is essential to prioritise safety protocols and ensure that workers are adequately trained to avoid such incidents.

Alcohol and drug misuse can cloud judgment and raise the possibility of accidents in the construction sector (Brumfield et al., 2023). Compared to other industries, construction workers are particularly vulnerable to fatal accidents (Kaymedical, 2023). Unattended power tools and other equipment can potentially cause accidents (He et al., 2023). Training, updated procedures, improved monitoring, and the development of a safety culture are required to prevent accidents (Arzahan et al., 2022). Companies in the construction industry can safeguard their employees by complying with regulations by bodies like the Occupational Safety and Health Administration (OSHA). Compliance is encouraged, and workplace safety is ensured by following safety procedures and rules (Viscusi & Cramer, 2023). Construction organisations can use the collected data to gauge the safety behaviour in the workplace to make data-driven decisions about how to prioritise. Considering the arguments, the following research questions (RQs) are proposed:

RQ1: What are the most common types of unsafe behaviours observed at construction sites?

RQ2: How do these unsafe behaviours contribute to accidents and incidents at construction sites?

RQ3: What Machine Learning (ML) algorithms are suitable for predicting safety compliance in the construction industry?

To cater to the highlighted RQs, the corresponding research objectives (ROs) are as follows:

RO1: To identify the most common types of unsafe behaviour that contribute to accidents at construction sites and their impact on worker safety.

RO2: To develop an ML model for predicting safety compliance in the construction industry.

The study is divided into the following sections. The Introduction in Section 1 is followed by a detailed literature review in Section 2. Section 3 presents the materials and methods used to accomplish the ROs. The results and discussions are presented in Sections 4 and 5, respectively. Section 6 discusses the study's practical implications for construction management. Finally, the paper concludes with Section 7.

1. Literature review

1.1. Safety behaviour indicators: input and output indicators

Compared with other industries, the construction sector faces challenges due to low labour productivity, inefficient production, and technological advancements (Woodhead et al., 2018). Research on automated labour monitoring and risk-avoidance strategies is still in its infancy. Globally, research efforts are concentrated on automated control of risky construction behaviours, mobility monitoring, and real-time risk identification (Kumar et al., 2020; Rao, 2022). Construction workers' behavioural patterns and safety inclinations have been predicted using ML algorithms. Real-time worker behaviour and dangerous events can be predicted using simulation models that have demonstrated encouraging results. ML models make more accurate predictions and help identify workers at risk of engaging in risky behaviours. The safety behaviour of construction employees can be measured using virtual reality (VR) techniques, which also help improve workplace safety (Gao, 2022).

The construction sector has used ML research to identify perceived risks with excellent accuracy. Automation techniques, such as supervised algorithms and wearable biosensors, offer more accurate and affordable worker behaviour and workplace safety monitoring than conventional techniques (Xu et al., 2021). It has proven successful to monitor employee risk perception using non-invasive techniques. ML tools are required to recognise typical physical and psychological reactions related to industrial accidents (Lee, 2021). Continuous data is provided by biosensors for tracking psychophysical motions. ML models, such as Leave-One-Subject-And-Context-Out Cross Validation (LOSCOCV), improve the precision of real-time bio signal monitoring and recording for worker safety (Lee et al., 2022).

Construction employees must adhere to safety regulations, and if they do not, accidents may not be covered by insurance. Worker safety can be efficiently monitored and managed in real-time by an automated system. When physical supervision was challenging during the COVID-19 pandemic, ML-based models enabled precise risk assessment. ML can use smart devices to address work-related problems, providing early warnings and enhancing safety. By anticipating and averting serious accidents in the construction sector, ML models have demonstrated effectiveness in Australia (Kamal, 2020; Duan, 2022; Alkaissy, 2023).

Computer-aided techniques have been widely useful for identifying, following, patterning and monitoring in the construction industry. A large number of research studies have been conducted to understand the prediction capacity of various ML algorithms. The results of growing experimental research on the use of ML algorithms in the construction industry have helped identify gaps and trends in preventing unsafe construction situations (Liu, 2019). Research experiments on safety management using programmed safety vests have proved useful to avoid accidents in the construction industry. The colour-coded vests and their movements were measured using image-processing devices, and deviations that may lead to accidents were identified. ML algorithms are used to assess and classify the nature of movements in the workplace environment (Seong, 2018).

Worker safety violations frequently result in accidents in the construction sector. It is difficult to manually supervise employees due to their erratic, unconscious movements (Han, 2012). Computer vision models and motion tracking algorithms are used in ML programs to provide accurate predictions and analyses of risky behaviour. Monitoring irregularities and taking preventive measures are made possible by real-time data gathering and analysis (Tang, 2021). Worker posture, the use of PPE, tool handling, and proximity to dangers can all be observed by multi-tasked recognition models. Wearable equipment and observed photographs help assess severity and improve worker safety (Yiu et al., 2022).

1.2. Smart construction industry and advanced digital technologies

The smart construction industry combines data analytics, real-time monitoring, and software visualisation. Captured visuals and images are compared with the recommended safety procedures to identify discrepancies in workers' real-time postures and movements. Deep learning (DL) techniques are used to predict construction safety monitoring (Zhang, 2022). Research is in progress to integrate the entire lifecycle of the construction industry with ML platforms. The stages of designing architecture, selection of materials, structural design, manufacturing in off-site locations, construction management, project progress control, etc., are all included in the automation process for easier monitoring and prediction of workers' safety. Technologies, such as smart vision-based sensors, data cleaning methods, data storage and analysis methods are used to improve the working environment in the construction industry (Baduge, 2022).

ML is essential for bridging the divide between technology and its applications and for the growth of the smart construction sector. The health and safety monitoring of construction workers can be improved through hybrid vision, real-time data collection, and the Internet of Things (IoT) devices (Fang, 2022). The future of the sector lies in sophisticated systems with broad sensor integration and error-free monitoring. The breakthroughs in physiological computing, artificial intelligence (AI), and ML provide precise, portable monitoring of workers' safety and behaviour (Khan et al., 2022; Khan, 2022). Digital twin (DT) and Industrial Internet of Things (IIoT) technologies provide real-time monitoring and measurement of workplace safety. Automated deep learning structures, such as stacked auto-encoders (SAEs), monitor unusual or unsafe labour movements to identify potential accidents. Bluetooth Low Energy (BLE), for example, is an intelligent service system that aids in construction (Zhan, 2022).

Construction robots are currently researched as a potential solution to the labour crisis and to increase efficiency in the construction sector. Research in China is concentrated on developing efficient construction robots, especially in response to the present pandemic, even though complete substitution is not yet realistic. Construction operations and safety regulations are transformed by automation and machine-human collaboration enabled by technologies like Industry 4.0 and ML (Javaid et al., 2022; Shayesteh, 2023). Body language analysis is one of the scientific methods used to comprehend, forecast, and prevent labour movements and accidents. The construction site can be made safer by using construction robots, ML, automatic warning systems, and safety training (Tavakoli et al., 2020; Ma, 2022; Ding, 2022). Techniques for human-robot collaboration are more affordable and secure than other solutions. Although AI is still used sparingly in managing complicated international building projects, the deployment of AI and ML in monitoring employee safety is becoming increasingly significant. The industry urgently needs the development and adoption of verified AI-based monitoring solutions (Saka, 2023).

2. Research methods

2.1. Data collection and questionnaire design

In this study, data were collected using a self-reported questionnaire developed using extant literature on assessing workplace safety conditions. The authors are indebted to the contributions of Yin et al. (2022), Xie et al. (2022), and Ghodrati et al. (2022), which were extensively employed for creating the questionnaire for this study. Additionally, this study was conducted in the Indian construction landscape; hence, multiple brainstorming sessions were held with management from the construction organisations, including the contractors, supervisors, and labourers working at the ground level. Multiple input safety indicators were either removed or modified to align with the Indian construction sector context. The questionnaire was circulated among several participants for pilot testing. It was observed that the wording of some indicators was complicated to understand. Therefore, the ambiguous indicators were rephrased to increase comprehensibility. One interesting observation was made by a participant in the pilot testing phase, suggesting that the questionnaire should be translated into the native language (Hindi) to make it more convenient for people who were not comfortable communicating or understanding English. The authors translated the questionnaire for the selected respondents, and finally, the data were collected.

The questionnaire was designed to collect information on numerous factors impacting workplace safety habits. Participants were asked for demographic information, including gender, age, job experience, and educational level. The questionnaire assessed the six major input indicators influencing the output indicator "safety behaviour" at construction sites: "management safety practices", "organisational support", "safety climate", "supervisor's support", "reckless habits", and "safety motivation". Each of these constructs was evaluated using a series of questions to which participants responded with either "yes" or "no". In the "Management safety procedures" section, for example, participants were asked to answer whether they agreed with statements such as "All project staff must receive safety training" and "Conduct frequent safety inspections". Similarly, the "Organisational support" section asked participants whether they supported the organisation. The final questionnaire is presented in the Appendix section. With a target population size of 80, a confidence level of 90 %, and a margin of error of ±5 %, a sample size of 63 was required. To secure sufficient, valid, and representative responses, the questionnaires were distributed online and offline to construction personnel, including managers, contractors, supervisors, and labourers, resulting in 125 respondents. After three rounds of administration, 65 responses were returned, yielding a response rate of 52 %. There were no missing responses in the collected data. The participants were appropriately instructed on the need for confidentiality and anonymity during this data collection. They were also told that the questions were subjective and that there was no right or wrong answer. The procedures described above were primarily intended to address common method variance that may have entered the study (Podsakoff et al., 2003).

2.2. Machine learning (ML) classifiers used in the study

In this study, multiple ML classifiers are applied to categorisation problems. Based on feature values, logistic regression (LR) calculates the chance that an observation belongs to a given class. Support vector machines (SVMs) choose the best border to separate classes in the feature space. Based on input features and their results, decision trees (DTs) build a model that resembles a tree. Each method has advantages and disadvantages. For example, LR is straightforward and effective but struggles with non-linear correlations. SVMs can accommodate non-linear boundaries but are expensive to compute. DTs can be interpreted; however, they are sensitive to slight data changes and prone to overfitting. It is possible to find the best classification result with the least amount of error by using many classifiers (Zabor et al., 2022; Ebrahimi et al., 2022; Liu & Huang, 2022; Park et al., 2022).

2.3. Optimal model

Model tuning is crucial for improving the performance of ML models on unseen data. Hyperparameter optimisation is used to find the best parameter values that minimise prediction error. Various hyperparameters, such as the regularisation strength in LR, kernel type and C parameter in SVMs, number of trees and maximum depth in random forest, and the smoothing parameter in Naive Bayes, can influence model performance. Adjusting these hyperparameters helps prevent overfitting and enhances the model's ability to generalise to new data. The study utilises a 10-fold cross-validation method, dividing the dataset into ten subsets. Each model is trained on nine subsets and validated on the remaining subset, repeating this process ten times. The average performance of the models across the ten validation sets is then calculated. Cross-validation helps select the best model and hyperparameters, while addressing overfitting. Evaluating the model across multiple validation sets ensures better performance on new, unseen data (Zabor et al., 2022).

3. Research results

3.1. Classification performance of different classifiers

ML classifiers are evaluated based on their ability to correctly classify objects and the errors they incur. The evaluation metrics are based on the number of correctly and incorrectly classified objects. When a model correctly predicts the positive class, it is referred to as a "true positive" (TP), while a correct negative prediction is a "true negative" (TN). An incorrect positive prediction is called a "false positive" (FP), and an incorrect negative prediction is called a "false negative" (FN).

Initial information about the performance of ML techniques can be obtained by observing the correctly and incorrectly classified instances. This information is gathered in a matrix that shows the model's correct and incorrect predictions, and how they relate to the true outcomes or labels. Table 1 shows the correctly and incorrectly classified instances by each classifier as indicated by the confusion matrix. In ML, the following metrics are commonly used to evaluate the classifier's performance.

3.1.1. Precision

Precision measures the proportion of TPs out of all positive predictions (TP + FP).

It indicates the classifier's ability to correctly identify positive instances without including FPs.

3.1.2. Recall or sensitivity

Recall, also known as sensitivity, measures the proportion of TPs out of all actual positive instances (TP + FN).

Tab. 1. Correct and incorrect classification by each classifier

	LR		SVM		DT	
	Correctly classified instances	Incorrectly classified instances	Correctly classified instances	Incorrectly classified instances	Correctly classified instances	Incorrectly classified instances
WSB1	60 (92.3%)	5 (7.7%)	59 (90.8%)	6 (9.2%)	60 (92.3%)	5 (7.7%)
WSB2	46 (70.8%)	19 (29.2%)	43 (66.2%)	22 (33.8%)	43 (66.2%)	22 (33.8%)
WSB3	42 (64.6%)	23 (35.4%)	44 (67.7%)	21 (32.3%)	37 (56.9%)	28 (43.1%)
WSB4	36 (55.4%)	29 (44.6%)	36 (55.4%)	29 (44.6%)	36 (55.4%)	29 (44.6%)
WSB5	41 (63.1%)	24 (36.9%)	47 (72.3%)	18 (27.7%)	38 (58.5%)	27 (41.5%)
WSB6	41 (63.1%)	24 (36.9%)	48 (73.8%)	19 (26.2%)	38 (58.5%)	27 (41.5%)

It indicates the classifier's ability to correctly identify all positive instances without missing any.

3.1.3. Specificity

Specificity measures the proportion of TNs out of all actual negative instances (TN + FP).

It indicates the classifier's ability to correctly identify all negative instances without including FPs.

3.1.4. ROC (Receiver Operating Characteristic) curve

The ROC curve is a graphical representation of a classifier's performance across various classification thresholds.

It plots the true positive rate (TPR) against the false positive rate (FPR) at different threshold values. A good classifier will have an ROC curve closer to the top-left corner, indicating high TPR and low FPR.

3.1.5. F-measure

The F-measure combines precision and recall, to provide a more balanced view of a classifier's performance.

It is the harmonic mean of precision and recall, given by the formula: 2 * (precision * recall) / (precision + recall). The F-measure considers both false positives and false negatives and provides a single score that reflects the classifier's performance.

Table 2 summarises the performance metrics of the classifiers for each of the six decision outcomes.

It is clear that LR outperforms SVMs and DTs in classification across all six decision outcomes. The performance of LR is equally appreciable for the recall characteristics for all the decision outcomes, except for WSB5 and WSB6, where random forest takes the lead. Specificity shows a mix of performance levels across all classifiers. As shown in Graph C, random forest is best for WSB3, WSB5, and WSB6,

Tab. 2. Performance characteristics of classifiers for the six decision outcomes

ROC characteristic				Precision			
	LR	SVM	DT		LR	SVM	DT
WSB1	97.3	83.6	83.5	WSB1	92.6	90.8	92.1
WSB2	72.5	63.5	54.3	WSB2	71.0	65.7	64.9
WSB3	76.1	66.8	54.1	WSB3	65.5	67.5	56.4
WSB4	59.1	49.1	41.0	WSB4	58.2	52.5	50.2
WSB5	67.2	61.9	48.6	WSB5	64.1	70.2	53.7
WSB6	67.2	61.5	48.0	WSB6	63.0	70.6	54.0
Measure				**Recall**			
	LR	SVM	DT		LR	SVM	DT
WSB1	92.4	90.8	92.2	WSB1	92.3	90.8	92.3
WSB2	70.9	65.9	63.8	WSB2	70.8	66.2	66.2
WSB3	64.7	67.5	56.5	WSB3	64.6	67.7	56.9
WSB4	56.1	53.3	51.4	WSB4	55.4	55.4	55.1
WSB5	63.5	70	55.6	WSB5	63.1	72.3	58.5
WSB6	63.5	69.4	55.6	WSB6	63.1	71.9	58.3
Specificity							
	LR	SVM	DT				
WSB1	75	72.7	80				
WSB2	61.5	56.5	60				
WSB3	58.8	65.4	52				
WSB4	41.9	35.3	30.8				
WSB5	40.9	58.3	23.1				
WSB6	41.0	58.0	22.7				

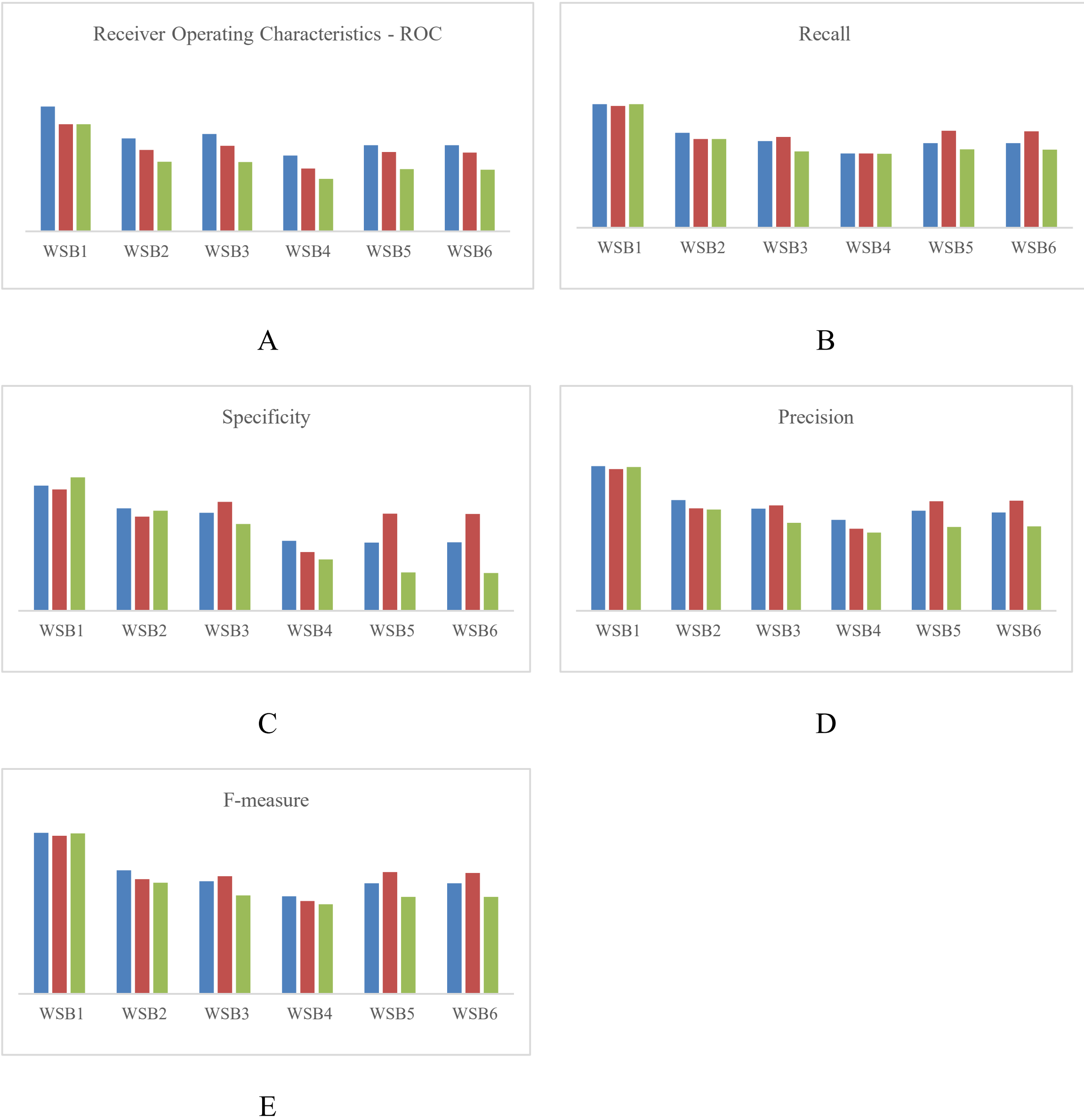

Fig. 1. Graphs representing the performance classifiers

whereas LR performs best for WSB2 and WSB4. The situation is rather like the precision characteristic, where LR and random forests are the closest competitors. DTs are found to be the worst performers across all the performance characteristics for all six decision outcomes. Fig. 1 shows the graphs for each performance characteristic for the six decision outcomes.

3.2. Feature selection

The best features for decision outcomes were chosen using a combination of performance indicators. The odds ratio and the ranker approach were used in logistic regression (LR) to determine the most significant features. Support vector machine (SVM) models were trained using the sequential minimal optimisation (SMO) algorithm, with the ranker approach used for feature selection. When choosing features for the J48 decision tree algorithm, the CfsSubsetEval search method considered each feature's capacity for prediction as well as its compatibility with other features. For automatic parameter selection, 10-fold cross-validation was used (Zabor et al., 2022). The set of important features for each of the six decision outcomes for the three classifiers is reflected.

Tab. 3. Best features selected for Workplace Safety Behaviour 1 (WSB1) by each classifier

WSB1	
Best feature set	
LR	It is critical to limit the likelihood of workplace accidents, my supervisor tries their best to enforce safety rules, experience, I have a healthy and nurturing relationship with my supervisor, colleagues appreciate efforts, safety rules protocols and processes are properly documented
SVM	It is critical to always maintain safety, supervisor uses innovative methods to encourage safety behaviours, keep workers informed of safety hazards, do not smoke, supervisor holds periodical meetings to sensitise employees to safety behaviours, management encourages employees to recommend safety tips
DT	Collaborative decision-making, it is critical to always maintain safety, my supervisor encourages us to participate in setting safety goal, it is critical to limit the likelihood of workplace accidents, my supervisor encourages us to participate in setting safety goal

Tab. 4. Best features selected for Workplace Safety Behaviour 2 (WSB2) by each classifier

WSB2	
Best feature set	
LR	Accidents and events are constantly recorded and reported, experience, supervisor holds periodical meetings to sensitise employees to safety behaviours, my supervisor tries best to enforce safety rules
SVM	Supervisor uses innovative methods to encourage safety behaviours, keep workers informed of safety hazards, gender, dedication to the projects aim
DT	Keep workers informed of safety hazards, strict disciplinary actions in the event of violation of rules, education, do not smoke

Tab. 5. Best features selected for Workplace Safety Behaviour 3 (WSB3) by each classifier

WSB3	
Best feature set	
LR	Experience, age, education, accidents and events are constantly recorded and reported, my supervisor tries best to enforce safety rules, smoking while at work
SVM	Gender, it is critical to always maintain safety, do not smoke, supervisor holds periodical meetings to sensitise employees to safety behaviours, handle all circumstances as though there is a chance of an accident
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, my supervisor tries best to enforce safety rules, it is critical to always maintain safety

Tab. 6. Best features selected for Workplace Safety Behaviour 4 (WSB4) by each classifier

WSB4	
Best feature set	
LR	Keep workers informed of safety hazards, accidents and events are constantly recorded and reported, management organises meetings and get-togethers to build a cordial environment, smoking while at work, strict disciplinary actions in the event of violation of rule
SVM	Dedication to the projects aim, do not smoke, gender, supervisor uses innovative methods to encourage safety behaviours
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, dedication to the projects aim, do not smoke, gender, supervisor uses innovative methods to encourage safety behaviours

Tab. 7. Best features selected for Workplace Safety Behaviour 5 (WSB5) by each classifier

WSB5	
Best feature set	
LR	Age, handle all circumstances as though there is a chance of an accident, accidents and events are constantly recorded and reported
SVM	Gender, dedication to the projects aim, supervisor holds periodical meetings to sensitise employees to safety behaviours, strict disciplinary actions in the event of violation of rule, smoking while at work, it is critical to limit the likelihood of workplace accidents, do not smoke
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, do not smoke, education, it is critical to limit the likelihood of workplace accidents, strict disciplinary actions in the event of violation of rules

Tab. 8. Best features selected for Workplace Safety Behaviour 6 (WSB6) by each classifier

WSB6	
Best feature set	
LR	Age, handle all circumstances as though there is a chance of an accident, accidents and events are constantly recorded and reported, supervisor uses innovative methods to encourage safety behaviours, supervisor acknowledges my job requirements
SVM	Gender, strict disciplinary actions in the event of violation of rules, supervisor holds periodical meetings to sensitise employees to safety behaviours, it is critical to limit the likelihood of workplace accidents, smoking while at work, do not smoke
DT	Supervisor holds periodical meetings to sensitise employees to safety behaviours, do not smoke, education, it is critical to limit the likelihood of workplace accidents, strict disciplinary actions in the event of violation of rules

Table 3 highlights the best features for Workplace Safety Behaviour 1.

Table 4 highlights the best features for Workplace Safety Behaviour 2.

Table 5 highlights the best features for Workplace Safety Behaviour 3.

Table 6 highlights the best features for Workplace Safety Behaviour 4.

Table 7 highlights the best features for Workplace Safety Behaviour 5.

Table 8 highlights the best features for Workplace Safety Behaviour 6.

3.3. Comparison of different models

To get the most accurate classification performance, the study evaluates multiple ML approaches. To evaluate performance using measures such as accuracy, recall, F-measure, and the area under the ROC curve, statistical significance tests, such as paired sample t-tests, are used. The dataset, algorithm parameters, and chosen ML techniques (logistic, SVMs, and DTs) are set up for the experiment. To ensure statistically significant results, many runs with different random seeds or cross-validation folds are performed. Depending on the evaluation metric, paired t-tests or nonparametric tests are used to compare the results across techniques. Table 9 presents the results of the paired sample t-tests for testing the classification performance of each ML technique on evaluation metrics statistically.

Precision, recall, F-measure, and the area under the ROC curve have been used to test each classifier's performance. It can be observed that, for each decision outcome, almost all classifiers exhibit comparable performance. The output from Waikato Environment for Knowledge Analysis (WEKA) software (Frank et al., 2010) suggests that the values are not statistically significantly different from those of the LR regression. However, in several cases, such as in Tables A and C, DTs are observed to perform inferiorly to LR, and the inferiority is statistically significant. In Tables E and F, SVMs outperform LR with a statistically significant margin. Overall, the classification performance of all classifiers is very similar. In this situation, the decision on the best classifier for safety compliance classification lies entirely with the user, and any classifier can yield satisfactory performance. However, its simplicity, interpretability, and robustness to data noise make LR the most popular algorithm for classification tasks.

4. Discussions of the results

This study aims to investigate the major factors affecting workplace safety behaviour using ML techniques. WSB is influenced by various socio-technical variables. Socio-technical elements are workplace social and technological components that might influence an individual's safety behaviour, attitudes, and decision-making. It is noteworthy that the major determinants of all WSB categories predominantly lie in the "Supervisor's support", "Reckless habits", and "Safety motivation" categories. It can thus be concluded that, regardless of the presence of strict safety protocols and regulations at construction sites, keen supervision and support from the supervisors are essential to ensure workplace safety. Additionally, workers need to be constantly motivated to follow safety practices and stay vigilant of any deviation from safety protocols.

The decision to use the essential safety equipment to complete the task (WSB1) is observed to be critically influenced by the perceived criticality of limiting the likelihood of workplace accidents, as indicated by the factor "It is critical to limit the likelihood of workplace accidents". Those who understand the potential hazards of failure to use safety equipment are more likely to use the essential equipment to protect them-

Tab. 9. Comparison of classification performance using paired sample t-test

WSB1				WSB2			
	LR	SVM	DT		LR	SVM	DT
Precision	0.98	0.97	0.94	**Precision**	0.76	0.73	0.7
Recall	0.97	0.98	0.96	**Recall**	0.72	0.78	0.85
f-measure	0.97	0.97	0.95	**f-measure**	0.71	0.73	0.76
ROC	0.99	0.9	0.78*	**ROC**	0.73	0.63	0.59
WSB3				**WSB4**			
	LR	SVM	DT		LR	SVM	DT
Precision	0.76	0.72	0.55*	**Precision**	0.71	0.65	0.63
Recall	0.67	0.75	0.68	**Recall**	0.65	0.75	0.78
f-measure	0.69	0.72	0.59	**f-measure**	0.66	0.69	0.69
ROC	0.73	0.67	0.51*	**ROC**	0.59	0.52	0.51
WSB5				**WSB6**			
	LR	SVM	DT		LR	SVM	DT
Precision	0.8	0.77	0.72	**Precision**	0.8	0.77	0.72
Recall	0.73	0.88v	0.83	**Recall**	0.72	0.88v	0.83
f-measure	0.75	0.81	0.76	**f-measure**	0.75	0.81	0.76
ROC	0.72	0.64	0.55	**ROC**	0.72	0.64	0.55

selves from injury. This finding is consistent with observations on the risk factors of occupational accidents in the construction sector, where inadequacies in workplace safety procedures and untrained workers incapable or unwilling to use safety equipment were cited as the major reasons for the occurrence of accidents (Nayak et al., 2022). "My supervisor tries best to enforce safety rules", asserts that the supervisor's involvement in enforcing safety guidelines is equally critical in ensuring WSB1. An employee's conduct may be influenced if the supervisor has a reputation for valuing safety and supporting the use of safety equipment. Workers may be more motivated to use safety equipment if they believe their supervisor is concerned about safety and encourages its use. Experience can also influence an employee's decision to use safety equipment. If a person has been injured on the job or knows someone who has, they are more inclined to wear safety equipment in the future. They are more aware of the hazards because they have direct knowledge of the potential implications of failure to use safety equipment. The strength of an employee's connection with their supervisor can also impact safety behaviour, as pointed by the indicator "I have a healthy and nurturing relationship with my supervisor", and is ranked higher among the factors influencing WSB1. Employees who have a pleasant and supportive connection with their boss are more likely to follow safety standards and use safety equipment. This is because they believe their supervisor supports and values them, which might improve their drive to participate in safe conduct. Similar observations were made in the study involving the examination of employee perceptions of supervisor behavioural integrity, where it was reported that mediation between top-management safety climate and safety behaviours through safety motivation was stronger for employees who reported high supervisor behavioural integrity for safety. In this regard, the findings of the existing study align with Peker et al. (2022).

Appreciation from co-workers can also motivate for safe conduct, as indicated by the statement "Colleagues appreciate efforts". Employees who believe their co-workers appreciate safety efforts and encourage the use of safety equipment are more likely to engage in safe behaviour. They believe that colleagues notice and reward their safety efforts, which may improve their drive to continue behaving safely. Lastly, good documentation of safety regulations, protocols, and processes may have a big impact on workers' safety conduct, as indicated by the statement, "Safety rules, protocols, and processes are properly documented". Employees are more likely to behave safely if they have clear, accessible information about the importance of safety and the proper use of safety equipment ("It is critical to maintain safety at all times"), which makes them aware of potential hazards. Workers are more aware of the hazards if they are regularly informed about potential safety issues. Such incrementally improved knowledge can encourage workers to adopt safety equipment, such as PPE, to keep themselves safe. Workers, for example, are more likely to use protective gloves, goggles, or masks if they are warned about hazardous chemical exposure. The above finding is reinforced by the observation made in a study conducted to investigate the psychological causes for workplace accidents, where the cognitive factors were shown to propel unsafe behaviour of construction workers. The study recommends that management address stress and safety issues by organising stress management seminars, regular safety inspections, performance appreciation and recognition, and effective communication (Liang et al., 2022).

Smoking in the workplace may be hazardous, especially in industries that use flammable or combustible products, such as the construction industry. Workers are less likely to participate in conduct that increases the risk of a workplace accident if smoking is prohibited. Furthermore, separating smoking locations from dangerous products reduces the likelihood that employees will contaminate their PPE or cause a fire hazard. Workers are involved in detecting and addressing workplace safety hazards through "collaborative decision-making". Workers are more invested in the outcome and feel more accountable for their own safety when they participate in decision-making. They may be more motivated to use safety equipment if they have a sense of ownership over the process and consequences. Employees are more likely to take responsibility for their personal safety and feel involved in the process when they are encouraged to participate in defining safety goals. They may discover areas for improvement and implement adjustments that better represent workers' needs and viewpoints by incorporating them in the process. Workers may be more motivated to use safety equipment and other safety measures if they believe their feedback has been considered.

Adherence to safety protocols in every situation (WSB2) is found to be significantly influenced by factors such as indicated in statements "Accidents and events are constantly recorded and reported", "Experience", "Supervisor holds periodical meetings to sensitise employees to safety behaviours", and "My supervisor tries best to enforce safety rules". "Accidents and events are constantly recorded and reported", implying that there is a well-established system for recording and evaluating workplace mishaps. This provides better knowledge of different accidents that occur, as well as the identification of trends and areas for improvement. Keeping a record of accidents and incidents also communicates that safety is a seriously taken concern. Workers with more work experience may be more aware of potential risks and more likely to follow established safety procedures, which can positively influence adherence to safety measures, as indicated by the role of the factor "Experience" in determining WSB2. Nevertheless, expertise alone is insufficient to ensure adherence to safety measures; continual training and reinforcement of safety practices are also required. "Supervisor arranges periodical sessions to sensitise staff to safety behaviours" indicates a proactive approach to workplace safety, with monthly meetings to discuss and promote safe behaviours. This can help foster a safe culture and inspire employees to take responsibility for their own and their co-workers' safety. The statement, "My supervisor tries best to enforce safety rules", shows that the supervisor is dedicated to ensuring that safety measures are followed and that employees understand their significance. Such measures can increase responsibility and guarantee that everyone in the workplace is following the required procedures to keep the workplace safe. In construction projects, it is crucial to observe safety regulations and have effective communication. Workers' adherence to safety procedures can be positively influenced by a commitment to the project's objectives, ensuring that accidents and injuries do not impede progress. Education can be used for people to better comprehend the need for safety procedures and the potential repercussions of non-compliance. People who are well-informed are more likely to adhere to safety regulations and recognise their significance. Additionally, such steps as quitting smoking can influence how safety rules are followed. Smoking impairs lung health and may cause an individual to take more risks or disregard safety precautions. Non-smokers might be more devoted to adhering to safety precautions, more focused, and more alert. To develop a culture of safety and reduce hazards, building sites can encourage clear communication, education, and healthy practices.

Several factors are instrumental in ensuring the safety behaviours at construction sites, namely those indicated in statements "When doing the work, adhere to all safety precautions (WSB3)" and "Promote the safety programme enthusiastically (WSB4)".

Experience, for instance, is one of the primary indicators used to establish WSB3 and WSB4. Veterans and highly experienced construction personnel are likely to have encountered a wide range of hazards and accidents and have developed their own safety practices and protocols to mitigate those risks; hence, they are more likely to adhere to safety rules and follow safety practices. This is supported in the article published by Areia et al. (2022). Age is another factor that can significantly influence workers' adherence to safety protocols. Older individuals may be more risk-averse than the younger generation, and thus, they are more inclined to follow workplace safety practices. Workers' level of experience and age affect their dedication to safety procedures. Accident reporting and recording raise workers' awareness of potential risks and encourage safer behaviour. Workers should be made aware of the repercussions of breaking safety regulations to encourage accountability and attentiveness. Strict disciplinary measures, such as warnings and dismissal, can guarantee compliance with safety procedures. Innovative techniques, such as virtual reality simulations, improve the efficacy of safety training. According to Dahl et al. (2020), formal health and safety training in Norway has a beneficial effect on effective occupational safety and health management systems.

The last two safety behaviours, namely "Make further efforts to promote workplace safety (WSB5)" and "When co-workers are in perilous situations, assist them (WSB6)", have some common determinants. Older employees may have more experience, be more risk-averse, and be more inclined to promote workplace safety and assist co-workers in danger. Younger workers may be more prone to risk-taking and may require better training and direction to understand the necessity of safety. The mentality of approaching all situations as though there is a potential for an accident can increase safety and make personnel more aware of possible risks. Employees who are always concerned with safety are more likely to take measures and assist their co-workers in risky circumstances. It is vital to reduce the possibility of workplace accidents, emphasise the significance of safety, and encourage employees to take measures and assist co-workers in risky situations. A better understanding of employee job requirements among supervisors and managers can guarantee that safety precautions are taken to safeguard workers from potential risks. This can enhance safety and inspire employees to assist their co-workers in hazardous situations. Severe disciplinary procedures for breaking safety rules can force workers to take safety seriously and assist their co-workers in risky circumstances. Severe disciplinary measures can deter and motivate employees to be more cautious. Several studies emphasised that promoting workplace safety and responding effectively to workplace accidents are important aspects of maintaining a safe work environment. Some key findings of these studies align with the findings of the current study, including immediate action in the event of an accident or injury, proper protocols to report the incidents to management or regulatory agencies, and provide emotional support and access to resources for those involved (Zhang et al., 2020; Jung et al., 2020; Sattari et al., 2021).

Conclusions

This study highlights the importance of different drivers underlying various safety behaviours to develop targeted measures for cultivating safe workplace behaviours. ML techniques are valuable tools for exploring complex patterns among safety behavioural data. This research aimed to provide a categorisation framework for construction workers' safety behaviours using ML techniques, such as LR, SVMs, and DT, involving three critical steps: data collection and preprocessing, modelling and algorithm implementation, and optimal model acquisition. For this study, a random and representative sample of India-based construction personnel was used to validate the classification framework. The results demonstrate that WSB is primarily influenced by the supervisor's support, reckless habits at workplace including smoking and drinking, and safety motivation, and critical subfactors within each of the main category influencing WSB include "It is critical to limit the likelihood of workplace accidents", "My supervisor tries best to enforce safety rules", "Experience", "I have a healthy and nurturing relation with my supervisor", "Colleagues appreciate efforts", "Safety rules, protocols, and processes are properly documented", "It is critical to maintain safety at all times", "Supervisor uses innovative methods to encourage safety behaviours", "Keep workers informed of safety hazards", "Do not smoke", "Supervisor holds periodical meetings to sensitise employees to safety behaviours", "Management encourages employees to recommend safety tips", "Accidents and events are constantly recorded and reported", "Supervisor holds periodical meetings to sensitise employees to safety behaviours", "My supervisor tries best to enforce safety rules", "Keep workers informed of safety hazards", "Dedication to the projects aim", "Strict disciplinary actions in the event of violation of rules", "Education", "Do not smoke", "Experience", "Accidents and events are constantly recorded and reported", "Handle all circumstances as though there is a chance of an accident", "Strict disciplinary actions in the event of violation of rule", "Smoking while at work", and "Supervisor acknowledges my job requirements".

Although the study accomplished its objectives, a few limitations must be addressed in future research. Even though the ML approach has been created to overcome the small sample size issue, and some studies have employed smaller sample sizes, additional data is needed for future studies. Second, because the study employed an Indian sample, more research is needed to evaluate whether the findings can be applied to other countries/regions. Finally, the study did not identify all the elements that influence safety behaviours, and their interrelationships are unclear. Consequently, an additional in-depth study is needed in this respect. Fourth, the suggested categorisation system is general, and many construction sites are included.

Managerial implications

Based on the research findings, some important implications for industry practitioners can be used to ensure workplace safety. Some of the notable implications are mentioned below:

- It is paramount that management ensures the safety rules and protocols are properly documented and always accessible to workers. This will help increase workers' awareness of potential hazards and encourage them to comply with safety requirements. A safety manual, for instance, can be very effective and used during working hours. Additionally, a well-documented system for recording and evaluating workplace accidents and incidents should be developed, as it can potentially provide valuable insights into risk types present at a construction site.
- If workers are involved in collaborative decision-making of identifying and addressing safety hazards, they will feel more invested in the process, are more likely to take personal responsibility for their own safety and be motivated to use safety equipment.
- Construction management should train every employee, including senior management, supervisors, contractors, workers, and field workers, to enforce safety guidelines. Workers who share a good working relationship with their supervisors are more likely to follow safety standards and use safety equipment. High-quality training should be provided by specialised and skilled trainers with state-of-the-art technology. It is critical to introduce technology-driven safety methods in the construction sector, which is arguably the most hesitant sector to adopt new technologies.
- Workers with a consistent good record of adherence to safety rules and regulations should be awarded and recognised periodically. This helps establish trust and confidence in management as employees feel that their efforts are valued, hence, they stay motivated to remain compliant.
- Organising periodic meetings and sessions to sensitise employees towards safety behaviours can foster a safety culture, where all employees feel accountable for their own and their colleagues' safety.
- Encouraging employees to refrain from smoking or drinking during working hours can help them stay attentive, remain focused, and committed to safety protocols, reducing the risks of accidents and unwanted delays.
- Managers should ensure that their teams have a mix of experienced and younger personnel to increase safety on building sites. The former have their own safety procedures and protocols, which they may share with the younger generation. Experienced people are also more likely to observe safety guidelines, making them valuable assets to any building job.
- Workers should be informed about the consequences of violating safety rules, such as verbal or written warnings, suspension, or termination. This promotes vigilance, accountability, and hazard reduction. Consistent enforcement by management encourages compliance and sets safety as a top priority, fostering a safety culture where workers prioritise their own and co-workers' safety. To enhance safety training, virtual reality simulations can provide immersive experiences that simulate construction situations and teach workers about dangers and safety procedures. Interactive workshops, role-playing activities, and gamification tactics are also effective methods to engage employees and reinforce safety regulations.

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APPENDIX

Gender: Male (1), Female (2)
Age: <20 (1), 20-30 (2), 31-40 (3), 41-50 (4), >50 (5)
Experience: <3 (1), 3-10 (2), 11-15 (3), 16-20 (4), >20 (5)
Educational level: Below primary (1), Primary (2), Secondary (3), Certificate/Diploma (4), College or higher (5)

Input Indicators

a. Management safety practices (answer by 1 (Yes) or 2 (No))

- All project personnel must get safety training.
- Conduct frequent safety inspections.
- Responds quickly to safety concerns.
- Keep workers informed of safety hazards.
- Helps maintain a clean work area.
- Set safety performance targets.
- Immediate accident reporting is required.
- When meeting with contractors, prioritise safety.
- Prompt feedback on job performance.
- Dedication to the project's aim.
- Timely correction of any safety issues to prevent accidents.
- Handle all circumstances as though there is a chance of an accident.

b. Organisational support (answer by 1 (Yes) or 2 (No))

- Decision-making process satisfaction.
- Collaborative decision-making.
- Leadership assistance is provided.
- Colleagues are willing to assist teammates.
- Colleagues appreciate efforts.
- Colleagues recognise potential.
- Management organises meetings and get-togethers to build a cordial environment.

c. Safety Climate (answer by 1 (Yes) or 2 (No))

- The performance expectations are quite clear.
- Safety rules, protocols, and processes are properly documented.
- Strict disciplinary actions in the event of violation of rules.
- Accidents and events are constantly recorded and reported.
- Management encourages employees to recommend safety tips.
- The project manager monitors the safety of the employees.
- The whole project team is dedicated to safety.

d. Supervisor's support (answer by 1 (Yes) or 2 (No))

- Supervisor uses innovative methods to encourage safety behaviours.
- Supervisor holds periodical meetings to sensitise employees to safety measures.
- Good safety conduct is rewarded.
- My supervisor encourages us to participate in setting safety goals.
- My supervisor tries their best to enforce safety rules.
- My supervisor recognises my achievement.
- Supervisor acknowledges my job requirements.
- Supervisor understands and identifies bottlenecks.
- I have a healthy and nurturing relationship with my supervisor.

e. Reckless habits (answer by 1 (Yes) or 2 (No))

- Smoking while at work.
- Do not smoke.
- Drinking while at work.
- Do not drink.

f. Safety Motivation (answer by 1 (Yes) or 2 (No))

- Workplace health and safety are critical.
- Maintaining or improving my personal safety is advantageous to me.
- It is critical to maintain safety at all times.
- It is critical to limit the likelihood of workplace accidents and mishaps.

Output Indicators

g. Safety behaviour (answer by 1 (Yes) or 2 (No))

- Use the essential safety equipment to complete the task.
- Adherence to safety protocols in every situation.
- When doing the work, adhere to all safety precautions.
- Promote the safety programme enthusiastically.
- Make further efforts to promote workplace safety.
- When co-workers are in perilous situations.