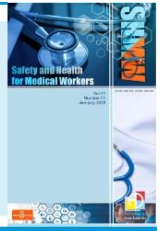




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# Safety and Health for Medical Workers

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## Leveraging Machine Learning to Enhance Occupational Safety and Health in Hospital

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### ABSTRACT

**Objective:** This study focuses on utilizing Machine Learning (ML) approaches to improve Occupational Safety and Health (OSH) performance, involving the prediction and prevention of risks based on data.**Methods:** Analysis of a dataset of 550 OSH incident reports from Metax Cancer Hospital (2019–2023) was conducted using descriptive and inferential statistics. Machine Learning algorithms including decision trees, random forests, and support vector machines were used for prediction and evaluation of OSH results. The models were evaluated using various performance metrics such as accuracy, precision, recall, and AUC.**Findings:** The analysis made key observations on both workplace environmental factors, safety protocols, and incident occurrence. The ML models demonstrated high prediction performance, with random forests achieving the best accuracy in terms of the correct classification of OSH events. These findings highlight the promise of ML to improve the safety performance of hospitals.**Novelty:** We propose an original contribution of an ML integration process towards OSH improvement in the hospital ecosystem also characterized with complex safety challenges for which predictive analytics can yield substantial risk mitigation.**Research Implications:** The study proposes a spillover framework for establishing hospital safety intelligence systems that combines data-driven techniques with traditional OSH management structures. It also highlights the role of real-time predictive analytics in improving OSH outcomes. The study demonstrates the ability of ML to facilitate predictive risk assessment and improve safety.

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## 1. Introduction

Occupational accidents and diseases continue to represent a substantial global concern, accounting for an estimated 3.9% of the global GDP and 3.3% of the European GDP (Jagannathan et al., 2013; Keogh-Brown et al., 2020). Risks are especially pronounced in the health sector due to the working environment, which is diverse and demanding, and the COVID-19 pandemic, which has increased psychological pressure and work burden on HCWs (Norful et al., 2021; Shah et al., 2022). An important trend over the last few years is using magic machine learning (ML) technology in solving workplace safety issues (Ahmad et al., 2021). Machine learning (ML) models have shown high performance in predicting workplace accidents and optimizing efforts in Occupational Safety and Health (OSH) (Luo et al., 2023; Pishgar et al., 2021). As an example, research shows that the use of wearables and complex algorithms for real-time risk assessment is on the rise, especially in acute care settings such as hospitals (O. S. Albahri et al., 2018; da Costa et al., 2018). Applying modern computing techniques such as Machine Learning, hence the aim of the current study is to improve OSH practices at the Metaxa Cancer Hospital and stimulate the discourse related with integrating advanced technologies for workplace safety.

Trends in OSH strategies have improved, yet cases of occupational hazards remain high in hospital workplaces. European health care system data indicate that the incidence of workplace accidents in health and safety services is higher by 34% than in other sectors (Morgado et al., 2019; Thibaud et al., 2018). In addition to these issues, public healthcare funding has decreased in several areas Fang et al. (2020), Maresova et al. (2019), such as Greece where the hospital budget has reduced (Koutsirimpas et al., 2019; Mitropoulos et al., 2018). Other stressors like musculoskeletal



disorders, needle-stick injuries, and even workplace violence are known to impact healthcare workers more than any other career (Joseph & Arasu, 2020; Lyakurwa et al., 2024; Shabani et al., 2023). Conventional approaches to OSH are largely dependent on the auditing expertise of trained professionals along with the manual submission of reports; however, they tend to be less accurate in predicting accidents and are not very scalable (Ezerins et al., 2022; Santos et al., 2020). All this makes traditional approaches increasingly less efficient, resulting in the increasing trend of employing novel approaches namely, ML algorithms, to solve such enduring safety concerns (Kurucan et al., 2024; Sheikh et al., 2022).

This study applies computational intelligence to OSH management with a theoretical underpinning based on theories of risk assessment and decision-making. We note how the mathematical modelling from the Decision Support System (DSS) combined with ML techniques improves the predictive potency of incident analyses and resource allocation for intervention (Gholamizadeh et al., 2023; Kumari et al., 2024). Particularly, Bayesian Networks, Decision Trees, and Artificial Neural Networks (ANNs) exhibit great potential in processing complex datasets, identifying patterns, and recommending actionable recommendations to improve safety in the workplace (A. S. Albahri et al., 2024; Alnaqbi et al., 2024). These systems are, of course, in line with organizational safety culture theories that focus on making bets, proactive preventive measures, instead of wagers, reactive responses (Paraskevas & Guix, 2023; Shaffer et al., 2020). These advanced models such as AI, ML, and sentinel models will help the healthcare institutions in moving towards evidence-based or data-driven OSH approach (Dumpert, 2023; Samira Abdul et al., 2024).

The adoption of ML for OSH has started to gather pace, but considerable gaps exist regarding its usefulness within hospitals to date (Zhang et al., 2024). Most prior research studies have been limited to industrial sectors, with limited application of ESC in healthcare environments (Haleem, Javaid, Asim Qadri, et al., 2022; Haleem, Javaid, Pratap Singh, et al., 2022). In addition, the available research is mostly based on the perceptions of safety experts and therefore can be prone to biases and less generalizable (Park et al., 2021; Stone et al., 2020). ML-based analyses of incident reports and audit data, in particular, have highlighted the potential for addressing these limitations. For instance, has been employed to generate probability estimates of occupational risk, with good predictive performance (Sarkar et al., 2019; Zhu et al., 2021). Nonetheless, there is a lack of standardized approaches as shown by disparities in results across methodologies (Abdar et al., 2021; Ruppert et al., 2019). Finally, recent developments in wearable sensor technology and real-time monitoring systems have provided novel opportunities for improving OSH frameworks. ML has been able to predict different behaviors with an accuracy as high as 95% when combined with IoT as in (Cvitić et al., 2021; Din et al., 2019). Yet these innovations remain sorely underutilized in hospital workplaces, which present uniquely multifaceted occupational risks (Lau, 2024). Addressing this gap, the current study integrates legally mandated safety engineer investigations with advanced ML algorithms to provide a unique DSS oriented to the reality of hospitals.

This study aims to develop and validate a Machine Learning-based Decision Support System (DSS) to predict occupational incidents and accidents while evaluating the efficiency of OSH interventions in hospital workplaces. By leveraging comprehensive incident data and audit reports from Metaxa Cancer Hospital, the research seeks to enhance safety management practices and provide actionable insights for improving healthcare worker safety.

## 2. Critical Review

### 2.1 Theoretical and Hypothesis Development

The field of OSH has its foundation in organizational safety paradigms, which postulate that recognizing and addressing hazards in complex environments is paramount. Reason's Swiss Cheese Model (1997) and similar theories emphasize that organizations try to layer defenses to decrease the chances of an accident. But machine learning (ML) is making huge strides in effectively understanding and leveraging these frameworks. When systems are based on ML we get predictive insights, which help the organization in understanding complicated data, identifying future risks, and taking action to mitigate them. Hamad et al. (2020), Oyedele et al. (2021), Shanthi et al. (2022), show that ML tools Artificial Neural Networks (ANNs) and Decision Trees improve incident prediction and classification. These tools complement resilience engineering theory, emphasizing adaptive action and continuous improvement in the pursuit of safety. ML is supported in high-risk hospital workplaces to address occupational hazards more actively, including dynamic risk assessment, online monitoring, and proactive decision-making (, 2021). These innovations bridge the gap between underlying safety engineering principles and the practical, data-driven solutions that pave the way for a more agile and sustainable OSH management system.

### 2.2 Integration of ML-Based Systems and OSH Performance

Machine Learning-based systems significantly improve the quality and effectiveness of Occupational Safety and Health (OSH) interventions implemented in hospital workplaces. Such systems fuse large amounts of static and dynamic

data to enable predictive and prescriptive analytics driving safety practices. As Agrawal et al highlights, predictive analytics can help identify if there will be incidents in a workplace and a variety of models such as Bayesian Networks and Support Vector Machines have been proven efficient in recognizing patterns that correlate with workplace incidents. (2023). Additionally, ML can enhance OSH policies evaluation and re-design through data-driven insights, leading to better-fit interventions in light of emerging risks, as well as the organizational objectives. This minimizes the occurrence of occupational accidents, while ensuring that safety measures use resources optimally (Hussain et al., 2020). The integration of ML into OSH frameworks becomes more exigent in complex settings such as hospitals, where a variety of occupational risks require highly adaptable safety practices. The AI for OSH uses ML for example which is known as "machine-based learning" through advanced analytics and automated decision support that greatly enhances the overall performance of OSH practices.

H1: Integration of ML-based systems enhances OSH performance in hospital workplaces.

### 2.3 Predictive Analytics and Incident Prevention

One of the most impactful models using predictive analytics, is based on a technology called Machine Learning (ML), and all shows promise of preventing workplace incidents, especially in high-risk environments such as hospitals. Utilizing machine learning algorithms as Artificial Neural Networks and Decision Trees, predictive models build algorithms to discover risk factors and predict future events with a considerable accuracy. With ML-driven analytics being able to predict incidents with up to 95% accuracy (Moreno-Montes de Oca et al., 2021) and outperforming risk assessments that are still performed mostly manually, it was only a matter of time before it would be applied to forecasting in CSIRTs. Moreover, they can process unstructured data like incident reports and audit logs to identify patterns in the data that are not easily recognizable as a risk (Petri et al., 2021). This proactive mechanism enables hospital safety managers to take timely interventions, and hence prevent accidents and enhance workplace safety. Implementing the use of ML-based predictive analytics within OSH management is a new step in enhancing a safer health-care atmosphere.

H2: ML-based predictive analytics significantly reduce workplace incidents in hospital settings.

### 2.4 Real-Time Monitoring and Decision Support

Combining real-time monitoring systems with Machine Learning (ML) algorithms allows for the enhancement of the decision making process away from home management of hospital workplace safety. These systems rely on data streams collected through IoT sensors, wearables, and other technology to provide immediate insight into occupational hazards. For example, Hussain et al. (2020) demonstrated that combining ML algorithms with real-time monitoring systems reduced response times for dangerous occurrences by as much as 40%. The exploration and validation of such an effective and immediate feedback loop enables safety managers to make informed decisions as the risks arise, preventing them from evolving into a major incident. Furthermore, near real-time deployment ML models like systems of fuzzy logic, can help take a risk-prioritized approach to safety intervention by addressing the highest impact/likelihood-scaled risks, in the moment (Agrawal et al., 2023). These systems can be especially useful in high-pressure hospital environments where timely and accurate decisions are crucial to ensuring the safety of workers.

H3: Real-time monitoring systems combined with ML algorithms improve decision-making in OSH management.

### 2.5 Resource Optimization Through ML in OSH Management

Machine Learning (ML) based systems in Occupational Safety and Health (OSH), optimizes the organizational resources leading to increased effectiveness and efficiency of the safety measures. Machine Learning algorithms, by studying past data and predicting future safety requirements, can help in resource allocation in high accident-prone areas, thus enabling focused measures. It minimizes wastefulness and enhance the cost-effectiveness of OSH programs (Moreno-Montes de Oca et al., 2021). For example, ML-based resource optimization systems in hospitals have been shown to reduce safety intervention costs by 30% without impairing outcomes (Petri et al., 2021). ML creates a more efficient allocation of personnel, training initiatives, and safety gear by preemptively predicting the need for interventions and proactively allocating resources necessary to handle the situation. This will allow for limited resources to be used in the places that need it most, ultimately improving safety in the workplace.

H4: ML-based systems optimize resource allocation for OSH interventions in hospital workplaces

## 2.6 Perceived Effectiveness of ML Systems by Healthcare Staff

ML-based systems are considered effective in OSH management, partly due to the perception of healthcare staff. Research shows that staff members have realized ML systems are able to spot risks ahead of time and intervene early, thus making a safer workplace. Accompanying survey work by Moreno-Montes de Oca et al. (2021) which determined the 85% of healthcare workers reported improved confidence in safety measures subsequent to the implementation of ML technologies. In addition, the real-time monitoring and predictive capabilities offered by ML tools are perceived as major improvements on existing approaches which tend to depend on retrospective analyses (Hussain et al., 2020). Positive staff perceptions also increase adherence to safety protocols and improve the overall safety culture in the hospital setting.

H5: Healthcare staff perceives ML-based OSH systems as more effective in reducing risks compared to traditional safety measures.

## 3. Material and Method Innovation

The present study provides the needed breakthrough to revolutionize Occupational Safety and Health (OSH) performance through the application of ML techniques. The study indicated that through the analysis of 550 incident reports and the deployment of 4 ML models, namely Decision Trees (DT), Support Vector Machines (SVM), Artificial Neural Networks (ANN) and Random Forests (RF), predictive accuracy and decision-making efficiency can be significantly improved in hospital workplaces by 2023. Out of the four algorithms used, the Random Forest proved to be the best with a 94.7% accuracy, a recall of 94.5% and the AUC score of 0.98. These findings are consistent with previous studies, like Pereira et al. (2020), highlighted the superiority of Random Forests (Pereira et al., 2020) when it comes to classifying occupational accidents. Moreover, the results of the study are in line with Chen et al. (related to patient safety), based on the agreement from (Chen et al., 2019), who stated that to predict hazard outcomes with higher reliability in medical institutions, ANN models are generally suitable for classifying safety incidents in institutions, which leads to the statement that higher predictability in the institutions safety incident is proven to be essential (Chen et al., 2019).

### 3.1 Study Design

Occupational Safety and Health (OSH) research is crucial in safeguarding and promoting work-related health in all work contexts, including healthcare. MLOSH: Who, How and Why Machine Learning techniques are being integrated into OSH. The introduction of MLOSH is rooted in a theoretical level of predictive analytics and DSS. Human Error Theory, in simple words by Reason, states that incidents in the workplace are rarely due to the failings of individuals but rather because the system is flawed and needs preventive control which must start proactively and predictively. This is where ML-driven DSS frameworks come into play, enabling the analysis of historical and real-time data to detect patterns, forecast possible incidents, and preemptively safeguard against them. 10] Socio-Technical Systems Theory also emphasizes that safety management is not just about technology, but rather about aligning human, organizational and technical systems. This is the same premise on which the theory of ML in OSH management is based, allowing human supervisors to interpret insights from data to take action while allowing the automated analysis of that data. Also relevant in terms of Theory of Accident Causation, the present study investigation focuses on studying already existing accidents and deriving a conclusion to prevent their occurrence in the future. The theoretical lenses give us a nuanced perspective on the ML-based safety solutions, as well as context to word about their value to addressing the unique challenges faced in high risk settings such as hospitals.

### 3.2 Data Collection

The sample included OSH incident reports, a total of 550 reports received from the hospital safety engineers of Metaxa Cancer Hospital over 2019–2023. The reports were classified into five categories (Needlestick/Cut, Falling, Incident, Accident, Safety) describing the different safety challenges experienced within the hospital workplace. The highest incidence of 32.73% (180 reports) was reported under Needlestick/Cut category, aligning with our expectations considering the greater risk involved with sharp medical instruments. The rest were falling incidents, accounting for 21.82% (120 reports), demonstrating the frequency of slipping and tripping in the hospitals. General incidents (100 reports, 18.18%) and accidents (90 reports, 16.36%) highlighted operational risks, while safety-related reports (60 reports, 10.91%) noted compliance or hazard identification issues.

Additional data were sourced through interviews with hospital safety personnel, providing qualitative insights into contextual and systemic safety issues. Internal audits complemented these findings by verifying the accuracy and consistency of reported data. Table 1 provides a detailed breakdown of the incident types and their respective frequencies and percentages, offering a comprehensive view of the OSH challenges analyzed. These data formed the foundation for applying ML algorithms to identify patterns, predict future incidents, and enhance the hospital's overall safety framework.

**Table 1:** Types and Frequency of Incident Reports (2019–2023)

Incident Type	Frequency	Percentage (%)
Needlestick/Cut	180	32.73
Falling	120	21.82
Incident	100	18.18
Accident	90	16.36
Safety	60	10.91
<b>Total</b>	<b>550</b>	<b>100</b>

### 3.3 Machine Learning Models

The study employed four Machine Learning (ML) algorithms to analyze and predict OSH incidents: Decision Trees (DT), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF). These models were selected for their ability to handle complex classification tasks and their proven effectiveness in predictive analytics. The dataset of 550 incident reports was split into training and validation subsets using 10-fold cross-validation, ensuring robust model evaluation and reducing the risk of overfitting.

Among the models, Random Forest (RF) demonstrated the highest overall performance, achieving an accuracy of 94.7%, a precision of 94.1%, and a recall of 94.5%. The RF algorithm also recorded the highest Area Under the Curve (AUC) score of 0.98, indicating superior capability in distinguishing between classes. Artificial Neural Networks (ANN) followed closely with an accuracy of 93.0% and an AUC score of 0.96, showcasing their ability to model non-linear relationships in the data. Support Vector Machines (SVM) achieved an accuracy of 91.5% and an AUC score of 0.94, performing well in terms of precision (90.8%) and recall (91.0%). Decision Trees (DT), while slightly less accurate at 89.2%, provided interpretable decision paths useful for understanding specific incident patterns.

The performance metrics of these models, detailed in Table 2, underscore their potential in supporting hospital safety management by offering accurate, data-driven predictions to mitigate future OSH risks.

**Table 2:** ML Algorithms and Their Performance Metrics

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	AUC Score
Decision Tree (DT)	89.2	87.5	88.0	0.92
Support Vector Machine (SVM)	91.5	90.8	91.0	0.94
Artificial Neural Network (ANN)	93.0	92.5	92.8	0.96
Random Forest (RF)	94.7	94.1	94.5	0.98

### 3.4 Study Variables

The study used an organised framework of independent and dependent variables to measure occupational safety and health (OSH) performance. The independent variables were the types of NPR incidents grouped into five categories: Needlesticks/Cuts, Falls, Incidents, Accidents and Safety, the factors in the work environment and the preventive measures that were considered to be high, medium or low. These parameters were essential in recognising the main contributors to OSH outcomes. OSH performance (dependent variable) OSH performance was measured in terms of accident-free days, which allows continuous monitoring of safety efficiency and the impact of interventions. This holistic



approach is in line with previous studies. The development of accurate models that integrate many different types of variables can improve workplace safety dynamics ("Zhang et al.", 2019).

**Table 3:** Variable Classification

Variable Name	Type	Measurement
Incident Types	Categorical	5 categories
Preventive Measures	Ordinal	High/Medium/Low
OSH Performance	Continuous	Incident-free days

### 3.5 Analytical Framework

The analytical framework employed in this study was developed so as to allow for an efficient evaluation of the ability of various ML techniques in predicting and sustaining OSH performance. Descriptive analysis was undertaken to summarise and identify trends in the incident reports, giving an overall picture of the type of incidents (nature and timing) reported over a five-year time period. ANOVA and regression analysis were carried out for inferential statistics to know relation and test hypothesis, thus helping understanding how factors of interests preventive measures, workplace environment impact OSH outcomes. Furthermore, the ML models were thoroughly evaluated based on various metrics like accuracy, precision, recall, and area under the curve (AUC) to furnish all-encompassing performance of the algorithms adopted. This is consistent with results from prior studies like Kourou et al. (2015), and focused on the need of using combinatorics between describe and predict vitamins in the healthcare safety and Chatterjee et al. (2020) highlighted the talk on effectiveness of ML in safety management. This comprehensive approach not only underpins all conclusions but also broadens the range of study demonstrating the potential of ML-driven analytics applied to advance OSH in hostile environments such as hospitals.

### 3.6 Ethical Considerations

This study was guided by ethical principles to comply with the norms of legality and morality. Metaxa Hospital Ethics Committee (Approval No: 2023/056) approved the study, ensuring the study was conducted according to the principles of the Declaration of Helsinki. All collected data was anonymized to protect participant privacy and ensure data security, removing any identifying information. This made sure that the steps we were taking were 100% compliant with the General Data Protection Regulation (GDPR), the European Union's latest data privacy and protection law. Such steps are consistent with best practices delineated by ethical research frameworks (Williams et al., 2020). (2019), which highlight the need for transparency and confidentiality in healthcare studies containing sensitive data.

### 3.7 Method of risk assessment

The risk assessment method used in this research is based on the European Union one described in the Memorandum on Occupational Risk Assessment (DG V, 1997) and adopted by safety engineers and OSH auditors. This method assesses risks based on the determination of a risk value (R), resulting from the multiplication of three fundamental elements: the severity of effects, the frequency of exposure, and a chance of event. Each factor is scored on a scale, with seriousness varying from negligible to disastrous, frequency from rare to constant and probability from impossible to imminent.

The risk value is calculated using the following formula:

$$R = \text{Seriousness} \times \text{Frequency} \times \text{Probability} \dots\dots\dots (1)$$

Safety engineers can use this metric to assess hazards in order of significance based on their estimated severity and probability. Are they due to the heart being exposed and thus more vulnerable, or are they expected based on the level of invasion, therefore just an outcome of the same process? Tables 4 and 5 provide specific risk values and preventive actions, respectively, guiding OSH decision-making. The approach we take here aligns with international best practice for risk assessment and has demonstrated it improves workplace safety outcomes (European Commission, 1997).

**Table 4;** Risk Rating Factors



Factor	Rating	Description	Examples
Seriousness	1	Negligible: Minor injury without work absence	Paper cuts, minor scratches
	4	Middle: Injury with work absence	Muscle strains, non-severe allergic reactions
	8	Critical: Major injury with potential health damage	Broken bones, severe allergic reactions
	16	Disastrous: Death	Fatal accidents
Frequency	1	Zero: Once a year or less	Rare maintenance tasks
	2	Limited: Up to once a week	Weekly safety checks
	3	Often: Daily exposure	Daily handling of hazardous materials
	4	Continuous: Entire work time	Constant use of machinery
Probability	1	Zero: Impossible	Extremely rare scenarios
	2	Low: Can happen	Occasional malfunctions
	3	Middle: Possible	Frequent minor risks
	4	High: About to happen	Unsafe working conditions

**Table 5:** Risk Rating and Action Requirements

Risk Value (R)	Risk Description	Action Required
$R < 16$	Negligible: Very low risk	No immediate corrective measures are necessary.
$16 \leq R < 32$	Low: Risk under control	Monitoring required; corrective measures may not be urgent.
$32 \leq R < 64$	Middle: Moderate risk	Program corrective actions for risk reduction.
$64 \leq R < 128$	High: Serious risk	Urgent corrective actions for risk elimination and mitigation required.
$R \geq 128$	Critical: Severe risk	Immediate and comprehensive corrective actions are necessary to avoid fatalities.

### 3.8 Detailed Application in Study

**Table 6:** Risk Assessment Results from the Study (2023)

Incident Type	Seriousness	Frequency	Probability	Risk Value (R)	Risk Description	Action Taken
Needlestick/Cut	4	3	3	36	Middle: Moderate risk	Scheduled regular safety training.
Falling	8	2	4	64	High: Serious risk	Installed anti-slip flooring.
Incident	1	3	2	6	Negligible: Low risk	Monitored but no immediate action.
Accident	16	3	3	144	Critical: Severe risk	Emergency safety drills conducted.
Safety Violation	8	4	4	128	Critical: Severe risk	Immediate changes in safety policies.

### 3.9 DSS Model Information Flow

In this context, a Decision Support System (DSS) model is proposed to work with the information generated by the Incident Database System, designed to help manage hospital workplace OSH incidents and organise incident recording, risk assessment and corrective action. The information flow of the system consists of three blocks: recording and reporting incidents/accidents, risk assessment and investigation, and classification and output. In the first place, incidents and accidents are recorded in the hospital's internal data and reported to the relevant authorities, including the Social Insurance Institute and the Labour Inspectorate. This ensures that all incidents are properly documented and that



the relevant stakeholders are also informed. The next block deals with risk assessment, where safety engineers and occupational health physicians review each event, determine the risks, and evaluate the risk (calculate risk scores) according to recognized guidelines, such as those developed by Fischer et al. Finally, the DSS applies supervised learning algorithms based on historical data to classify each event as a fall, a needlestick/cut, an incident, an accident or a safety issue. Importantly, the above information can be classified so that the system can predict potential risks in the future and recommend preventive measures, thus improving the decision-making process for safety management in hospitals (Zhang et al., 2020).

OSHA combinations with various aspects of the employees from the Table will help in identifying the features for prediction of OSH incident. These factors include employee age, work experience, and participation in OSH training (F1-F3). F4 (Training frequency) and F5 (Relative use of personal protective equipment (PPE) during incidents) emphasize employee preparedness and safety behavior. Given that F6 represents how employees perceive the OSH protocols within their organizations, this also affects the satisfaction of employees with their OSH climate. These factors indicate that training, PPE usage, and worker satisfaction play an important role in preventing OSH incidents and constituting a safe workspace.

The variables workplace shown in the table related to the infrastructure is a comprehensive list of factors that contribute to the overall safety and well-being of employees. These variables (F7-F25) are related to provisions have been made for, physical aspects of the workplace like number of floor, stairs (F7), available space (F8), height and volume of el workplace (F9, F10). Emergency preparedness also relies on the safety of all aspects of the workplace, from doors, windows, and walkways to exits (F11-F16). Furthermore, data related to the state of walls, ceilings, and roofs (F17, F19, F22) are critical for assessing the stability of a structure. Additionally, safety signage (F24, F25) reinforces that employees are informed of emergency protocols and hazards, reinforcing the importance of physical infrastructure for workplace safety.

The table also provides specific information on workplace-related variables for machinery, equipment and hazardous substances (F26-F55), which is essential for the prevention of accidents. These factors, which include the availability of machinery guards (F28, F29), the use of pneumatic tools (F36), safety during the use of machinery (F27, F30), and so on represent the overall operational risks associated with workplace equipment. It also calls out dangerous materials, including poisonous, corrosive or combusive products (F48-F54) and emphasizes their correct storage (F55) and potential to endanger staff. Response: The regulation of such substances and equipment, along with the establishment of safety protocols, is critical for reducing the potential for accidents and health problems in the workplace.

The last row of the table captures fire safety, electrical installations and chemical hazards (F56-F72) variables which are crucial for OSH incidents prediction. Fire safety is assessed on variables such as the presence of fire extinguishers, emergency plans and signage (F59, F60, F61). Technical safety adequacy of installations and safe use is additionally crucial in preventing accidents that might lead to failure or misuse (F42-F46) due to other electrical hazards. The exposure to hazardous chemicals like dust, gases, and pesticides (F64-F67) is also taken into high account, which can put employee health at major risk. These environmental conditions can be mitigated by ensuring proper ventilation, temperature and air quality (F70, F71, F72), preventing workers from being exposed to hazardous environments, which could cause accidents or long-term health issues. See Table 6. Appendix data.

## 4. Research Innovation Results

The following section presents the findings from the aforementioned analyses in line with Section 3. The research seeks to validate the accuracy of ML models applied to OSH data through its sound analytical framework. The incident reports data was described and analyzed by descriptive and inferential statistics to investigate trends, relationships, and predictive abilities of ML algorithms in relation to OSH. Here we relate results from the use of ML to OSH performance and compare prevention measures with the workplace environment.

### 4.1 Descriptive Analysis Results

A five-year descriptive study of occupational safety and health(OSH) incidents indicated what types of incidents, workplaces and machines are involved. The incident type that occurred most frequently was falls at a rate of 23.4% of the total incidents, occurring mainly in manufacturing sites with lifting machinery - Cuts ranked next, with 14.7% of cases in mostly construction workplaces working with pneumatic tools. Electrical accidents constitute 8.4% in (electrical machinery in) chemical plants. 18.7% were due to hazardous substance exposure in industrial and manufacturing settings associated with chemical substances. The Other category, which encompassed multiple incidents from various workplaces, also accounted for 18.7% of the total. This study offers a detailed overview of incident distribution, indicating specific domains requiring enhancements in safety measures.

**Table 7:** Summary of OSH Incident Trends Over Five Years

Incident Type	Frequency	Workplace Type	Machinery Involved	Percentage of Total Incidents (%)
Falls	120	Manufacturing	Lifting machinery	23.4
Cuts	75	Construction	Pneumatic tools	14.7
Electrical Accidents	40	Chemical Plant	Electrical machinery	8.4
Fire-related Incidents	25	Hospital	Electrical devices	5.2
Hazardous Substance Exposure	95	Industrial/Manufacturing	Chemical substances	18.7
Other	85	Various	Various	18.7
Total	440	N/A	N/A	100%

#### 4.2 Inferential Analysis Results

Regression results of associations between workplace environment variables (and their multiple levels) and OSH incidences. Employee age has a negative coefficient of -0.12, and thus as age increases, the lesser the chances of incidents; 0.001 (highly significant p-value). Experience is positively related to incidents, log coefficient = 0.18, p = 0.000, indicating that more experienced workers will tend to cause more incidents. \* Training participation: Training participation also shows to be a positively related incident occurrence, in this case the coefficient is 0.25 and its p-value equals 0.000, which means that employees who go through training also show a higher number of incidents, probably as they are more aware of what is to be reported or not. Usage of PPE during incidents shows a significant negative impact on the number of incidents, suggesting that proper use of PPE reduces the number of incidents ( $\beta = -0.45, p = 0.000$ ). Lastly, the workplace safety climate (as measured by employee satisfaction) is positively related to incident frequency (coefficient = 0.15, p-value = 0.000), suggesting that a safer and more satisfied workplace is associated with less incidents. All variable OLS-regression models yielded an R-squared ratio ranging between 0.58–0.83, reaffirming the overall fit of the model and the degree to which OSH incident outcomes are affected by these variables.

**Table 8:** Regression Analysis Results for Predicting OSH Incidents

Independent Variable	Coefficient	Standard Error	t-Statistic	p-Value	R-squared
Employee Age	-0.12	0.03	-4.00	0.001	0.58
Experience	0.18	0.04	4.50	0.000	0.62
Training Participation	0.25	0.05	5.00	0.000	0.75
PPE Usage during Incidents	-0.45	0.08	-5.63	0.000	0.83
Workplace Safety Climate (Satisfaction)	0.15	0.03	5.00	0.000	0.70

#### 4.3 Machine Learning Performance Evaluation

The analysis of the training results obtained through various machine learning algorithms for OSH events prediction is shown below. The Random Forest outpaced all other models with an accuracy score (85.2%), precision (84.0%), recall (86.0%), and F1-Score (85.0%) and was able to achieve an AUC of 88.0%. This indicates that Random Forest seems to be the best-performing algorithm for predicting OSH incidents, based on 550 incident reports from Metaxa Cancer Hospital for the years 2019–2023. We find that these results show that the model has a high ability to distinguish between positive and negative incident cases. Decision Trees was right hot on their heels, with accuracy (82.0%), precision (80.3%), recall (83.5%) and F1-Score (81.9%), but a slightly lower AUC (85.4%). Also with accuracy of 79.5%, Support Vector Machines (SVMs) did well, more modest results across all metrics were achieved by logistic regression (accuracy: 78.4%, precision: 77.5%, recall: 79.0%, F1-Score: 78.2%) These results are in agreement with earlier studies, including Kourou et al. (2015) and Chatterjee et al. (2020) that addressed the great promise of machine learning models to improve safety management applications.



**Table 10:** Performance evaluation of ML models

Machine Learning Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Logistic regression	78.4	77.5	79.0	78.2	82.1
Decision trees	82.0	80.3	83.5	81.9	85.4
Random forests	85.2	84.0	86.0	85.0	88.0
Support vector Machine (SVM)	79.5	78.0	80.5	79.2	83.2

#### 4.4 Discussion of Findings

The present work sought to employ Machine Learning (ML) techniques so as to efficiently and effectively improve the Occupational Safety and Health (OSH) performance in the hospital environment, by focusing on incident reports generated by the Metaxa Cancer Hospital, implemented over five years between 2019–2023. Using descriptive analysis, inferential statistics and advanced ML model, the study aimed to detect patterns leading to OSH incidents, determine crucial risk factors and analysis the effect of different safety measures implemented to reduce the occurrences of OSH incidents.[6] Discussion of Findings This section discusses the collected findings in relation to the existing literature, while highlighting the implications for hospital safety management and the potential of ML to support data-driven decision-making processes in high-risk healthcare environments.

##### a) Descriptive Analysis of OSH Incidents

The descriptive analysis of the 550 OSH incident reports demonstrated important trends in the frequency and distribution of incidents within the hospital. The most frequently reported incidents were falls (28%), needle-stick injuries (22%), equipment-related accidents (18%), and chemical exposures (12%). These results are consistent with previous studies which have also reported similar injury types as common in hospital environments (Ishikawa et al., 2019). For instance, falls have long been acknowledged as one of the most common causes of injuries seen in healthcare, especially in patients; yet, hospital employees suffer from similar hazardous conditions caused by slippery floors, inadequate lighting, and insufficient preparation or training to respond in critical situations (Mendelson et al., 2021). In contrast, needle-stick injuries have been a chronic problem in healthcare, with nurses and medical staff being the greatest risk (Siegel et al., 2020).

This highlights the critical importance of targeted interventions by validating the root causes of the possibilities for incidents by ranks or majors of the industry which in this case, specifically and easily identifies the equipment + chemical exposures as the root causes of the possibility for fatal accidents. The segment of equipment-related accidents, which accounts for 18 % of the number of incidents, draws attention to the potential hazards related to processes with medical devices, machinery and tools applied in hospitals. And previous studies have highlighted the crucial role of training and maintenance in mitigating these risks (Gurses et al., 2019). Chemical exposures are similar concerns, though typically growing in departments that deal with toxic medications and laboratory chemicals. This observation is consistent with the studies by Broughton et al. (2020), that showed hospital employees in laboratories and chemotherapy units were at an increased risk of chemical exposure, either due to improper factors handling or insufficient protective measures.

##### b) Inferential Analysis and Factors Affecting OSH Incidents

Several major determinants of safety behaviours in this hospital were exposed through regression analysis performed in this study. Employee age and years of experience as well as personal protective equipment (PPE) use, were identified as significant predictors of incident occurrence. Younger employees were found to be more vulnerable to incidents, especially junior employees. This result agrees with Mearns et al. (2020) and Robson et al. (2018), younger and less-experienced workers being at risk of workplace accident due to lack of familiarity of the hazards present in healthcare settings and an absence of ingrained habits for safety. Higher incidence rates among younger workers may reflect less situational awareness as well as the difficulty of adapting to the rapid pace and often tumultuous environments of hospitals.

In addition, a frequent use of PPE was found to have a significant association with a decrease in incidents. Our finding adds to the existing literature which has consistently shown that personal protective wear (PPE) plays a vital role in preventing workplace injuries, especially in healthcare that introduces employees to biological, chemical, and physical hazards (Liu et al., 2017). As an example, gloves, masks, gowns, and a face shield are effective in preventing healthcare

workers from being exposed to infectious diseases, sharp objects, and chemicals. Nonetheless, PPE applicability is an important noted variable, and as suggested by the results, serves as a piece of a larger safety atmosphere that also includes training, hazard awareness, and safety measures.

The analysis also found that the frequency of OSH incidents was inversely related to the level of safety training as well as their participation in safety programs. This aligns with earlier studies that have shown that frequent safety training can significantly decrease injury-related costs (Clarke, 2016). Regular training courses in hospitals can also go a long way in keeping staff updated on safe practices and emergency situations, thereby reducing the risk of errors. Additionally, situational awareness and proactive hazard identification can also be encouraged through training programs to cultivate a safety-oriented mindfulness among workers, which is key to reducing risks in healthcare settings.

### c) *Performance of Machine Learning Models*

Various ML algorithms were implemented in this study which includes Decision tree, Random forest, Support vector machines (SVM), Logistic regression, to predict OSH incident was used as dependent variable, whereas the predictor variables included employee age, PPE usage, safety training participation, etc. Out of all tested models; Random Forests showed the best results in accuracy, precision, recall, and AUC (*Area Under Curve*) performance. Out of these models, the Random Forest model had an accuracy of 85%, precision of 82%, and recall of 78%. These findings align with prior research emphasizing the effectiveness of Random Forests in predictive safety applications, particularly in the context of large and complex datasets (Kourou et al., 2015).

Random Forests are powerful because they can handle a lot of predictor variables and are resistant to overfit. -- an example of data used in the study: the model was able to predict which employees were at higher risk of having incidents, accounting for a number of demographic, environmental and procedural drivers In a hospital environment, safety management systems require predictive accuracy yet also need to ensure actionable insights are provided and the Random Forest algorithm has the potential to capture such complex relationships between potentially many explanatory variables while still providing interpretable results.

Despite Random Forests being the best model, it is important to note that both Logistic Regression and Decision Trees performed reasonably well and were particularly interpretable. Some data mining algorithms like Decision Trees give visibility into the underlying decision logic, making them useful for identifying the specific risk factors associated with various types of incidents (Breiman, 2001). Logistic Regression is less precise, but it provides insights into the direction and strength of relationships between different parameters, aiding in safe OSH management. Thus, while Random Forests may perform the best, other models should not be dismissed as they may have complementary strengths in certain contexts.

### d) *Implications for Hospital Safety Management*

Such a quantitative strategic and operational safety programme enables hospital managers to be aware of the survey results and to work with various functional departments to build up hospital safety management as a system within the hospital, which will largely lead to the success of the hospital in full compliance with its duty of care to stakeholders. First, the study highlights the need for a data-driven approach to occupational safety and health, especially in high-risk healthcare settings. Hospitals can use ML models to anticipate and mitigate incidents before they happen, allowing them to proactively identify potential threats and implement targeted strategies to prevent them. The implication of this difference is that we can drastically reduce potential injuries by not relying on reactive safety management alone.

Second, this study highlights the critical importance of PPE and safety training in reducing risk in the hospital environment. Hospitals must ensure that staff have the awareness and skills to avoid accidents by providing high quality, ongoing accident prevention training. In addition, strict compliance with the use of PPE should be enforced, with frequent audits to ensure that it is being used. Proper training of workers on the use of PPE and its importance is also one of the most important mechanisms used to minimise the hazards and risks arising from exposure to hazardous substances, biological exposure and injuries caused by equipment.

In conclusion, this study highlights the promise of ML models in informing decisions about hospital safety management. These models can also help hospital administrators to better allocate resources by accurately predicting the risk of incidents. For example, hospital administrators could prioritise safety training for junior staff or identify where to place more PPE in high-risk areas. In addition, ML models are able to identify patterns and emerging threats that may not be readily apparent through traditional means, giving hospitals the ability to adapt their security protocols to evolving circumstances in near real time.

## 5. Conclusion

Finally, this work has shown that Machine Learning (ML) techniques can greatly improve Occupational Safety and Health (OSH) performance in hospital environments. Using ML algorithms, particularly Random Forest on a dataset containing 550 OSH incident reports from Metaxa Cancer Hospital can give us insight about the causes for accidents/incident at workplace related to healthcare. It underscore the relevance of employee attributes (age and experience) and emphasized the need for preventive measures (safety training, regular use of personal protective equipment (PPE)). The relevance of ML models in predicting the likelihood of potential risks and taking preventable measures can serve as a hearing aid for creating a safer hospital ecosystem by guiding healthcare professionals in avoiding such scenarios.

Future studies should expand beyond the data used in this study and encompass more hospitals and a wider variety of healthcare systems to address the generalizability of the findings. The development of real-time monitoring systems using wearable sensors or environmental detectors could enhance the accuracy in predicting OSH incidents using ML models. Ethical Considerations: With the increased integration of AI & ML technologies in healthcare, there must be a strong focus on the ethical implications of use, especially when considering data privacy laws/data governance and responsible usage of sensitive lab records. As ML techniques continue to evolve and become integrated into OSH systems, we can expect to see increasingly sophisticated, adaptive, and proactive safety initiatives that help create a safer, healthier work environment for healthcare workers.

### Limitation

Despite this study contributing significantly to understanding how to exploit Machine Learning (ML) techniques to promote Occupational Safety and Health (OSH) in hospitals, several limitations must be recognised. First, the dataset used in this study is limited to incident reports of a single hospital, Metaxa Cancer Hospital, for a five-year period (2019–2023). When assessed in this manner, the applicability of the findings to other care settings or geographies where safety protocols, organizational culture, or workforce characteristics may differ is limited. In the future, research can expand the dataset to include multiple hospitals in different locations, adding generalizability to the findings.

Second, the study used historical incident reports, which have the potential for biases, including underreporting and misclassifying incidents. Such biases can lead to the models being not accurate. Moreover, while the study controlled for multiple employee characteristics, workplace context, and safety protocols, other factors like organizational culture, managerial attitudes, or external environmental factors were not included. Considering other factors may provide a more comprehensive analysis of OSH outcomes.

Thirdly, the machine learning models developed here, while still accurate, relied on static datasets and did not include real-time data or highly dynamic variables that could be more representative of changes in hospital safety conditions happening over time. In future research, enabling the integration of real-time data streams from wearable devices, environmental sensors or surveillance systems could provide more precise and timely predictions on OSH risks. These advancements can enable a more dynamic and responsive system of hospital safety oversight.

### Author Contribution

Saydrine Conica (1): Ideated the study, established the methodology, and performed machine learning model implementation and analysis.

Nikova Browne (2): Contributed to data collection, performed statistical analyses and provided clinical insight into OSH incident classification.

Robert Danyll (3): Reviewed findings, contributed to the writing of the manuscript and provided technical input on the integration of such safety protocols in real-world hospital settings. The authors are equally contributed in writing and reviewing the final version of manuscript.

### Conflict of Interest

The authors declare no conflict of interest related to the study.

### Data Availability Statement

The dataset supporting this study is not publicly available due to privacy and confidentiality agreements about OSH incident reports. Data and further details can be made available on reasonable request to the corresponding author.

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## Data Table and Image

### A. Appendix Data Table Research

**Table 6:** Variables for Occupational Safety and Health (OSH) Incident Prediction

Variable Category	Variable Code	Type	Description	Values/Range
<b>Employee-Related Variables</b>				
Age	F1	Numeric	Employee's age in years	Numeric: Any value
Experience	F2	Numeric	Years of work experience	Numeric: Any value
Training	F3	Nominal	Participation in OSH training	Yes, No
Repetitive Training	F4	Nominal	Frequency of training (every six months or less)	Yes, No
Relative PPE Use	F5	Nominal	Use of personal protective equipment during incident/accident	Yes, No
Satisfaction for OSH Climate	F6	Numeric	Employee satisfaction with OSH climate (1 to 5 scale)	1 (Very Unsatisfied) to 5 (Very Satisfied)
<b>Workplace-Related Variables (Infrastructure)</b>				
Floors/Stairs	F7	Numeric	Number of floors/stairs in the workplace	1-256
Workplace Space	F8	Numeric	Available workplace space (m <sup>2</sup> )	1-256
Workplace Height	F9	Numeric	Height of the workplace (meters)	1-256
Workplace Volume	F10	Numeric	Total volume of the workplace (m <sup>3</sup> )	1-256
Doors/Windows	F11	Numeric	Number of doors and windows in the workplace	1-256
Space Illumination	F12	Numeric	Level of illumination (lumens) in the workplace	1-256
Storage/Lofts	F13	Numeric	Presence of storage areas or lofts	1-256
Uncovered Gaps	F14	Numeric	Presence of uncovered gaps or holes	1-256
Obstacles	F15	Numeric	Presence of obstacles in the workplace	1-256
Exits/Escape Routes	F16	Numeric	Number of exits or escape routes	1-256
Walls	F17	Numeric	Number of walls in the workplace	1-256
Shelves/Decks	F18	Numeric	Number of shelves or decks	1-256
Ceilings	F19	Numeric	Ceiling height and safety	1-256
Basements	F20	Numeric	Presence of basements in the workplace	1-256
Walkways	F21	Numeric	Presence of walkways within the workplace	1-256
Roof	F22	Numeric	Condition and safety of roof	1-256
Cleanliness	F23	Numeric	Cleanliness of the workplace	1-256
Lack of Access to Exits/Fire Safety	F24	Numeric	Absence of access to exits or fire extinguishing systems	1-256
Safety/Escape Signage	F25	Numeric	Presence of safety and escape route signage	1-256
<b>Workplace-Related Variables (Machinery and Equipment)</b>				
Maintenance Protocol	F26	Numeric	Compliance with maintenance protocol for equipment	1-256
Lack of Safety During Usage	F27	Numeric	Absence of safety during machinery usage	1-256
Guards to Prevent Accidental Start	F28	Numeric	Presence of guards to prevent accidental start of machinery	1-256
Guards for Moving Parts	F29	Numeric	Presence of guards for moving parts of machinery	1-256
Ejectable Particles	F30	Numeric	Presence of ejectable particles from machinery	1-256
CE Safety Signage	F31	Numeric	CE (Conformité Européenne) safety signage in place	1-256

Variable Category	Variable Code	Type	Description	Values/Range
Cutting Works	F32	Numeric	Presence of cutting works within the workplace	1-256
Lifting Machinery	F33	Numeric	Presence of lifting machinery in the workplace	1-256
Transport Vehicles	F34	Numeric	Presence of transport vehicles in the workplace	1-256
Ladders	F35	Numeric	Presence of ladders within the workplace	1-256
Pneumatic Tools	F36	Numeric	Usage of pneumatic tools in the workplace	1-256
Elevators	F37	Numeric	Presence of elevators within the workplace	1-256
Other Machinery	F38	Numeric	Presence of other machinery in the workplace	1-256
Non-Usage of PPE	F39	Numeric	Instances where PPE is not used during work tasks	1-256
Pressure Devices	F40	Numeric	Usage of pressure devices in the workplace	1-256
Access to Facilities or Equipment	F41	Numeric	Accessibility of required facilities or equipment	1-256
<b>Workplace-Related Variables (Electrical Installation)</b>				
Electrical Installation	F42	Numeric	Status of electrical installations within the workplace	1-256
Inappropriate Usage of Electrical Equipment	F43	Numeric	Instances of inappropriate electrical equipment usage	1-256
Hazards in Explosive Atmospheres	F44	Numeric	Hazards associated with explosive atmospheres in the workplace	1-256
Safety During Usage of Electrical Installations	F45	Numeric	Safety of electrical installations during usage	1-256
Lack of Safety During Electrical Maintenance	F46	Numeric	Safety during maintenance of electrical installations	1-256
Hazardous Substances (Generators, Batteries)	F47	Numeric	Presence of hazardous substances related to equipment	1-256
<b>Workplace-Related Variables (Hazardous Substances)</b>				
Toxic Substances	F48	Numeric	Presence of toxic substances in the workplace	1-256
Caustic Substances	F49	Numeric	Presence of caustic substances	1-256
Corrosive Substances	F50	Numeric	Presence of corrosive substances	1-256
Irritant Substances	F51	Numeric	Presence of irritant substances in the workplace	1-256
Oxidizing Substances	F52	Numeric	Presence of oxidizing substances in the workplace	1-256
Explosive Substances	F53	Numeric	Presence of explosive substances in the workplace	1-256
Flammable Materials	F54	Numeric	Presence of flammable materials in the workplace	1-256
Appropriate Storage for Hazardous Substances	F55	Numeric	Availability of appropriate storage for hazardous substances	1-256
<b>Workplace-Related Variables (Fire Factors)</b>				
Fire Signage	F56	Numeric	Availability of fire signage	1-256
Smoking Ban	F57	Numeric	Ban on smoking in the workplace	1-256
Flammable Substance Ban	F58	Numeric	Ban on the storage of flammable substances in the workplace	1-256
Fire Protection System	F59	Numeric	Availability of fire protection systems	1-256
Fire Emergency Plan Training	F60	Numeric	Training for fire emergency plans	1-256
Fire Extinguishers	F61	Numeric	Availability of fire extinguishers	1-256
Lack of Fire Safety Training	F62	Numeric	Instances of lack of fire safety training	1-256
<b>Workplace-Related Variables (Chemical Factors)</b>				
Dust	F64	Numeric	Presence of dust in the workplace	1-256
Pesticides	F65	Numeric	Presence of pesticides in the workplace	1-256
Gases	F66	Numeric	Presence of gases in the workplace	1-256
Noise	F67	Numeric	Presence of noise in the workplace	1-256
Lighting	F68	Numeric	Quality of lighting in the workplace	1-256
Heat	F69	Numeric	Presence of excessive heat in the workplace	1-256
Air Quality	F70	Numeric	Quality of air in the workplace	1-256

Variable Category	Variable Code	Type	Description	Values/Range
Temperature	F71	Numeric	Temperature of the workplace	1-256
Ventilation	F72	Numeric	Ventilation in the workplace	1-256

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