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An integration of intelligent approaches and economic criteria for predictive analytics of occupational accidents[☆]

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ABSTRACT

Occupational accidents are a significant concern, resulting in human suffering, economic crises, and social issues. Despite ongoing efforts to comprehend their causes and predict their occurrences, the use of machine learning models in this domain remains limited. This study aims to address this gap by investigating intelligent approaches that incorporate economic criteria to predict occupational accidents. Four machine learning algorithms, Random Forest (RF), Support Vector Machine (SVM), Multivariate Adaptive Regression Spline (MARS), and M5 Tree Model (M5), were employed to predict occupational accidents, considering three economic criteria: basic income (BI), inflation index (II), and price index (PI). The study focuses on identifying the most suitable model for predicting the frequency of occupational accidents (FOA) and determining the economic criteria with the greatest influence. The results reveal that the RF model accurately predicts accidents across all income levels. Additionally, among the economic criteria, II had the most significant impact on accidents. The findings suggest that a reduction in FOA is unlikely in the coming years due to the increasing growth of II and PI, coupled with a slight annual increase in BI. Implementing appropriate countermeasures to enhance workers' economic welfare, particularly for low-income employees, is crucial for reducing occupational accidents. This research underscores the potential of machine learning models in predicting and preventing occupational accidents while highlighting the critical role of economic factors. It contributes valuable insights for scholars, practitioners, and policymakers to develop effective strategies and interventions to improve workplace safety and workers' economic well-being.

1. Introduction

Occupational accidents have emerged as a pressing global concern, garnering significant attention from the international community due to their profound impact on public health in the current century [1–3]. These accidents often result in fatalities, physical disabilities, loss of productivity, medical expenses, and substantial economic burdens [4–6]. Notably, in 2020, the European Union witnessed 2.7 million non-fatal work-related accidents and 3355 fatal accidents, indicating a ratio of approximately 815 non-fatal accidents for each fatal accident [7]. These statistics further reveal that there were 1.77 fatal accidents and 1444 non-fatal accidents per 100,000 individuals in the European Union during the same period [7]. Moreover, occupational accidents rank as the second leading cause of death in Iran [8]. In addition, Joghataei et al. (2023) [9] demonstrated that the disability-adjusted life years and deaths related to occupational injuries in Iran significantly are 169 and 523 in 2011 and 86 and 235 in 2018, respectively.

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Moreover, it is essential to acknowledge that while various factors contribute to the occurrence of occupational accidents, economic crises in developing countries can significantly amplify the risk and frequency of such incidents (FOA) [10]. This holds particularly true for countries like Iran, where economic challenges have escalated in the past decade, primarily driven by heavy economic sanctions. These adverse economic conditions, characterized by soaring inflation rates, escalating price indices, and inadequate basic incomes for workers across diverse industries, have created a perilous environment [11]. The combination of these factors exacerbates the vulnerability of workers and raises concerns about the prevalence and severity of occupational accidents within the country. Understanding the intricate relationship between economic crises and occupational accidents is crucial for devising effective interventions and policies that address both the economic well-being of workers and their safety in the workplace. Therefore, this study aims to investigate the impact of economic factors on the frequency of occupational accidents in Iran, highlighting the urgent need for comprehensive strategies to mitigate the risks associated with economic crises and promote a safer working environment for all individuals.

The central hypothesis underlying this study posits that economic indicators exert a significant influence on the FOA. Economic crises hold tremendous sway over the lives of Iranians, and numerous studies have demonstrated the crucial role played by the inflation rate in shaping the quality of life of Iranian workers [12,13]. However, it is crucial to recognize that the impact of economic crises extends beyond workers' quality of life and permeates their working conditions within the workplace [14,15]. Research indicates that during favorable economic conditions, low income can have a profound effect on job satisfaction, enhancing employee motivation, fostering compliance with workplace regulations, and consequently reducing the occurrence of occupational accidents [16,17]. Thus, this study aims to analyze data on occupational accidents, which serve as a robust indicator of safety conditions in industries, with a specific focus on the fluctuations of the economic crisis. By investigating the relationship between economic indicators and FOA, this study seeks to provide valuable insights that can inform the development of targeted interventions and policies to enhance workplace safety in the face of economic challenges.

Despite the prevalence of occupational accidents across various industries, there remains a notable gap in comprehensive research focused on predicting the frequency of occupational accidents by incorporating changes in economic indicators. Conducting such a study holds immense potential in forecasting the impact of economic indicators on accident rates, thereby serving as a valuable tool for proactively controlling and managing work-related accidents in the future. This proactive approach can be utilized as a fundamental criterion for governing industrial operations within countries [18], aiding in the formulation of appropriate intervention strategies. Furthermore, this research aligns with the United Nations Sustainable Development Goals, specifically Goal 8 — decent work and economic growth. By integrating economic indicators into the prediction of FOA, this study contributes to the overarching aim of fostering safe and conducive working environments while driving sustainable economic development.

By bridging the gap between occupational accident prediction and economic indicators, this research offers significant practical implications. The findings can empower policymakers, industry stakeholders, and regulatory bodies to make informed decisions and implement targeted measures to reduce the frequency of accidents, enhance workplace safety, and improve workers' overall well-being. Moreover, this study serves as a stepping stone towards a more proactive approach to occupational safety management, facilitating early intervention and prevention strategies that prioritize the reduction of accidents based on economic indicators. Such proactive measures are crucial in promoting sustainable industrial development while ensuring the safety and welfare of workers, thereby contributing to the broader global agenda of achieving sustainable economic growth and decent work conditions.

Studying the impact of economic conditions on occupational accidents necessitates the utilization of advanced and precise analytical tools. The application of advanced statistical methods enables the evaluation of economic indicators' influence on occupational accidents and facilitates the prediction of future accidents based on accident reports and the effects of these parameters [19]. The primary reason for employing such methods lies in their ability to explore the intricate and interactive effects of various factors during accident investigations [20]. While numerous statistical methods exist for occupational accident prediction, their operational accuracy is often limited due to a lack of adequate flexibility. Traditional statistical approaches, in particular, tend to diminish the study's predictive accuracy when it comes to FOA, primarily due to the high level of uncertainty in bulk data analysis [21]. Consequently, there arises a pressing need to leverage advanced statistical methods in this context.

In contrast, the utilization of Machine Learning (ML) techniques offers a distinct advantage in predicting accidents [22]. ML approaches exhibit significant strengths over traditional statistical methods, owing to their inherent capacity for adaptability, flexibility, and precise prediction [19]. ML algorithms have the capability to discern complex patterns, capture non-linear relationships, and handle vast volumes of data, thereby facilitating accurate and reliable predictions of FOA. By harnessing the power of ML, researchers can unlock valuable insights hidden within occupational accident data, enabling them to develop robust models capable of accurately forecasting future accident frequencies based on economic indicators. The adoption of advanced statistical methods and ML approaches represents a pivotal advancement in the field of occupational accident prediction, promising enhanced precision and a deeper understanding of the underlying dynamics between economic conditions and accident occurrence [19].

The increasing inflation rate and the subsequent decline in purchasing power, particularly among low-income workers, have ignited concerns regarding the occurrence of occupational accidents. In light of this, predicting the FOA assumes paramount importance as it provides a roadmap for government bodies and managers to implement targeted countermeasures. The primary contribution of this study lies in the comparative analysis of various machine learning algorithms for predicting the incidence of occupational accidents within a large statistical population while considering the influence of economic indicators.

The present study seeks to address several key research questions to shed light on the complex interplay between economic indicators and occupational accidents:

(a) What has been the trend of occupational accidents over the past decade across different income levels of workers?
(b) Which economic criteria exert a significant impact on the occurrence of occupational accidents?
(c) What is the projected trajectory of occupational accidents based on economic criteria for the next five years?
(d) Among the economic criteria, which one holds the most substantial influence on occupational accidents?
(e) Which ML model demonstrates the highest efficacy in predicting FOA compared to other available models?

By answering these crucial questions, this study aims to provide valuable insights that can inform policymakers, government agencies, and industry stakeholders about the dynamics of occupational accidents concerning economic indicators. The findings will aid in formulating evidence-based strategies and intervention plans to mitigate the risks associated with occupational accidents and promote a safer working environment for individuals across diverse income levels. Additionally, identifying the most suitable machine learning model for predicting work-related accidents will contribute to the development of accurate and reliable predictive tools that can be employed in real-world settings to enhance occupational safety and achieve sustainable economic growth.

The rest of this paper continues as follows. Section 2 offers a comprehensive literature review that explores the application of ML techniques in predicting occupational accidents and investigates the impact of economic crises on accident frequencies. Section 3 delves into the intricacies of criteria extraction and provides a detailed description of the prediction models employed in this study. Moving forward, Section 4 presents the key findings encompassing the extracted criteria, job classification based on income levels, FOA prediction, and an evaluation of the models' reliability. In Section 5, we engage in in-depth discussions regarding the methodologies employed and compare our findings with relevant studies in the field. Finally, in the concluding section, we summarize the main implications drawn from this research and propose avenues for future research. Through this comprehensive exploration, our study aims to contribute to the growing body of knowledge surrounding the utilization of machine learning methods in predicting occupational accidents and sheds light on the critical role played by economic indicators in shaping workplace safety.

2. Literature review and research gaps

2.1. Studies related to machine learning and occupational accidents

The existing body of literature on the application of machine learning in predicting occupational accidents predominantly revolves around the construction industry, as evidenced by the studies presented in Table 1. However, a notable challenge encountered in these studies is the utilization of small statistical samples, which can potentially limit the generalizability of the findings. While previous research has primarily focused on the application of machine learning and artificial intelligence methods in analyzing and predicting occupational accidents, there appears to be a lack of specialized studies that undertake a comparative analysis of these methods specifically within the context of occupational accidents.

Furthermore, it is worth noting that the majority of studies have concentrated on the severity of accident outcomes, rather than the prediction of the actual number of accidents. This discrepancy suggests a gap in the existing research landscape. By recognizing these gaps, this current study aims to bridge the knowledge divide by examining and comparing various machine learning algorithms for predicting the occurrence of occupational accidents. Moreover, this research seeks to address the prediction of accident frequency, offering valuable insights into the future trends of occupational accidents based on economic criteria.

The literature review was expanded and updated to elucidate how the research contributes to the field of analytics, with a specific focus on the prediction and analysis of occupational accidents at a national level. While previous research has primarily concentrated on the application of machine learning techniques in accident prediction, the limitations of these studies have been acknowledged, such as their reliance on small statistical samples and the limited generalizability of findings. A gap in the literature has been identified in terms of conducting a comprehensive comparative analysis of various machine learning algorithms for the prediction of national-level occupational accidents. This research aims to bridge this gap by providing a detailed examination of these machine-learning methods. By doing so, not only are accidents predicted, but also the analytical framework is broadened to encompass the national scale, enabling more informed decisions regarding accident frequency, resource allocation, and proactive safety measures. Consequently, the study makes a significant contribution to the field of analytics by extending its application to the crucial domain of national-level occupational accident prediction, with far-reaching implications for both societal and economic considerations.

The present study takes on a predictive perspective, focusing on the frequency of occupational accidents and their intricate interactions with various economic criteria, enabling proactive risk management and resource allocation. Moreover, this study introduces a distinctive comparative element by comprehensively evaluating different machine learning algorithms, aiding the community in selecting the most effective approach for analyzing national-level occupational accidents. This combined effort enhances decision-making within the field, aligning with the broader trajectory of analytics where predictive and comparative analyses converge to empower stakeholders with valuable insights for complex decision environments.

2.2. Studies related to the impact of the economic criteria on accidents

The existing literature review reveals that studies exploring the impact of economic crises on accidents have primarily focused on the transportation sector. For instance, Liao et al. (2022) [23] compared occupational accidents between non-standard workers (workers who are employed with low daily wages) and standard workers in the construction industry and showed that the accidents rate and resulting injuries in non-standard workers are higher than standard workers and they attributed this difference to poor job security and protection in non-standard workers. In addition, Koc and Gurgun (2022) [24] introduced income, along with factors such as age and experience, as the most influential factors related to the severity of occupational accidents.

Furthermore, Amoadu et al. (2023) [25] highlighted that professional drivers in low- and middle-income countries (LMICs) face precarious working conditions, including high job demands, solo driving, irregular shifts, long hours, and limited job control. Factors such as job insecurity, effort-reward imbalance, and performance-based pay contribute to risky driving situations. Their research underscores the significant impact of these psychosocial work factors on driving performance in LMICs, emphasizing the connection between economic circumstances, workplace conditions, and accident rates on the road. The economic situation can be seen even in transport drivers. A study by Yang et al. (2023) [26] in Guangzhou, China showed that from 2017 to 2020, vulnerable road users, such as motorized two-to-three-wheeler drivers and migrant workers, were casualties in more than 80% of the cases. This illuminates how economic factors manifest in the safety and well-being of drivers, accentuating the complex relationship between economic conditions and the vulnerability of individuals on the road.

In addition, there remains a significant research gap in terms of specialized studies examining the influence of economic crises on occupational accidents. This knowledge gap constitutes the third gap in past studies.

Building upon these insights, the present study has been designed to address the three identified gaps. Previous studies have predominantly concentrated on predicting the frequency of occupational accidents using common machine learning methods, without conducting a comparative analysis of their effectiveness. Thus, the present study aims to fill this gap by comparing the performance of different machine learning models in predicting the occurrence of occupational accidents.

Moreover, while valuable studies have been conducted in this field, there is a need for further research to explore additional gaps. Previous studies have primarily focused on specific industries, and more comprehensive and accurate findings could be achieved by including a more diverse population from various workplaces. Furthermore, when examining economic indicators and income, it is essential to consider complementary factors such as inflation rate and price index. The integration of economic indicators with occupational accidents has not yet been thoroughly investigated in specialized studies. Additionally, there is a lack of quantitative comparisons of machine learning models in analyzing occupational accidents and monitoring economic indicators, which are crucial influencing factors that have been overlooked in previous research.

These challenges related to occupational accidents and the economic crisis faced by workers form the basis of the present research. The study aims to address these existing challenges by predicting the frequency of occupational accidents in the coming years while also

Table 1
Studies conducted in the field of the application of machine learning in predicting occupational accidents.

Study	Field of the study	Methods used	Comparison between methods
Sarkar et al. (2019) [19]	Predicting accidents and near-miss	Support Vector Machines (SVM), Artificial Neural Networks (ANN)	Yes
Kang et al. (2019) [27]	Predicting constructions accidents	Random Forest (RF)	No
Zhu et al. (2021) [28]	Predicting the severity of outcomes in construction accidents	Decision Tree (DT), SVM, Logistic Regression (LR), Naïve Bayes, K-nearest Neighbor (KN), Multi-layer preceptor (MLP), Auto-ML	Yes
Yedla et al. (2020) [29]	Predicting the severity of safety outcomes in mining operations	DT, RF, ANN	Yes
Zaranezhad et al. (2019) [30]	Predicting the maintenance-related accidents	ANN, Fuzzy System, Genetic Algorithm, Colony Optimization Algorithm	Yes
Lee et al. (2020) [31]	Predicting accidents in the constructions industry	SVM, DT	No
Kakhki et al. (2019) [32]	Predicting the severity of agribusiness industries	SVM, Boosted Tree, Naïve Bayes	Yes
Sarkar et al. (2020) [33]	Predicting the severity of outcomes	SVM, Naïve Bayes, RF, ANN, Classification and Regression Tree	Yes
Sarkar et al. (2016) [34]	Predicting occupational accidents	DT	No
Baker et al. (2020) [35]	Predicting the severity of outcomes in construction accidents	XGBoost, SVM	No
Lou et al. (2023) [1]	Predicting the severity of outcomes in occupational accidents	RF	No
Zermane et al. (2023) [36]	Predicting fatal fall from heights accidents	Extreme Gradient Boosting, DT, RF, MLP, KN, SVM, Logistic Regression (LR)	Yes
Gatera et al. (2023) [37]	Comparing between machine learning models performances in predicting traffic accidents	RF, SVM	Yes
Present study	Predicting occupational accidents in Iran based on economic criteria	SVM, RF, M5 model, Multivariate adaptive regression spline (MARS)	Yes

comparing the superiority of various machine learning models. By doing so, the study endeavors to provide valuable insights that contribute to the prevention and management of occupational accidents, taking into account the impact of economic indicators. Ultimately, this research aims to improve the understanding of the complex relationship between economic factors and occupational accidents, enabling policymakers and stakeholders to implement effective interventions and strategies to enhance workplace safety and workers' economic well-being.

3. Materials and methods

The study consists of three main phases, as depicted in Fig. 1. In the first phase, data pertaining to occupational accidents and economic indicators are collected and meticulously classified. These data serve as the foundation for subsequent analyses. The second phase focuses on predicting the FOA utilizing ML models, leveraging the data gathered in the first phase. The ML models are employed to generate accurate predictions based on the identified patterns and trends in the dataset. Finally, in the third phase, the performance and effectiveness of the selected ML techniques are evaluated and assessed. This rigorous evaluation allows for the determination of the most suitable ML models for predicting FOA, ensuring the reliability and validity of the study's findings.

3.1. Collecting a data

In this study, a comprehensive dataset of accident data related to insured workers across all industries in Iran was collected from 2007 to 2017. The dataset consisted of a total of 191,879 accidents and was obtained from the comprehensive report of the Social Security Organization, a national organization that covers insured workers throughout the country. The collected information encompassed various details, including the worker's occupation, the date of the accident, the type and cause of the accident, and the number of days the worker was absent from work.

The accident data was further categorized based on the workers' income level. Each accident was assigned to one of three income categories: low-income (income below 2.5 million Tomans ≅ \$100), medium-income (income between 2.5 million and 5 million Tomans ≅ \$100 to \$200), and high-income (income above 5 million Tomans ≅ >\$200). This categorization allowed for a more nuanced analysis of the relationship between income and accident occurrence.

Alongside the accident data, economic indicators were also extracted for the period of 2007–2017. Three primary economic indicators were considered in this study: basic income (BI), price index (PI), and inflation index (II). These indicators were identified as influential factors affecting the lives of workers in previous studies [38] and were therefore included in the analysis.

The collected accident data and economic indicators served as the foundation for subsequent investigations and analyses conducted in this study. The relationship between these factors and their impact on occupational accidents was examined in detail, leading to valuable insights and findings.

3.2. Machine learning algorithms

3.2.1. Random Forest (RF)

The Random Forest (RF) regression model is a powerful ensemble learning method that combines multiple decision trees to make predictions [39]. Each tree in the RF model is built through a process of recursive splitting of the input space into homogeneous subspaces, resulting in a collection of diverse trees [40]. One of the key strengths of the RF model is its ability to handle complex relationships and capture nonlinear effects and higher-order interactions among the predictors [41]. This is achieved through the combination of multiple

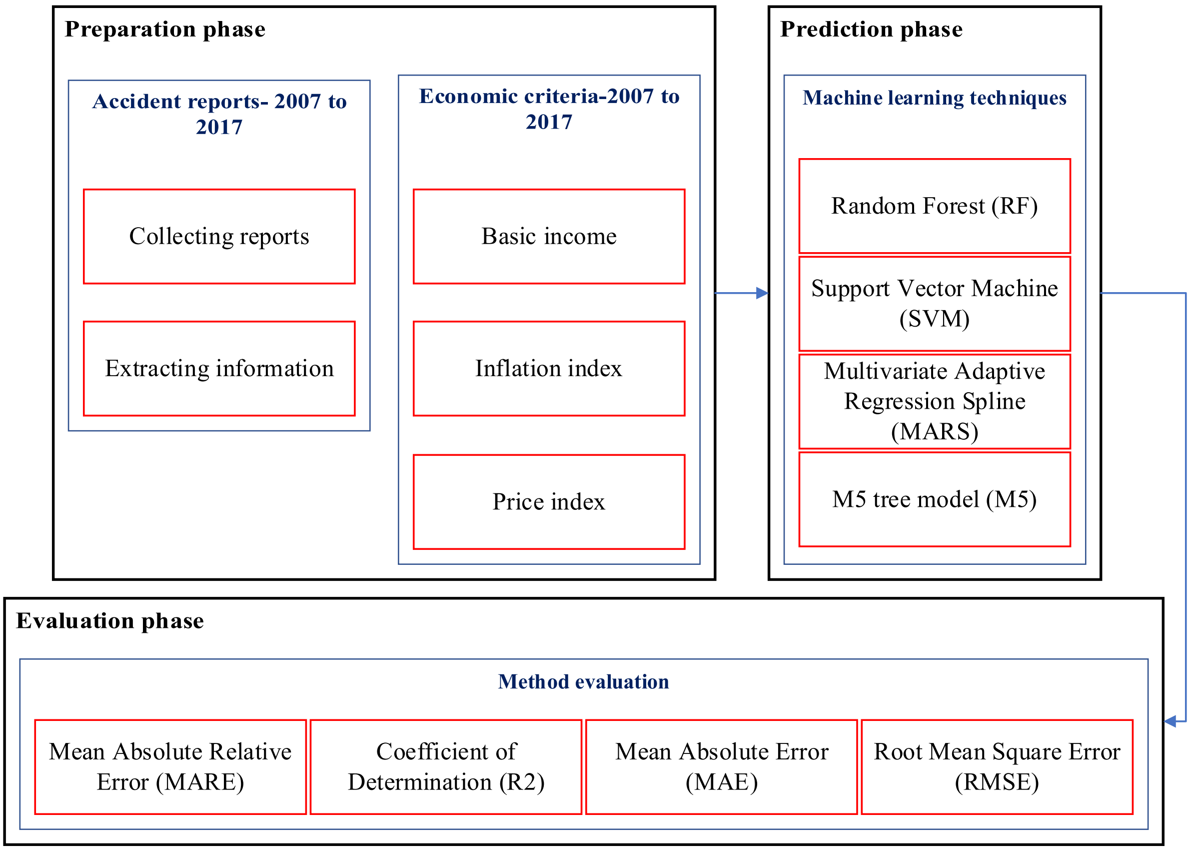

Fig. 1. The research phases.

trees, each trained on a different subset of the data and a random subset of predictors [42]. By aggregating the predictions from individual trees, the RF model produces a more robust and accurate overall prediction [43].

In the RF model, the importance of predictors can be assessed by examining their role in the creation of trees. Predictors that contribute significantly to the splitting decisions in the trees are considered to be the most important predictors [41]. This feature of the RF model allows for the identification of the key predictors that have the strongest influence on the frequency of occupational accidents (FOA) in our study.

To determine the fundamental predictors affecting the FOA, the influence of each predictor was evaluated. The rate of increment in forecast error was calculated by selectively withholding the data for a particular predictor while keeping the other predictors constant [43]. This analysis helps in understanding the relative importance of predictors and provides valuable insights into their contributions to the prediction of FOA. Relative importance (%IncMSE) is a statistical metric used in machine learning to assess the contribution of individual predictor variables to the mean squared error (MSE) of a predictive model. It quantifies the extent to which each variable influences the model's overall performance, with higher values indicating greater importance. This metric helps identify which features have the most significant impact on the model's accuracy, assisting in feature selection and understanding variable contributions [44]. For more detailed information on the Random Forest regression model, the study by James G et al. (2013) [45] is recommended as a comprehensive resource that delves into the intricacies and applications of RF in predictive modeling.

3.2.2. Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a widely used method in statistical learning for classification and regression tasks [46,47]. In regression problems, the SVM technique aims to approximate the dataset in a high-dimensional space using a linear function [48]. This method employs a loss function that takes into account both the empirical error and a regularization norm, allowing for effective regularization and avoidance of overfitting [49,50]. By minimizing the expected error of the learning machine, SVM not only seeks to accurately fit the training data but also aims to enhance its generalization performance for prediction tasks [51]. This characteristic of SVM contributes to its ability to handle unseen data and make reliable predictions in real-world scenarios [52]. The function of SVM in regression tasks can be mathematically represented by Eq. (1) [53]:

$$y = k(x) = w\lambda(x) + b \tag{1}$$

where:
x is the input vector
y shows the corresponding output value
w represents the weight vector
b is the bias
$\lambda(x)$ indicates a nonlinear function in vector space.

SVM's effectiveness in handling regression problems lies in its ability to find an optimal hyperplane that maximizes the margin between different classes or approximates the data points with minimum error in the case of regression [51,54]. This optimization process allows this approach to achieve a robust and accurate regression model, capable of capturing complex relationships and achieving high predictive performance.

The SVM method has been widely employed in various domains due to its flexibility, generalization ability, and solid theoretical foundations [55–57]. Researchers have successfully utilized it in predicting various outcomes and it has demonstrated favorable performance in different applications. Therefore, it offers a valuable approach for our study in predicting the frequency of occupational accidents based on economic criteria, contributing to a better understanding of the relationship between these factors and enhancing workplace safety.

3.2.3. Multivariate adaptive regression spline (MARS)

Multivariate Adaptive Regression Spline (MARS) is a powerful nonlinear regression model widely used in statistical learning theory [58]. It offers a flexible approach for predicting continuous numeric outcomes and can be viewed as an enhancement of the classification and regression tree method [59]. One of the key advantages of this model is its nonparametric nature, which eliminates the need for making specific assumptions about the functional relationship between predictor and outcome variables [60,61]. This characteristic allows the MARS model to adaptively capture complex and nonlinear patterns present in the data, making it suitable for modeling real-world phenomena that may involve intricate interactions between variables.

The MARS model constructs a regression function using a series of basis functions known as splines, which are piecewise-defined polynomials. These splines are automatically generated and adapted to different regions of the predictor space based on the observed data. By locally adjusting the shape and complexity of the splines, this model effectively captures the underlying patterns in the data and provides a highly flexible and interpretable regression model. The general form of the regression function in MARS can be represented by Eq. (2) [62]:

$$y = \beta_0 + \sum \beta_i \max(0, x_i - \upsilon_i)^* + \sum_{i \neq j} \beta_{ij} max(0, x_i - \upsilon_i)^* max(x_j - \upsilon_j)^* + \cdots \quad (2)$$

where:

$\beta 0$ shows the regression coefficients

β_i and β_{ij} represents some constant (known as knots).

The MARS model possesses several positive characteristics that make it a valuable tool in regression analysis. It can handle both numerical and categorical predictors, allowing for the inclusion of a wide range of variables in the model [63]. Moreover, it is capable of capturing interactions between predictors, detecting breakpoints in the relationships, and providing a clear representation of the nonlinear patterns in the data [64]. This interpretability makes this model not only a powerful prediction tool but also a useful tool for understanding the underlying mechanisms driving the outcomes of interest.

Given its flexibility and ability to handle complex relationships, the MARS model presents a promising approach for predicting the frequency of occupational accidents in our study. By incorporating economic indicators and their interactions, this model can effectively capture the nonlinear effects of these factors on the occurrence of accidents, thereby enhancing our understanding of the relationship between economic conditions and workplace safety.

3.2.4. M5 tree model (M5)

The M5 tree model (M5), introduced by Keshtegar et al. (2023) [65], is a machine-learning method that combines the advantages of binary decision support systems with linear regression in the leaf nodes to establish the relationship between predictor and outcome variables [66]. Unlike traditional regression tree learners, this model excels in simulating high-dimensional data, making it suitable for datasets with a large number of attributes [67].

The M5 model follows a two-phase process for constructing the regression tree. In the first phase, the data is partitioned into subsets using a splitting criterion, which leads to the creation of an initially overgrown tree. However, overgrown trees can be prone to overfitting, which may compromise the model's generalization ability. To address this, the second phase focuses on pruning the overgrown tree by replacing subtrees with linear regressions [68,69]. This pruning process helps simplify the model and enhances its interpretability without sacrificing its predictive accuracy. The overall form of this model can be represented by Eq. (3):

$$y = \beta_0 + \sum_i \beta_i \quad (3)$$

where:

β_i is linear regression coefficients [67].

The M5 tree model offers several positive characteristics that contribute to its effectiveness in regression analysis. It can handle both numerical and categorical predictors, allowing for a wide range of variables to be included in the model. Moreover, this model can capture both linear and nonlinear relationships between predictors and outcomes, providing a flexible framework for modeling complex data patterns. Additionally, the model's interpretability is enhanced by the linear regression models employed in the leaf nodes, which provide explicit equations that describe the relationship between predictors and outcomes [70].

In our study, the M5 tree model proves to be a valuable tool for predicting the frequency of occupational accidents. By leveraging its ability to handle high-dimensional data and incorporate both linear and nonlinear relationships, this model can effectively capture the complex interactions between economic indicators and accident occurrences. The interpretability of the model allows us to gain insights into the specific factors and their impact on occupational accidents, thereby facilitating the development of targeted interventions and preventive measures in the workplace.

3.2.5. Evaluating criteria

To evaluate and compare the forecast precision and efficiency of prediction models using the dataset in this study, several performance metrics were employed. These metrics include the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R2), and Mean Absolute Relative Error (MARE). These metrics provide standardized measures to assess the accuracy and effectiveness of the predictive models.

The RMSE is a widely used metric that quantifies the average magnitude of the differences between the observed and predicted values. A lower value indicates better forecast accuracy, as it signifies smaller deviations between the predicted and actual values [71]. Similarly, the MAE measures the average absolute difference between the predicted and observed values [72]. It provides a measure of the model's average prediction error and is also used to evaluate the model's accuracy. A lower value indicates a better forecast precision and a closer fit between the predicted and actual values [73].

In addition, the MARE is a relative error metric that measures the average absolute difference between the predicted and observed values, normalized by the mean of the observed values. It allows for the comparison of forecast accuracy across different scales and is particularly useful when dealing with datasets that have varying magnitudes. A lower value indicates a better forecast efficiency, as it indicates a smaller relative deviation between the predicted and observed values [74]. The coefficient of determination, R2, measures the proportion of the variance in the observed values that can be explained by the predicted values. It indicates the goodness-of-fit of the model and measures the agreement between the observed and forecast number of events. A higher value indicates a better agreement between the predicted and actual values, suggesting a stronger predictive performance of the model [75].

These performance metrics are computed using specific formulas, as represented by Eqs. (4), (5), (6), and (7), respectively. These metrics provide standardized measures for evaluating and comparing the forecast accuracy and efficiency of the models in predicting the frequency of occupational accidents in our study. In summary, by employing these performance metrics, we can objectively assess the predictive capabilities of the different machine learning models and identify the most accurate and efficient model for predicting the occurrence of occupational accidents based on economic indicators [43,76].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{observed} - y_{predicted})^2} \quad (4)$$

where:

N is the total number of data points or observations.

$y_{observed}$ represents the actual values or observations.

$y_{predicted}$ represents the values predicted by the model.

The lower the RMSE, the better the model's predictive accuracy. It penalizes larger errors more significantly.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_{observed} - y_{predicted}| \tag{5}$$

where:
N is the total number of data points or observations.
$y_{observed}$ represents the actual values or observations.
$y_{predicted}$ represents the values predicted by the model.

MAE provides a measure of the average magnitude of errors in the predictions. It is less sensitive to outliers compared to RMSE.

$$MARE = \frac{1}{N}\sum_{i=1}^{N}|\frac{y_{observed} - y_{predicted}}{y_{observed}}| \tag{6}$$

where:
N is the total number of data points or observations.
$y_{observed}$ represents the actual values or observations.
$y_{predicted}$ represents the values predicted by the model.

MARE is useful when you want to understand the average relative error in percentage terms. It helps gauge the model's performance in a relative context.

$$R^2 = \frac{\sum_{i=1}^{N}(y_{predicted} - y_{mean})^2}{\sum_{i=1}^{N}(y_{observed} - y_{mean})^2} \tag{7}$$

where:
N is the total number of data points or observations.
$y_{observed}$ represents the actual values or observations.\
$y_{predicted}$ represents the values predicted by the model.
y_{mean} represents the mean of the observed values.

R^2 ranges from 0 to 1, where a higher value indicates a better fit of the model to the data. An R^2 value of 1 indicates a perfect fit.

Machine learning analysis was conducted using packages of R (version 3.4.0) software of "e1071" Version 1.7–3 [77], "Random Forest" version 4.6–14 [78], "earth" version 5.1.2, [79], and "RWeka" version 0.4–42 [80] which are publicly available.

4. Results

4.1. Economic indicators and accidents occurrence

Table 2 provides a comprehensive breakdown of the descriptive statistics for various parameters within three distinct income groups: Low income, Medium income, and High income, across three different datasets: the entire dataset spanning from 2007 to 2017, a training dataset encompassing the years 2007 to 2015, and a test dataset covering the years 2016 to 2017. The analysis revealed that the average II was 18.18 (standard deviation: 8.303), the average PI was 63.91 (standard deviation: 34.460), and the average BI was 602 217.769 Tomans (standard deviation: 387 887.057 Tomans). These findings provide a comprehensive overview of the economic indicators considered in this study.

Furthermore, the distribution of accidents among different income groups was examined. It was observed that more than half of all accidents (58%) occurred among low-income workers. This highlights the vulnerability of this particular group to occupational accidents and emphasizes the need for targeted interventions to improve workplace safety.

To gain further insights into the trend of FOA among different income groups, a graphical representation was generated (see Fig. 2). The trend analysis indicated a decrease in the FOA among both low- and medium-income workers during the study period from 2007 to 2017. However, it is important to note that the changing trend exhibited a nonlinear pattern, suggesting the presence of more complex dynamics that warrant further investigation.

These initial findings provide valuable insights into the relationship between economic indicators, income levels, and the occurrence of occupational accidents. The data highlights the concentration of accidents among low-income workers and the varying trends in accidents across different income groups. However, to fully understand the underlying factors contributing to these patterns, more in-depth studies are necessary. Further research should explore the complex relationships between economic indicators, income levels, and occupational accidents to uncover the underlying dynamics and inform the development of targeted strategies for accident prevention and improved workplace safety.

4.2. Predicting and evaluating results

4.2.1. Machine learning algorithms' performance in predicting the FOA

The performance of models in terms of forecast precision and efficiency was evaluated using several metrics on the test sets. The results of this comparison are presented in Table 3. The findings indicate that the M5 model (RMSE: 3.19, MAE: 1.90, MARE: 0.04, and R2: 0.99) demonstrated the highest efficiency among the models, outperforming the others in terms of price index predictions. Additionally, the RF model (RMSE: 2.83, MAE: 2.15, MARE: 0.13, and R2: 0.93) exhibited superior performance in modeling and predicting the inflation index compared to the other models.

Moreover, the results highlight the RF model's efficacy in predicting the number of workers' accidents across different income levels. This model consistently outperformed other models in low-income (RMSE: 44.61, MAE: 35.24, MARE: 0.04, and R2: 0.94), medium-income (RMSE: 35.73, MAE: 28.42, MARE: 0.05, and R2: 0.92), and high-income (RMSE: 3.28, MAE: 2.69, MARE: 0.11, and R2: 0.84) categories.

To further illustrate the capabilities of the models, Fig. 3 (a–e) provides visual comparisons of their performance in the studied parameters. The figures offer a comprehensive overview of how each model fares in terms of forecast accuracy and efficiency across the different parameters examined. These results underscore the effectiveness of the RF model in modeling and predicting the occurrence of occupational accidents at various income levels. The superior performance of the M5 Tree model in predicting price index and the overall strong performance of the RF model validate their potential for informing decision-making processes related to accident prevention and workplace safety. The findings from this study contribute to the existing body of knowledge by providing insights into the comparative performance of different machine learning models and their suitability for predicting occupational accidents in relation to economic indicators.

4.2.2. Predictions based on selected models

The predictions for the PI (using the M5 model), II (using the RF model), and BI (using the RF model) are depicted in Fig. 4. These predictions provide valuable insights into the expected values of these economic indicators for March 2021.

According to the findings, the predicted inflation index for March 2021 is 12.05, indicating a projected increase in the overall price levels compared to the base period. The price index is forecasted to reach 173.78, representing a potential rise in the average prices of goods and services. Additionally, the estimated monthly base income is projected to be approximately 2,221,000 Tomans (equivalent to about $96).

These predictions offer valuable information for policymakers, businesses, and individuals to anticipate and plan for the economic conditions in the near future. By utilizing machine learning models, such as M5 for price index prediction and RF for inflation index and basic income prediction, these forecasts can support decision-making processes, budgeting, and resource allocation strategies.

It is important to note that these predictions are based on the available data and the assumptions underlying the models used. As with any forecasting exercise, there is inherent uncertainty, and actual values

Table 2
Descriptive analysis of economic & accident data in the study population.

	Parameter	Entire data (2007–2017)	Training set (2007–2015)	Test set (2016–2017)
Frequency of occupational accidents				
Low income	N	120	96	24
	Sum	109 868	91 605	18 263
	Minimum	536	556	536
	Maximum	1412	1412	941
	Median	900	955	761
	Mean	915.57	954.22	760.95
	Standard deviation	171.43	163.82	100.18
Medium income	N	120	96	24
	Sum	78 860	64 933	13 927
	Minimum	393	394	393
	Maximum	907	907	722
	Median	643	692	584.5
	Mean	657.17	676.38	580.29
	Standard deviation	118.86	118.72	84.67
High income	N	120	96	24
	Sum	3170	2532	638
	Minimum	11	12	11
	Maximum	41	41	39
	Median	27	26	28
	Mean	26.41	26.37	26.58
	Standard deviation	6.46	6.57	6.13
Economic variables				
Inflation index	N	120	96	24
	Sum	2305.90	2021.6	284.30
	Minimum	8.60	8.80	8.60
	Maximum	40.40	40.40	15.60
	Median	17.5	20.45	11.55
	Mean	19.21	21.05	11.85
	Standard deviation	8.33	8.23	2.85
Price index	N	120	96	24
	Sum	6578.10	4266.50	2300
	Minimum	19.70	19.70	88.50
	Maximum	105.90	87.40	105.90
	Median	45	37.20	94.85
	Mean	54.81	44.55	95.85
	Standard deviation	27.89	20.90	4.93
Basic income (Toman)	Minimum	183 000	183 000	712 425
	Maximum	812 166	608 910	812 166
	Median	360 150	296 910	762 295
	Mean	427 064.1	343 256.25	762 295
	Standard deviation	219 407.6	145 077.93	70 527.53

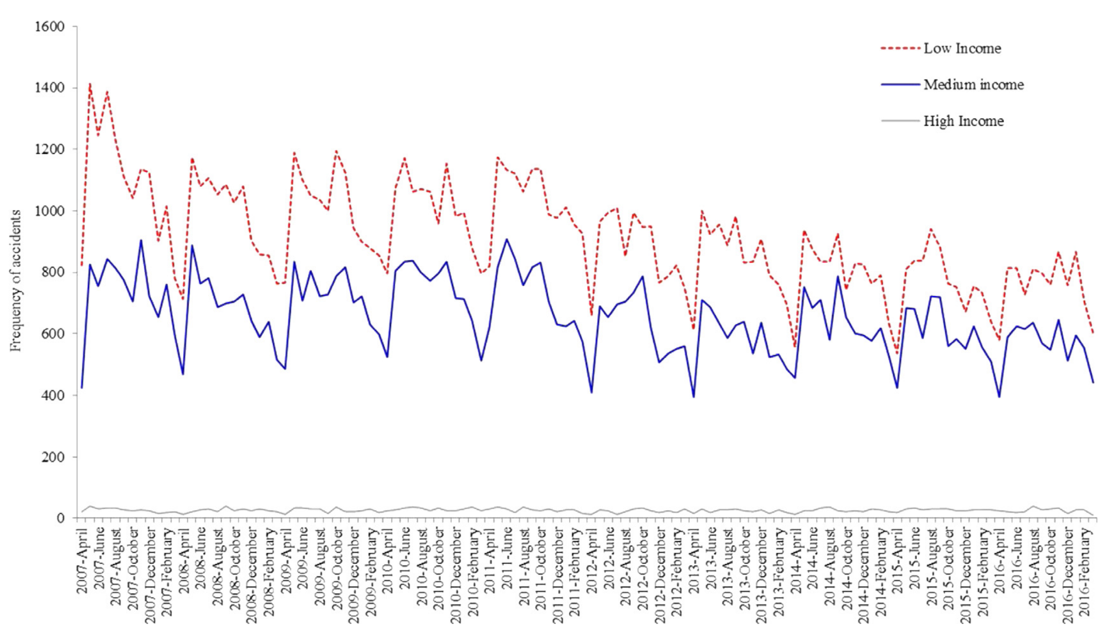

Fig. 2. Occupational accident occurrences based on the income levels.

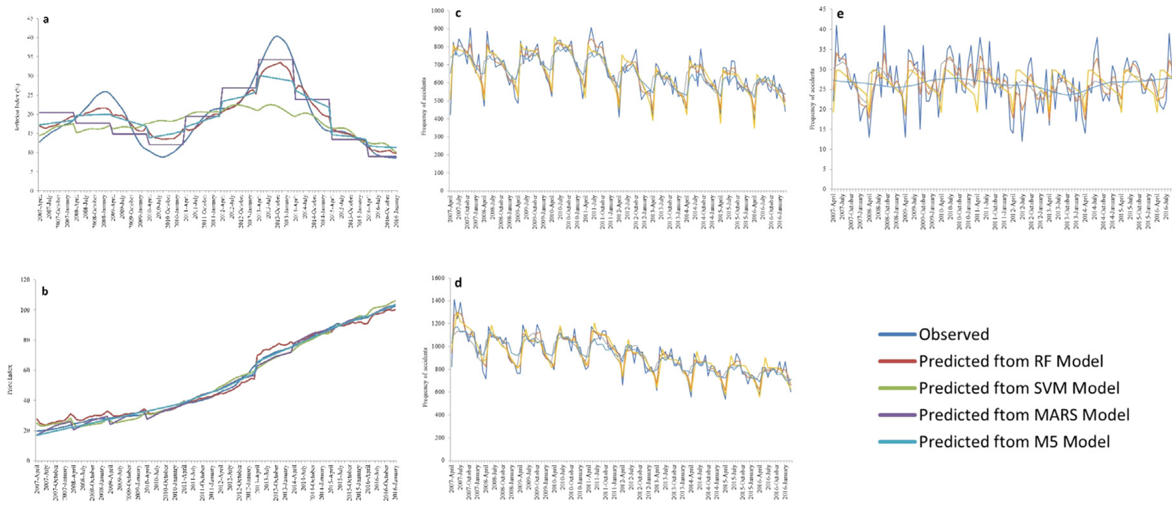

Fig. 3. Predicted vs. observed values for (a) Inflation index, (b) Price index, (c) Low-Income FOA, (d) Mid-Income FOA, and (e) High-Income FOA.

Table 3
The evaluation criteria of RMSE, MAE, MARE, and R2 statistics of RF, SVM, MARS, and M5 for the prediction of the monthly frequency of occupational accidents.

Statistics	Model	RMSE	MAE	MARE	R^2
Price index	RF	4.51	3.10	0.06	0.99
	SVM	5.08	3.14	0.06	0.98
	MARS	3.32	2.18	0.04	0.99
	M5	3.19	1.90	0.04	0.99
Inflation index	RF	2.83	2.15	0.13	0.93
	SVM	6.40	4.30	0.24	0.47
	MARS	3.95	3.09	0.17	0.77
	M5	3.89	3.08	0.19	0.85
Number of accidents (low income)	RF	44.61	35.24	0.04	0.94
	SVM	100.65	70.26	0.08	0.66
	MARS	75.98	58.90	0.06	0.80
	M5	90.39	67.33	0.08	0.73
Number of accidents (med income)	RF	35.73	28.42	0.05	0.92
	SVM	83.24	55.89	0.10	0.51
	MARS	52.46	41.76	0.07	0.80
	M5	69.96	53.66	0.09	0.68
Number of accidents (high income)	RF	3.28	2.69	0.11	0.84
	SVM	5.82	4.48	0.21	0.19
	MARS	5.74	4.71	0.20	0.20
	M5	6.34	5.16	0.23	0.03

may deviate from the predicted figures. Nonetheless, these forecasts serve as a useful reference for understanding potential trends in the economic indicators under consideration.

The predictions for the accidents until 2021 are presented in Fig. 5, providing insights into the anticipated trends in accident rates over the next five years (2017 to 2021). Based on the findings, it is projected that the FOA will not exhibit a significant decrease during this period. However, there are observed fluctuations in it, with noticeable decreases in March and April, followed by a relatively stable trend from May to August. In contrast, high-income jobs show a more consistent accident rate throughout the year. This stability could be attributed to factors such as job security and a higher level of confidence in income and welfare status among workers in these occupations.

It is essential to highlight that the accidents predictions are solely based on the 10-year trend observed in the study and the predicted economic indicators (as illustrated in Fig. 5). While these predictions provide valuable insights into the anticipated patterns of occupational accidents, it is crucial to consider that various factors, both internal and external to the workplace, can influence accident rates. Therefore, caution should be exercised when interpreting and relying solely on these predictions. The predictions presented in Fig. 5 contribute to the understanding of potential trends in the FOA and can serve as a reference for policymakers, occupational safety professionals, and employers in developing proactive strategies and interventions to mitigate workplace accidents. However, it is crucial to continuously monitor and assess the actual accident data to validate and refine these predictions, considering the dynamic nature of occupational safety and the potential impact of unforeseen factors on accident rates.

The importance of predictors in predicting the FOA based on income levels is demonstrated in Fig. 6. This figure provides insights into the relative influence of various predictors on the accidents, specifically focusing on different income categories.

According to the findings presented in Fig. 6, the months of the year emerge as the most influential predictors, exhibiting the highest impact on the FOA across all income levels. Specifically, the months of the year account for a substantial portion of the variance in predicting the accidents, with a relative importance of %IncMSE = 28, 35, and 17 in the low-income, medium-income, and high-income categories, respectively. This suggests that temporal factors, such as seasonal variations or specific periods of the year, play a critical role in determining accident frequencies in different income groups.

Additionally, among the economic indicators considered, the price index demonstrates the most significant impact on accidents. Across the three income categories, the price index is identified as a prominent predictor, contributing significantly to the variability in accident rates. The relative importance values (%IncMSE) of 20, 20, and 9 for the price index in the low-income, medium-income, and high-income categories, respectively, indicate that, within each income category, a one-unit change in the price index is associated with an expected change of approximately 20 units in FOA for low-income individuals, 20 units for medium-income individuals, and 9 units for high-income individuals. This suggests that the price index has a stronger predictive effect on FOA for low and medium-income groups compared to the high-income group. This implies that changes in the price index have a substantial influence on the occurrence of occupational accidents, particularly in lower-income and middle-income occupations.

The insights provided by Fig. 6 offer valuable information for understanding the driving factors behind occupational accidents and their relationship with income levels. By identifying the months of the year and economic indicators as crucial predictors, stakeholders and policymakers can prioritize targeted interventions and preventive measures during specific periods and address the underlying factors associated with the price index.

However, it is important to note that while these predictors have shown significant importance in forecasting the accidents, other factors not considered in this study may also contribute to accident occurrence. Therefore, a comprehensive approach that incorporates multiple

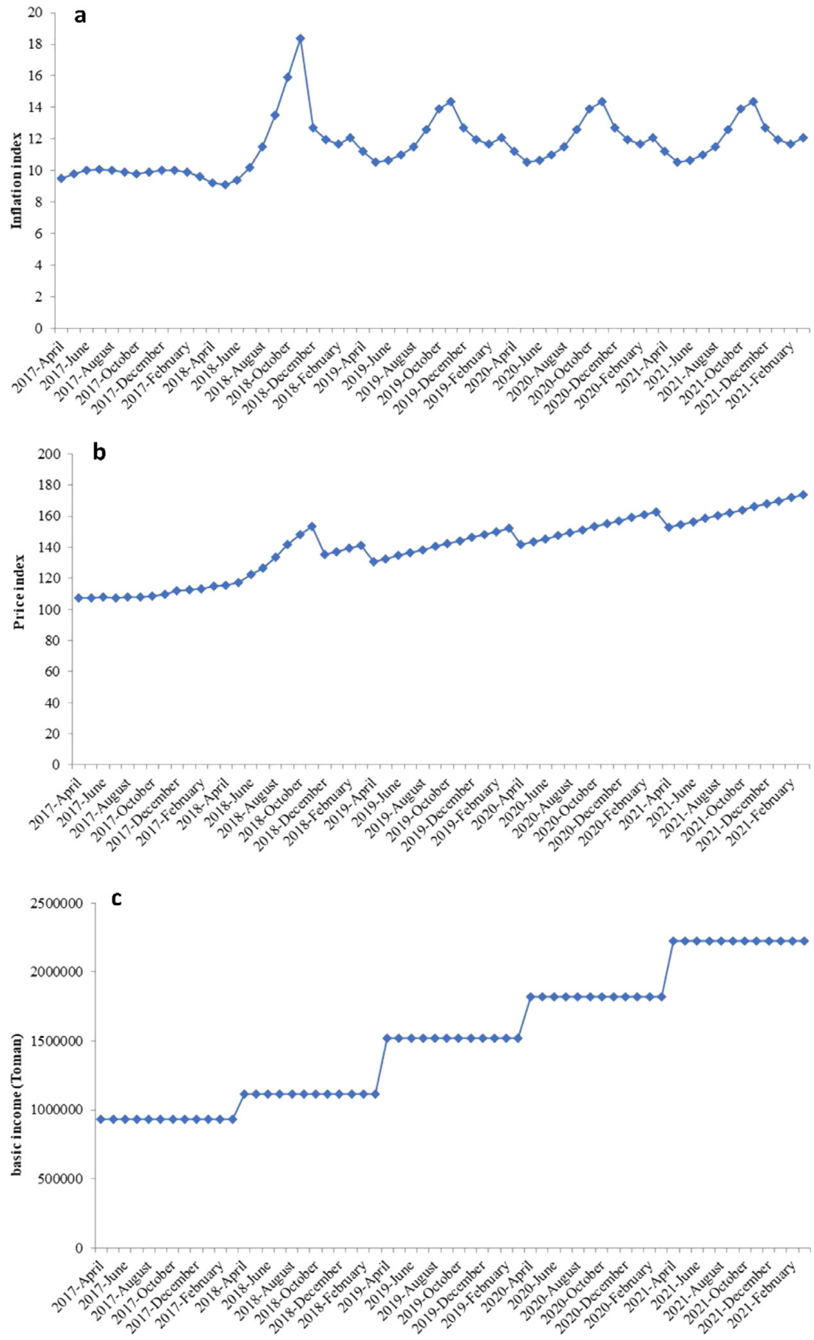

Fig. 4. Predicted economic indices from 2017 to 2021.

predictors and contextual factors is recommended for a more accurate prediction and effective accident prevention strategies.

5. Discussion

In this study, the findings shed light on several key aspects related to the economic and occupational accident trends over the period of 2007 to 2017. One of the significant observations was the considerable increase in the inflation index, price index, and basic income during this timeframe. Specifically, the inflation index experienced a five-fold increase, the price index rose 7.7 times, and the basic income witnessed an eight-fold increase. These upward trends signify a decline in the purchasing power of workers and a reduction in their overall economic welfare. Notably, between 2010 and 2013, the study identified a high inflation rate of 20%–30% along with a mere 15% increase in workers' income, further exacerbating the economic challenges faced by individuals.

Moreover, the findings revealed a striking correlation between the income level of workers and the occurrence of occupational accidents. Nearly 98% of the reported accidents took place among workers in low-income jobs, earning less than 5 million Tomans. This unequivocally underscores the undeniable influence of income level on the FOA. These results align with previous studies [14,15] that have emphasized the significant impact of income level on both the living and working conditions of individuals. The strong correlation between BI and FOA implies that workers with lower wages are more vulnerable to occupational accidents, potentially due to inadequate safety measures and working conditions associated with lower-income occupations.

Furthermore, the investigation into the trend of occupational accidents demonstrated a gradual decrease over time, with the lowest

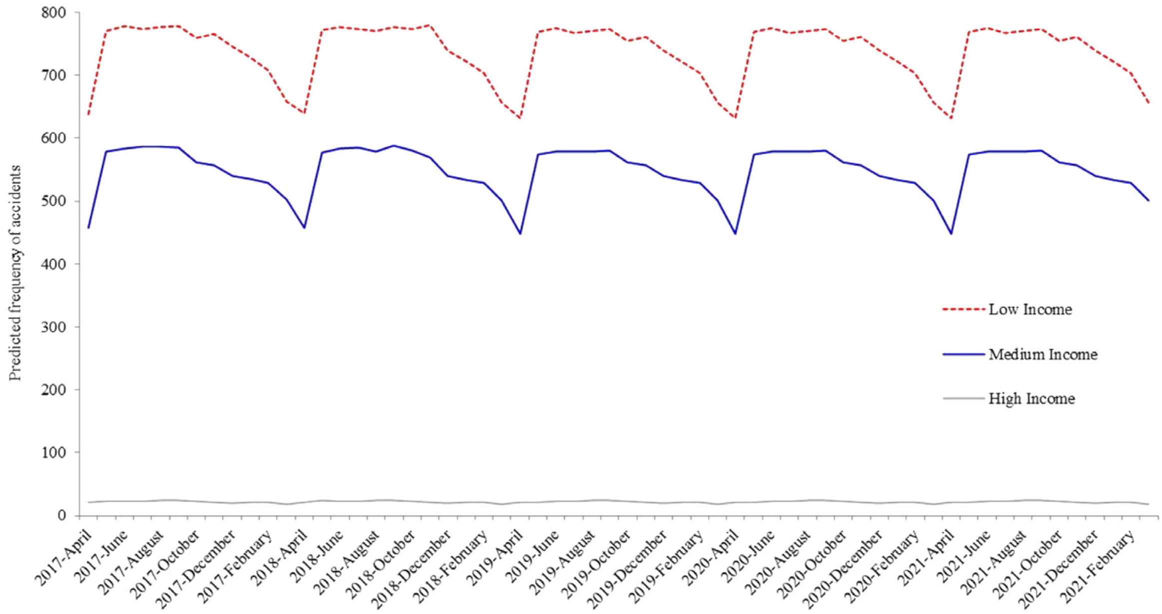

Fig. 5. Predicted frequency of accidents from 2017 to 2021.

FOA observed in 2015–2017. Remarkably, this finding coincided with the decline in the inflation rate during the same period. The study suggests that when the increase in primary income aligns with the rise in inflation, there is a substantial decrease in the FOA. These findings corroborate the research conducted by Tafti et al. (2012) [12] and Armesh et al. (2010) [13], who have identified inflation as a crucial socioeconomic factor influencing the lives of Iranians. The inverse relationship observed between the FOA and II underscores the importance of maintaining a stable economic environment and ensuring that income growth keeps pace with inflation to promote a safer working environment and reduce occupational accidents.

This study's findings emphasize the adverse impact of inflation and income levels on the occurrence of occupational accidents. The steady increase in inflation, coupled with limited income growth, has resulted in decreased purchasing power and compromised economic welfare for workers. Moreover, the concentration of accidents among low-income workers highlights the urgent need for interventions and policies targeting improved working conditions and safety measures in lower-income occupations. By addressing these socioeconomic factors and fostering an environment that promotes adequate income growth, it is possible to mitigate the occurrence of occupational accidents and enhance the overall well-being of workers.

These findings highlight the effectiveness of the selected models in accurately modeling and predicting monthly accidents. These models belong to the category of time series models, which are well-suited for capturing nonlinear patterns and handling high-complexity data. The comparison of these models revealed that the RF model outperformed the other three models in terms of precision when forecasting monthly accidents across the three income levels. The findings of the present study were in line with the study of Gatera et al. (2023) [37], despite their focus on road accidents. Both studies observed that the RF (Random Forest) model outperformed the SVM (Support Vector Machine) model by achieving a higher R2.

Furthermore, the assessment of goodness-of-fit indices consistently indicated that the RF model outperformed other models in forecasting and presenting both regular, recurring patterns of monthly accident values (periodic) and irregular, non-recurring patterns (non-periodic), regardless of the income level. The RF model exhibited better efficiency in capturing the variability of accidents and accurately predicting their occurrence compared to the SVM, MARS, and M5 models. Moreover, the RF model demonstrated the highest efficiency in capturing the peaks of accidents at all income levels.

The findings of this study reinforce the notion that the RF model possesses the capability to capture the underlying patterns in monthly accident data and identify the significant predictors influencing this outcome. This model's ability to leverage the collective insights of multiple decision trees and capture complex interactions among predictors contributes to its superior performance. By considering a diverse set of predictors and their interactions, this model effectively accounts for the intricate dynamics involved in the occurrence of accidents, resulting in more accurate and reliable forecasts.

The findings of this study support the adoption of the RF model as a valuable tool for organizations and policymakers in predicting and managing occupational accidents. The model's ability to accurately forecast accidents at different income levels can facilitate proactive measures to enhance workplace safety and reduce the incidence of accidents among workers. Additionally, the identification of crucial predictors by this model can guide interventions and strategies aimed at mitigating the factors contributing to accidents, ultimately promoting a safer work environment.

However, it is essential to acknowledge that no model is perfect, and there may be limitations and assumptions associated with the RF model and the other models evaluated in this study. Future research could focus on exploring additional predictors and refining the models to improve their forecasting accuracy further. Nonetheless, the present study establishes this model's efficacy in modeling and predicting monthly accidents and provides a solid foundation for its practical implementation in occupational safety and accident prevention initiatives.

The findings of this study highlight the substantial influence of monthly variations on the incidence of occupational accidents. These variations can be attributed to the prevailing social and economic conditions in Iran. Certain months exhibit unique circumstances, such as holidays, religious mournings, or celebrations, which impact the occurrence of accidents. These conditions may vary depending on the specific month and the corresponding social and cultural factors.

One important factor contributing to monthly variations is the observance of religious events and celebrations based on the Hijri lunar calendar. This calendar undergoes a yearly shift of approximately ten days, resulting in changes to the timing of religious observances. These events can have a significant impact on social activities and work patterns, potentially influencing the occurrence of occupational accidents. For instance, religious celebrations and mourning periods may entail specific customs and traditions that can affect the work

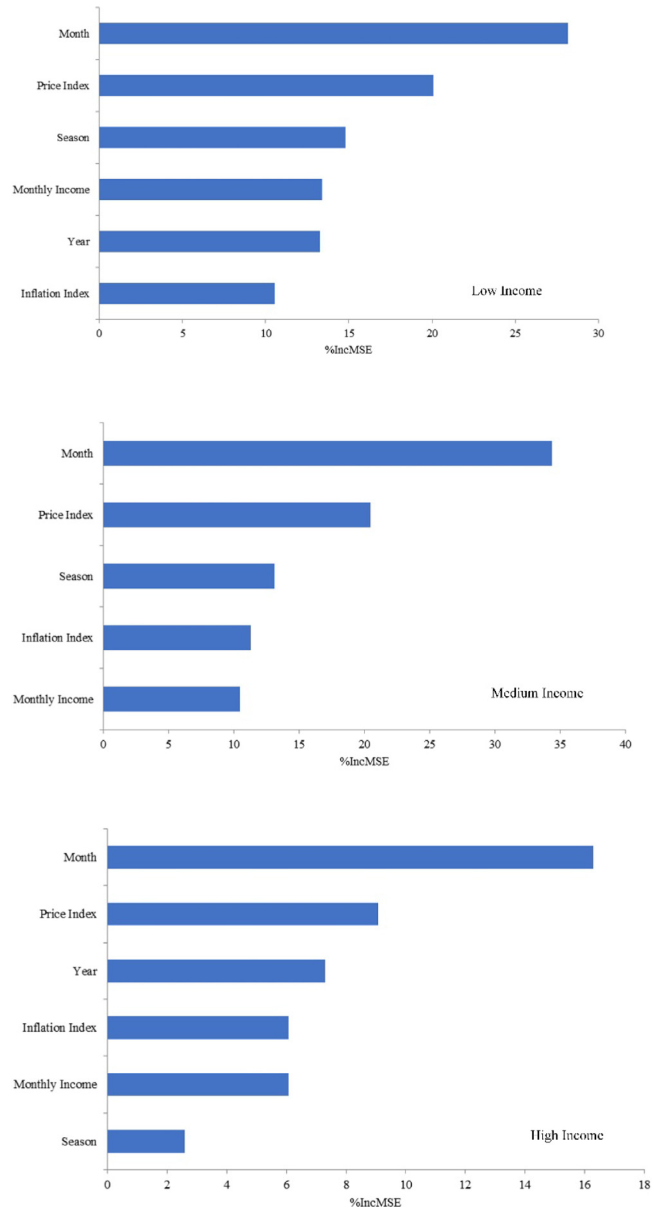

Fig. 6. The influencing factors for FOA.

environment and individuals' behavior, potentially increasing the risk of accidents during these periods.

Additionally, national celebrations in Iran are typically held in fixed months according to the official calendar. For example, the Nowruz holidays, which mark the Iranian New Year, consistently occur at the end of March and the beginning of April each year. These holidays are characterized by increased travel, gatherings, and festivities, which can introduce additional risks in various settings, including workplaces. The combination of increased activities, potential fatigue from holiday preparations, and the festive atmosphere may contribute to a higher likelihood of accidents during these periods.

Understanding the influence of monthly variations on accident rates is crucial for effective accident prevention strategies and resource allocation. Recognizing the specific months and conditions associated with higher accident risks can help inform targeted interventions and safety measures. For instance, during months with known high accident rates, employers and policymakers can implement enhanced safety protocols, provide additional training and supervision, and increase awareness campaigns to mitigate the potential risks.

It is worth noting that the study's focus on monthly variations in accident rates offers valuable insights into the temporal dynamics of accidents. However, it is important to consider other contextual factors that may interact with the monthly variations to further explain the occurrence of accidents. Future research could explore the interplay between monthly variations, socioeconomic factors, and cultural dynamics to gain a more comprehensive understanding of the underlying mechanisms influencing occupational accidents in Iran.

Our study's findings emphasize the significant impact of monthly variations on the incidence of occupational accidents in Iran. The observed patterns, influenced by social, cultural, and religious factors, highlight the need for targeted safety measures and accident prevention strategies. By identifying the months with higher accident risks, stakeholders can proactively address safety concerns and implement measures to ensure a safer work environment throughout the year.

Our study's findings highlight the significant influence of income levels and economic indicators on the FOA. The observed relationship between these factors and accidents may be attributed to job dissatisfaction and increased stress stemming from the prevailing economic crisis. Occupational stress has been widely acknowledged as a significant determinant of human performance, as it can lead to human error occurrence [81–83]. In fact, stress has been identified as one of the key factors influencing human reliability analysis [84–88].

Moreover, previous studies conducted by Hakimpoor et al. [89] and Zare et al. [90] have demonstrated a substantial link between the price index and the welfare of the Iranian population. However, these studies have also emphasized the need for more in-depth investigations into the causal relationship between the economy and job-related stress. It is crucial to understand the complex interplay between economic conditions, job stress, and their impact on occupational accidents.

To better comprehend these effects, it is necessary to consider a chain of conditions and psychological consequences. Workers face significant challenges when prices soar, as it becomes increasingly difficult to meet their families' basic needs such as food, housing, and clothing. Under such circumstances, workers are compelled to exert all their physical and mental capacities to make ends meet. The resulting family stress and the mental strain caused by coping with rising prices and inflation gradually deplete workers' psychological resilience. As a consequence, workers find themselves caught in a continuous cycle of financial pressure, leaving them mentally exhausted and distracted from their working conditions. Their attention becomes solely focused on addressing these economic challenges, leading to a deviation in thinking. This constant mental preoccupation compromises their ability to concentrate on workplace safety instructions and guidelines. The persistent mental fatigue and reduced concentration increase the likelihood of accidents due to lapses in attention and failure to adhere to safety protocols.

In light of these findings, it is imperative for employers, policymakers, and relevant stakeholders to recognize the significant impact of economic factors and income levels on job-related stress and occupational accidents. Efforts should be directed towards implementing effective strategies to mitigate stressors and promote a safe and supportive work environment. These strategies may include providing financial assistance programs, offering stress management resources, and fostering open communication channels to address workers' concerns. So future research should delve deeper into the causal mechanisms underlying the relationship between economic conditions, job stress, and occupational accidents. By gaining a more comprehensive understanding of these dynamics, policymakers and organizations can develop targeted interventions to reduce the incidence of accidents and improve overall worker well-being.

In addition, the findings of our study emphasize the close relationship between the economic criteria and the FOA in Iran. These economic criteria exert an indirect influence on FOA through their impact on workers' overall economic well-being and job satisfaction. Low economic well-being directly contributes to increased levels of stress among workers. Financial struggles, such as the inability to meet basic needs or provide for their families, add significant pressure and strain on individuals in the workplace. This financial stress becomes a primary source of intellectual conflicts for workers, as they constantly grapple with the challenges posed by economic hardship. The burden of financial worries and the associated strain on workers' mental capacities can significantly affect their job performance and well-being. These findings highlight the critical role played by economic factors in shaping the working conditions and safety outcomes of employees. It underscores the need for comprehensive interventions that address not only the physical aspects of workplace safety but also the socio-economic factors that impact workers' well-being. Policymakers and organizations should consider implementing measures aimed at improving economic conditions, providing financial support systems, and promoting job satisfaction and work-life balance to mitigate the negative consequences associated with economic distress.

Additionally, efforts to enhance workplace safety should encompass strategies to alleviate financial stressors and foster a supportive work environment. This may include initiatives such as financial counseling services, employee assistance programs, and policies that prioritize fair wages and benefits. By addressing the underlying economic factors contributing to job dissatisfaction and stress, organizations can create a safer and more conducive working environment, ultimately reducing the occurrence of occupational accidents.

Also, in this study, our accident prediction analysis provides a valuable complement to the research conducted by Zaranezhad et al. [30], who explored the application of SVM and other artificial intelligence methods in accident prediction. The consistent findings between our study and theirs further validate the efficacy of these advanced modeling techniques in the field of accident prediction. Furthermore, our results align with the findings presented by Sarkar et al. [33], who identified the RF method as a highly accurate and reliable approach for accident prediction. The convergence of our findings with theirs underscores the robustness and applicability of this method in predicting and mitigating occupational accidents across different contexts.

Moving forward, it is essential for future studies to investigate the complex interplay between psychological-cognitive factors and economic parameters in relation to occupational accidents. While our study focused on the influence of economic indicators on accident frequency, the role of psychological-cognitive aspects, such as worker mindset, decision-making processes, and attentional focus, should not be overlooked. Examining the interaction between these psychological-cognitive factors and economic parameters can provide a more comprehensive understanding of the underlying mechanisms contributing to occupational accidents.

Moreover, the integration of psychological-cognitive and economic parameters in accident prediction models has the potential to enhance the accuracy and effectiveness of preventive strategies. By considering both the psychological and economic dimensions, organizations can design targeted interventions that address the cognitive aspects of workers' behavior, while also accounting for the economic factors that shape their well-being and job satisfaction. This comprehensive approach can lead to more holistic safety management practices and contribute to the development of proactive measures for accident prevention in the workplace. So future research endeavors should strive to unravel the intricate relationships between these psychological-cognitive and economic parameters, employing advanced modeling techniques and data-driven analyses. A deeper understanding of these complex interactions will provide valuable insights for the design and implementation of tailored interventions and policies aimed at reducing occupational accidents and promoting a safer work environment.

The present study has several limitations that should be acknowledged. First, the data used in this study were extracted solely from the annual reports of the Social Security Organization. As a result, only accidents involving insured workers were considered, potentially overlooking a significant number of occupational accidents involving uninsured or informal workers. This limitation is particularly relevant for daily, seasonal, or migrant workers who may not be covered by insurance. Access to the Ministry of Labor's comprehensive database of work-related accidents in Iran could have provided a more comprehensive and representative sample.

Another limitation of this study was the lack of data availability for the years 2017 to 2022 due to organizational reasons within the Social Security Organization. This data gap restricted the temporal scope of the analysis, preventing a more up-to-date assessment of accident trends and patterns. Future studies should aim to overcome this limitation by incorporating more recent data from multiple sources, including the Ministry of Labor, the Social Security Organization, and forensic records.

Despite these limitations, the present study also had notable strengths. One of the main strengths was the inclusion of 10 years' worth of accident statistics covering various industries in Iran. This extensive time frame allowed for a comprehensive analysis of long-term trends and patterns in occupational accidents. Additionally, the technical strengths of the study, as demonstrated in Table 1, ensured a rigorous and robust analysis of the data. To address the limitations identified in this study, future studies could consider exploring additional variables and factors, such as organizational and cultural factors, to further deepen our understanding of the complexities surrounding occupational accidents and improve preventive strategies.

In conclusion, while this study contributes valuable insights into the relationship between economic indicators, occupational accidents, and accident prediction models in Iran, it is essential to acknowledge the limitations imposed by data availability and coverage. By addressing these limitations and building upon the strengths of this study, future research can advance our knowledge in this field and inform evidence-based policies and interventions aimed at reducing occupational accidents and promoting a safer working environment for all individuals.

6. Managerial and practical implications

The findings of this study underscore the significant impact of economic indicators on occupational accidents, highlighting the need for effective control strategies at both the government and organizational levels. Despite advancements in industrial safety and health, our projections indicate that occupational accidents are likely to persist over the next five years, emphasizing the urgency of addressing this issue.

At the government level, control measures should focus on logical regulation of the price and inflation indices. By implementing policies that prevent excessive price increases of consumer goods and minimize living costs for workers, the government can mitigate the economic pressures that contribute to accidents. This may involve interventions such as price controls, subsidies, or regulations that promote fair pricing practices in the market. Furthermore, the government should ensure that budgetary allocations are responsive to changes in economic indicators, enabling the determination of appropriate and sustainable levels of workers' basic income. Such measures will help preserve the purchasing power of workers and alleviate financial strain.

In addition to income-related interventions, the government can support workers by facilitating access to affordable housing through targeted loan programs. This assistance can significantly alleviate the economic crisis faced by workers, providing them with greater stability and financial security. By addressing the fundamental needs of workers, such as housing, the government can contribute to improving their overall economic well-being, which in turn may positively impact their occupational safety and reduce the likelihood of accidents.

At the organizational level, managers should implement various programs aimed at enhancing the financial situation of their workers. Ongoing incentives, such as performance-based bonuses or profit-sharing schemes, can serve as effective means of increasing workers' salaries and improving their economic conditions. Additionally, the distribution of essential foodstuffs or the provision of affordable meals within the workplace can help alleviate financial burdens and contribute to the well-being of workers. Moreover, constructing corporate housing facilities for workers can provide them with secure and affordable accommodation options, reducing their financial stress and improving their overall quality of life.

By combining government-level interventions to control economic indicators and organizational-level strategies to enhance workers' financial conditions, a comprehensive approach can be adopted to tackle the underlying factors contributing to occupational accidents. Such efforts require collaboration between policymakers, government agencies, and organizations to address the economic challenges faced by workers and promote a safer work environment. Future research should delve deeper into the effectiveness of these control strategies and explore additional measures that can further enhance occupational safety and health in the context of economic indicators.

7. Conclusion

In conclusion, this study has shed light on the persistent challenge of occupational accidents in Iran despite notable improvements in occupational safety and health. The projected stability in the number of accidents over the coming years can be attributed to the combination of rising inflation, growing price indices, and only marginal annual increases in workers' primary income. These economic factors contribute to an unfavorable crisis for working families, emphasizing the need for measures aimed at enhancing the economic welfare of workers, particularly those in low-income brackets.

Addressing the economic challenges faced by workers is not only crucial for their well-being but also has broader implications for the development of the industrial and economic cycles in Iran. By reducing the frequency of occupational accidents and improving work sustainability, these measures can contribute to a more stable and productive industrial environment. The findings of this study highlight the significance of utilizing machine learning approaches, particularly the RF method, as accurate and effective tools for predicting the incidence of occupational accidents based on economic criteria.

The insights gained from this study can serve as valuable management tools for controlling and preventing occupational accidents. The critical findings underscore the importance of the II as the most influential economic indicator impacting occupational accidents. Despite the considerable advancements in safety measures over the past decade, the study projects a sustained number of accidents in the next five years (2017–2021), primarily driven by the significant increases in the inflation and price indices in comparison to the basic income.

To address this issue, the study proposes appropriate policies aimed at curbing inflation and balancing price indices with the basic income. These policy interventions are crucial for reducing the number of occupational accidents in the future. The implementation of such measures requires collaborative efforts from government bodies, policymakers, and organizations to prioritize the economic welfare of workers and ensure a safer work environment.

While this study has provided valuable insights into the relationship between economic indicators and occupational accidents, it is essential to acknowledge its limitations. The study's reliance on data extracted from annual Social Security Organization reports only captures accidents among insured workers, thereby overlooking many employees who may have been involved in work-related accidents but are not covered by insurance, such as daily, seasonal, or migrant workers. Access to comprehensive databases, such as the Ministry of Labor's database, could address this limitation and provide a more comprehensive understanding of work-related accidents in Iran.

Furthermore, the findings of this study emphasize the significance of considering economic factors in occupational safety and health management. Future research should continue to explore the causal links between economic indicators and job stress, as well as investigate additional strategies to improve the economic welfare of workers and mitigate the occurrence of occupational accidents. By adopting a comprehensive and multidisciplinary approach, stakeholders can work together to create safer and more sustainable work environments in Iran and beyond.

Also, the study utilized data from 2007 to 2016, and access to data on incidents from 2016 to 2022 was unavailable, which restricted the predictions to the period of 2017 to 2021. Nevertheless, the notable increase in the inflation rate in Iran in 2022 further underscores the relevance and importance of this study's findings.

One notable limitation of the present study is the lack of comparable studies to assess the consistency of its results with existing literature. The absence of similar studies hinders direct comparisons and limits the ability to establish a broader context for the findings. Future research endeavors should aim to address this gap by conducting comparative studies and examining the psychological impact of inflation indicators on human error. Furthermore, there is a need for integrated organizational models that encompass the economic crisis, industrial conditions, occupational accidents, the politicization of ministries, and human factors.

By undertaking such multidimensional research, it will be possible to deepen our understanding of the complex interplay between economic factors, organizational dynamics, and human behavior in the context of occupational accidents. These insights can inform the development of comprehensive strategies and policies to mitigate the impact of economic crises on worker safety and well-being. Ultimately, the aim is to create safer and more resilient work environments that promote the health, productivity, and economic prosperity of workers in Iran and beyond.

While the present study has provided valuable findings and recommendations, further research is needed to expand upon the current knowledge base. Future studies should strive to overcome data limitations, conduct comparative analyses, and explore the psychological implications of economic indicators on human error. By incorporating a holistic approach that considers various organizational and societal factors, we can gain a deeper understanding of the complexities surrounding occupational accidents and develop more effective strategies to mitigate their occurrence.

Declaration of competing interest

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

Data availability

The authors do not have permission to share data.

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References

[1] X. Luo, X. Li, Y.M. Goh, X. Song, Q. Liu, Application of machine learning technology for occupational accident severity prediction in the case of construction collapse accidents, Saf. Sci. 163 (2023) 106138.

[2] L. Boudra, Y. Lémonie, V. Grosstephan, A. Nascimento, The cultural-historical development of occupational accidents and diseases prevention in France: A scoping review, Saf. Sci. 159 (2023) 106016.

[3] I. Mohammadfam, K. Gholamizadeh, Investigation of causes of plasco building accident in Iran using timed MTO and ACCIMAP methods, J. Fail. Anal. Prev. 20 (6) (2020) 2087–2096.

[4] N.G. Mutlu, S. Altuntas, T. Dereli, The evaluation of occupational accident with sequential pattern mining, Saf. Sci. 166 (2023) 106212.

[5] S.S. Oliveira, W. de Albuquerqu Soares, B.M. Vasconcelos, Fatal fall-from-height accidents: Statistical treatment using the Human Factors Analysis and Classification System–HFACS, J. Saf. Res. (2023).

[6] K. Gholamizadeh, M. Alauddin, M.M. Aliabadi, A. Soltanzade, I. Mohammadfam, Comprehensive failure analysis in tehran refinery fire accident: Application of accimap methodology and quantitative domino effect analysis, Fire Technol. 59 (2) (2023) 453–472.

[7] Eurostat, Accidents At Work Statistics, Luxembourg, 2022, Accidents statistics.

[8] P. Shafiei, M. Jabbari, M. Mirza Ebrahim Tehrani, Cause–responsibility analysis of occupational accidents in an automotive company, Int. J. Occup. Saf. Ergon. (2022) 1–10.

[9] A. Joghataei, R. Gholamnia, S.S. Khaloo, S. Khodakarim, R. Saeedi, Burden of injury due to occupational accidents and its spatiotemporal trend at the national and subnational levels in Iran 2011–2018, Int. Arch. Occup. Environ. Health (2023) 1–16.

[10] O. Mehmet, Economic Planning and Social Justice in Third World Countries, Routledge, 2014.

[11] M.R. Farzanegan, B. Hayo, Sanctions and the shadow economy: empirical evidence from Iranian provinces, Appl. Econ. Lett. 26 (6) (2019) 501–505.

[12] F.C. Tafti, Determinants of inflation in Islamic Republic of Iran, Int. J. Bus. Soc. Sci. 3 (6) (2012).

[13] H. Armesh, H. Salarzehi, N. Mohammad, Causes of inflation in the Iranian economy, Int. Rev. Bus. Res. Pap. 6 (3) (2010) 30–44.

[14] S.L. Baron, S. Beard, L.K. Davis, L. Delp, L. Forst, A. Kidd-Taylor, et al., Promoting integrated approaches to reducing health inequities among low-income workers: Applying a social ecological framework, Am. J. Ind. Med. 57 (5) (2014) 539–556.

[15] D. Martinez-Lopez, The underreporting of income by self-employed workers in Spain, SERIEs 4 (4) (2013) 353–371.

[16] D. Card, A. Mas, E. Moretti, E. Saez, Inequality at work: The effect of peer salaries on job satisfaction, Am. Econ. Rev. 102 (6) (2012) 2981–3003.

[17] D. Eskandari, M.J. Jafari, Y. Mehrabi, M.P. Kian, H. Charkh, M. Mirghotbi, A qualitative study on organizational factors affecting occupational accidents, Iran. J. Public Health 46 (3) (2017) 380.

[18] J. Ravenhill, Global Political Economy, Oxford University Press, 2017.

[19] S. Sarkar, S. Vinay, R. Raj, J. Maiti, P. Mitra, Application of optimized machine learning techniques for prediction of occupational accidents, Comput. Oper. Res. 106 (2019) 210–224.

[20] C.-W. Liao, Y.-H. Perng, Data mining for occupational injuries in the Taiwan construction industry, Saf. Sci. 46 (7) (2008) 1091–1102.

[21] L.N. Grendas, L. Chiapella, D.E. Rodante, F.M. Daray, Comparison of traditional model-based statistical methods with machine learning for the prediction of suicide behaviour, J. Psychiatr. Res. 145 (2022) 85–91.

[22] E. Zarei, F. Khan, R. Abbassi, How to account artificial intelligence in human factor analysis of complex systems? Process Saf. Environ. Prot. (2023).

[23] C.-W. Liao, T.-L. Chiang, Occupational injuries among non-standard workers in the Taiwan construction industry, J. Saf. Res. 82 (2022) 301–313.

[24] K. Koc, A.P. Gurgun, Scenario-based automated data preprocessing to predict severity of construction accidents, Autom. Constr. 140 (2022) 104351.

[25] M. Amoadu, E.W. Ansah, Sarfo J.O., Psychosocial work factors, road traffic accidents and risky driving behaviours in low-and middle-income countries: A scoping review, IATSS Res. (2023).

[26] T. Yang, H. Zeng, X. Yang, J. Kong, X. Chen, N. Zhou, et al., Characteristics of road traffic accident types and casualties in guangzhou, China, from 2007 to 2020: A retrospective cohort study based on the general population, Heliyon 9 (1) (2023).

[27] K. Kang, H. Ryu, Predicting types of occupational accidents at construction sites in Korea using random forest model, Saf. Sci. 120 (2019) 226–236.

[28] R. Zhu, X. Hu, J. Hou, X. Li, Application of machine learning techniques for predicting the consequences of construction accidents in China, Process Saf. Environ. Prot. 145 (2021) 293–302.

[29] A. Yedla, F.D. Kakhki, A. Jannesari, Predictive modeling for occupational safety outcomes and days away from work analysis in mining operations, Int. J. Environ. Res. Public Health 17 (19) (2020) 7054.

[30] A. Zaranezhad, H.A. Mahabadi, M.R. Dehghani, Development of prediction models for repair and maintenance-related accidents at oil refineries using artificial neural network, fuzzy system, genetic algorithm, and ant colony optimization algorithm, Process Saf. Environ. Prot. 131 (2019) 331–348.

[31] J.Y. Lee, Y.G. Yoon, T.K. Oh, S. Park, S.I. Ryu, A study on data pre-processing and accident prediction modelling for occupational accident analysis in the construction industry, Appl. Sci. 10 (21) (2020) 7949.

[32] F.D. Kakhki, S.A. Freeman, G.A. Mosher, Evaluating machine learning performance in predicting injury severity in agribusiness industries, Saf. Sci. 117 (2019) 257–262.

[33] S. Sarkar, A. Pramanik, J. Maiti, G. Reniers, Predicting and analyzing injury severity: A machine learning-based approach using class-imbalanced proactive and reactive data, Saf. Sci. 125 (2020) 104616.

[34] S. Sarkar, A. Patel, S. Madaan, J. Maiti (Eds.), Prediction of occupational accidents using decision tree approach, in: 2016 IEEE Annual India Conference (INDICON), IEEE, 2016.

[35] H. Baker, M.R. Hallowell, AJ-P. Tixier, AI-based prediction of independent construction safety outcomes from universal attributes, Autom. Constr. 118 (2020) 103146.

[36] A. Zermane, M.Z.M. Tohir, H. Zermane, M.R. Baharudin, H.M. Yusoff, Predicting fatal fall from heights accidents using random forest classification machine learning model, Saf. Sci. 159 (2023) 106023.

[37] A. Gatera, M. Kuradusenge, G. Bajpai, C. Mikeka, S. Shrivastava, Comparison of random forest and support vector machine regression models for forecasting road accidents, Sci. Afr. 21 (2023) e01739.

[38] J.V. Winters, Wages and prices: Are workers fully compensated for cost of living differences? Reg. Sci. Urban Econ. 39 (5) (2009) 632–643.

[39] J.K. Afriyie, K. Tawiah, W.A. Pels, S. Addai-Henne, H.A. Dwamena, E.O. Owiredu, et al., A supervised machine learning algorithm for detecting and predicting fraud in credit card transactions, Decis. Anal. J. 6 (2023) 100163.

[40] R. Sawhney, A. Malik, S. Sharma, V. Narayan, A comparative assessment of artificial intelligence models used for early prediction and evaluation of chronic kidney disease, Decis. Anal. J. 6 (2023) 100169.

[41] T.P. Barnett, L. Dümenil, U. Schlese, E. Roeckner, M. Latif, The effect of Eurasian snow cover on regional and global climate variations, J. Atmos. Sci. 46 (5) (1989) 661–686.

[42] S.K.S. Durai, M.D. Shamili, Smart farming using machine learning and deep learning techniques, Decis. Anal. J. 3 (2022) 100041.

[43] N. Shirmohammadi-Khorram, L. Tapak, O. Hamidi, Z. Maryanaji, A comparison of three data mining time series models in prediction of monthly brucellosis surveillance data, Zoonoses Public Health 66 (7) (2019) 759–772.

[44] C. Feng Chang, M. Astitha, Y. Yuan, C. Tang, P. Vlahos, V. Garcia, et al., A new approach to predict tributary phosphorus loads using machine learning and physics-based modeling systems, Artif. Intell. Earth Syst. (2023) 1–43.

[45] G. James, D. Witten, T. Hastie, R. Tibshirani, Statistical learning, in: An Introduction To Statistical Learning, Springer, 2013, pp. 15–57.

[46] M. Bansal, A. Goyal, A. Choudhary, A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning, Decis. Anal. J. 3 (2022) 100071.

[47] A. Cengiz, M. Budak, N. Yağmur, F. Balçik, Comparison between random forest and support vector machine algorithms for LULC classification, Int. J. Eng. Geosci. 8 (1) (2023) 1–10.

[48] A. Roy, S. Chakraborty, Support vector machine in structural reliability analysis: A review, Reliab. Eng. Syst. Saf. (2023) 109126.

[49] M.M. Hassan, M.M. Hassan, F. Yasmin, M.A.R. Khan, S. Zaman, K.K. Islam, et al., A comparative assessment of machine learning algorithms with the Least Absolute Shrinkage and Selection Operator for breast cancer detection and prediction, Decis. Anal. J. 7 (2023) 100245.

[50] V. Díaz, R. Montoya, S. Maldonado, Preference estimation under bounded rationality: Identification of attribute non-attendance in stated-choice data using a support vector machines approach, European J. Oper. Res. 304 (2) (2023) 797–812.

[51] O. Hamidi, J. Poorolajal, M. Sadeghifar, H. Abbasi, Z. Maryanaji, H.R. Faridi, et al., A comparative study of support vector machines and artificial neural networks for predicting precipitation in Iran, Theor. Appl. Climatol. 119 (3–4) (2015) 723–731.

[52] P.-Y. Hao, J.-H. Chiang, Y.-D. Chen, Possibilistic classification by support vector networks, Neural Netw. 149 (2022) 40–56.

[53] H. Yoon, S.-C. Jun, Y. Hyun, G.-O. Bae, K.-K. Lee, A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer, J. Hydrology. 396 (1–2) (2011) 128–138.

[54] L. Tapak, N. Shirmohammadi-Khorram, P. Amini, B. Alafchi, O. Hamidi, J. Poorolajal, Prediction of survival and metastasis in breast cancer patients using machine learning classifiers, Clin. Epidemiol. Glob. Health 7 (3) (2019) 293–299.

[55] P. Chhajer, M. Shah, A. Kshirsagar, The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction, Decis. Anal. J. 2 (2022) 100015.

[56] J. Li, J. Guo, J.S. Wijnands, R. Yu, C. Xu, M. Stevenson, Assessing injury severity of secondary incidents using support vector machines, J. Transp. Saf. Secur. 14 (2) (2022) 197–216.

[57] J. Tu, L. Hu, K.J. Mohammed, B.N. Le, P. Chen, E. Ali, et al., Application of logistic regression, support vector machine and random forest on the effects of titanium dioxide nanoparticles using macroalgae in treatment of certain risk factors associated with kidney injuries, Environ. Res. 220 (2023) 115167.

[58] J. Sharma, S.K. Mitra, Developing a used car pricing model applying Multivariate Adaptive Regression Splines approach, Expert Syst. Appl. (2023) 121277.

[59] A.H. Naser, A.H. Badr, S.N. Henedy, K.A. Ostrowski, H. Imran, Application of Multivariate Adaptive Regression Splines (MARS) approach in prediction of compressive strength of eco-friendly concrete, Case Stud. Constr. Mater. 17 (2022) e01262.

[60] A. Özmen, Y. Zinchenko, G.-W. Weber, Robust multivariate adaptive regression splines under cross-polytope uncertainty: an application in a natural gas market, Ann. Oper. Res. 324 (1–2) (2023) 1337–1367.

[61] K. Mushtaq, R. Zou, A. Waris, K. Yang, J. Wang, J. Iqbal, et al., Multivariate wind power curve modeling using multivariate adaptive regression splines and regression trees, Plos One 18 (8) (2023) e0290316.

[62] O. Kisi, K.S. Parmar, Application of least square support vector machine and multivariate adaptive regression spline models in long term prediction of river water pollution, J. Hydrol. 534 (2016) 104–112.

[63] A. Costantino, B.M. Festa, G. Spriano, A. De Virgilio, The use of machine learning for predicting complications of free flap head and neck reconstruction: Caution needed, Ann. Surg. Oncol. 30 (7) (2023) 4232–4233.

[64] A. Bose, C.-H. Hsu, S.S. Roy, K.C. Lee, B. Mohammadi-Ivatloo, S. Abimannan, Forecasting stock price by hybrid model of cascading multivariate adaptive regression splines and deep neural network, Comput. Electr. Eng. 95 (2021) 107405.

[65] B. Keshtegar, J. Piri, W.U. Hussan, K. Ikram, M. Yaseen, O. Kisi, et al., Prediction of sediment yields using a data-driven radial M5 tree model, Water 15 (7) (2023) 1437.

[66] M. Kheradm, M.A. Moghaddam, A. Zahiri, K. Ghorbani, Determining of stage-discharge relationship for meandering compound channels using M5 decision tree model, Int. J. Civ. Environ. Eng. 17 (7) (2023) 284–288.

[67] O. Kisi, J. Shiri, V. Demir, Hydrological time series forecasting using three different heuristic regression techniques, in: Handbook of Neural Computation, Elsevier, 2017, pp. 45–65.

[68] O. Kisi, B. Keshtegar, M. Zounemat-Kermani, S. Heddam, N.-T. Trung, Modeling reference evapotranspiration using a novel regression-based method: radial basis M5 model tree, Theor. Appl. Climatol. 145 (1–2) (2021) 639–659.

[69] G. Goel, S. Sachdeva, M. Pal, Modelling of tensile strength ratio of bituminous concrete mixes using support vector machines and M5 model tree, Int. J. Pavement Res. Technol. 15 (1) (2022) 86–97.

[70] J. Quinlan, Learning with continuous classes, in: A. Adams, L. Sterling (Eds.), 'AI'92: Proceedings of the 5th Australian Joint Conference on Artificial Intelligence, World Scientific, Singapore, 1992, pp. 343–348.

[71] Y.-C. Wang, T. Chen, M.-C. Chiu, An explainable deep-learning approach for job cycle time prediction, Decis. Anal. J. 6 (2023) 100153.

[72] A.K.H. Agbemenou, R. Motamed, A. Talaei-Khoei, A predictive analytics model for designing deep underground foundations using artificial neural networks, Decis. Anal. J. 7 (2023) 100220.

[73] S.M. Robeson, C.J. Willmott, Decomposition of the mean absolute error (MAE) into systematic and unsystematic components, Plos One 18 (2) (2023) e0279774.

[74] S. Lahmiri, S. Bekiros, C. Avdoulas, A comparative assessment of machine learning methods for predicting housing prices using Bayesian optimization, Decis. Anal. J. 6 (2023) 100166.

[75] S. Ohadi, S.A. Hashemi Monfared, M. Azhdary Moghaddam, M. Givehchi, Feasibility of a novel predictive model based on multilayer perceptron optimized with Harris hawk optimization for estimating of the longitudinal dispersion coefficient in rivers, Neural Comput. Appl. 35 (9) (2023) 7081–7105.

[76] M. Yazdi, N.A. Golilarz, A. Nedjati, K.A. Adesina, An improved lasso regression model for evaluating the efficiency of intervention actions in a system reliability analysis, Neural Comput. Appl. (2021) 1–16.

[77] D. Meyer, E. Dimitriadou, K. Hornik, A. Weingessel, F. Leisch, C.-C. Chang, et al., Package 'e1071'. R J, 2019.

[78] S. RColorBrewer, M.A. Liaw, Package 'RandomForest', University of California, Berkeley, Berkeley, CA, USA, 2018.

[79] M.S. Milborrow, Package 'earth', 2019, R Software package.

[80] K. Hornik, C. Buchta, T. Hothorn, A. Karatzoglou, D. Meyer, A. Zeileis, et al., Package 'RWeka', 2020.

[81] E. Zarei, F. Khan, R. Abbassi, An advanced approach to the system safety in sociotechnical systems, Saf. Sci. 158 (2023) 105961.

[82] E. Zarei, F. Khan, R. Abbassi, A dynamic human-factor risk model to analyze safety in sociotechnical systems, Process Saf. Environ. Prot. 164 (2022) 479–498.

[83] K. Gholamizadeh, E. Zarei, M. Yazdi, E. Ramezanifar, M.M. Aliabadi, A hybrid model for dynamic analysis of domino effects in chemical process industries, Reliab. Eng. Syst. Saf. 241 (2024) 109654.

[84] K. Gholamizadeh, E. Zarei, M. Omidvar, M. Yazdi, Fuzzy sets theory and human reliability: Review, applications, and contributions, in: M. Yazdi (Ed.), Linguistic Methods under Fuzzy Information in System Safety and Reliability Analysis, Springer International Publishing, Cham, 2022, pp. 91–137.

[85] M. Azadeh, A. Keramati, I. Mohammadfam, B. Jamshidnedjad, Enhancing the availability and reliability of power plants through macroergonomics approach 65 (2006) 873-878.

[86] E. Zarei, F. Khan, R. Abbassi, Importance of human reliability in process operation: a critical analysis, Reliab. Eng. Syst. Saf. 211 (2021) 107607.

[87] F. Ghasemi, K. Gholamizadeh, A. Farjadnia, A. Sedighizadeh, O. Kalatpour, Human and organizational failures analysis in process industries using FBN-HFACS model: Learning from a toxic gas leakage accident, J. Loss Prev. Process Ind. 78 (2022) 104823.

[88] K. Gholamizadeh, F. Ghasemi, Z. Pashootan, O. Kalatpour, Quantitative analysis on time delay factors influencing firefighters' response time in the process industries using fuzzy sets theory, Int. J. Occup. Hyg. 14 (1) (2022) 1–17.

[89] N. Hakimipoor, H. Ms-Akbaryan, Investigation on Causality Relationship Between Consumer Price Index and Producer Price Index in Iran, Hikari, Iran, 2016.

[90] H. Zare, A.J. Trujillo, J. Driessen, M. Ghasemi, G. Gallego, Health inequalities and development plans in Iran; an analysis of the past three decades (1984–2010), Int. J. Equity Health 13 (1) (2014) 42.