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Article

A Comprehensive Assessment of Mining Accident Severity Using Machine Learning Methods

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ABSTRACT

The mining sector is recognized as one of the riskiest in the world. However, there is a lack of a comprehensive understanding of the factors influencing accident severity. In this study, eight machine learning (ML) methods were systematically evaluated, among which Gradient Boosting and Random Forest emerged as the top-performing models. These ensemble models demonstrated consistently high performance across multiple evaluation metrics (Accuracy, Precision, Recall, F1-score, and ROC AUC), highlighting their robustness and reliability in distinguishing between fatal and non-fatal accident outcomes. Across both impurity-based (Gini importance) and robust model-agnostic (SHAP) frameworks, Risk Taking, Age, and Experience emerge as the most influential predictors. Social engagement metrics vary in importance, collectively indicating that social support systems may play a meaningful role in moderating the severity of accidents. These findings substantiate the utility of machine learning not only for accurate outcome classification but also for elucidating the multifaceted drivers of accident severity, thereby informing targeted intervention and prevention strategies.

KEYWORDS

Behavioral factors, mining industry, safety, accidents, machine learning.

1. Introduction

According to Zhang et al. (2020, 2017, 2016), the mining sector is recognized as one of the riskiest in the world, with a significant likelihood of mishaps or devastating events. Numerous studies have examined safety management theories to investigate the causes of safety incidents and have demonstrated that employees' unsafe behavior is the primary factor contributing to safety mishaps (Choudhry & Fang, 2008). There are certain commonalities between mining accidents, dangers, and disasters in terms of their substantial effects on the victims (Lyra, 2019), mine owners (Li et al., 2019), mine workers (Aliabadi et al., 2018), governments (Pons, 2016), policy-makers (Kong et al., 2018), economy (Zhang et al., 2020) and local communities (Lyra, 2019), as well the environment and human health (Omachi et al., 2018; Zhang et al., 2016). Poor safety culture has been cited as the cause of most

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significant incidents in the mining industry in recent years (Zhang et al., 2020). Developing a safety culture is one practical strategy to reduce mining accidents. According to the study, the factors that had the biggest impact on developing a positive safety culture were the behavioral component (47%), the situational dimension (29%), and the psychological dimension (24%) (Ismail, Ramli, and Aziz, 2021). Mine accident research often employs statistical analyses based on large datasets (Kecojevic, 2007; Baraza, 2023) and mathematical modeling studies based on partial data (Fatma Yaşlı & Bersam Bolat, 2018; Theophilus Joe-Asare, 2023). Due to their efficiency and automation, data mining and machine learning approaches are increasingly being used by researchers in this sector as artificial intelligence technology advances (Dimitrios Ziakkas & Konstantinos Pechlivanis, 2023).

According to Anurag Yedla (2020), predictive modeling combined with machine learning techniques has been recognized as beneficial (Sandoval et al., 2023). The approach was used to examine the relationship between mining injuries and missed workdays in the United States between 2000 and 2018, with the artificial neural network yielding the best results. Decision tree and artificial neural network approaches demonstrated notable performance in classifying and forecasting outcomes across 22,386 mining accidents in another study, which also found that machine learning techniques were effective in analyzing the influence of factors on lost-time accidents in mining. (Muhammet Mustafa Kahraman, 2021). Additionally, with an impressive accuracy score of 0.96, the hybrid classifier model (Javaid, 2023), based on numerous machine learning algorithms, performed best in classifying the cause of 46096 coal mining accidents.

Additionally, the use of machine learning to research specific types of mine accidents has become more sophisticated and is starting to take off. For example, determining the sources of mine water inrush (Jiang, 2022), predicting mine fire levels (Forssten, 2021), identifying gas hazards (Mayank Sharma & Tanmoy Maity, 2024), and excavating accident paths (Xuecai, 2022). Taken together, these machine learning technologies greatly improve workplace safety and accident prevention. They also demonstrate the reliability and robustness of machine learning methods for incident evaluation in underground coal mines.

Research on using machine learning to examine the relationship between accident severity and accident-causing factors is noticeably lacking, however. Such studies typically use statistical techniques for comparative analysis (Baraza, 2023; Yang, 2022), which makes it challenging to prioritize accident-control measures and identify the primary factors that determine accident severity. This is an area where machine learning naturally excels, as it can use feature importance to assess the relative importance of factors in predicting accident severity.

Machine learning offers significant benefits for detecting the contributing factors most likely to cause coal mine accidents and for distinguishing among minor, major, and deadly mining accidents. (Pinelli et al., 2020). Exploring the effect of elements in underground coal mine accidents using machine learning approaches is therefore very important. Appropriate mitigation, control, and preventative measures can be suggested based on the knowledge gathered by machine learning. In future mining operations, the probability and severity of mine accidents could be greatly reduced if risk-reduction strategies are reinforced and worker safety education is improved.

However, a notable gap exists: research using machine learning to examine the relationship between accident severity and contributing factors is limited. Existing studies typically rely on statistical comparisons, which do not systematically prioritize accident control measures or identify the principal factors determining severity gradation. Machine learning naturally excels at this task through feature importance metrics that quantify the relative contribution of factors to outcomes.

Compared with prior applications of machine learning in mining safety that focus on predicting accident occurrence, lost-time injuries, or specific hazards such as gas or water inrush, this study makes three key contributions. First, it directly models accident severity across four distinct levels, enabling prioritization of conditions associated with major and serious outcomes. Second, it jointly incorporates demographic, behavioral, and social-support factors, offering a more holistic view of the drivers of severity beyond traditional organizational or technical factors alone. Third, by combining multiple algorithms with both permutation importance and SHAP, the analysis not only identifies the most accurate models but also yields transparent, operationally interpretable insights for disaster risk reduction and safety management.

2. Literature Review

We will define and categorize these influencing elements based on earlier research, and we will examine their linkages in this part to clarify the relationship between the influencing factors and miners' conduct.

2.1. Factors affecting workers' unsafe behavior

To investigate the primary drivers of workers' risky behavior, researchers have examined a wide range of factors. The main individual factors are individual characteristics (Amponsah-Tawiah & Mensah, 2016; Seo et al., 2015), working stress (Duma et al., 2014; Melamed et al., 1989), educational level (Choudhry & Fang, 2008) and the main organizational factors are safety climate (Andrew Neal, 2000; DeJoy et al., 2010; Glendon & Litherland, n.d.; Kapp, 2012), safety culture (DeJoy et al., 2010) and safety management system (Han et al., 2014; Tharaldsen et al., 2008).

Furthermore, these academics disagree on the critical elements that influence workers' risky conduct. (DeJoy et al., 2010; Mohaghegh & Mosleh, 2009) identified the system, working pressure, and working intensity as the primary determinants of employee behavior. Using factor analysis, Glendon and Litherland further highlighted the significance of supervision and guidance in workers' safety behavior. There is a strong correlation between coal mine fatigue and accidents; thus, extra care was needed (Duma et al., 2014).

The study mentioned above leads us to conclude that different perspectives on the connections between contributing variables and employees' unsafe behavior have not been articulated. Additionally, researchers' examination of influencing variables primarily concentrates on two elements: organizational and human characteristics.

2.2. Individual factors

Employee behavior is significantly influenced by individual factors, including age, sex, education level, and years of experience, as per the findings of Deniz S. Ones (2002). Several researchers have also suggested that factors affecting employees' behavior include their own sense of safety, workplace pressures, and coworkers' actions. The theory of planned behavior (TPB) states that an individual's perception of how important others think safety is, or how important a given conduct is, may significantly influence both their intention to engage in that behavior and their subsequent behavior (Beck & Ajzen, 1991). Coal miners are more likely to engage in unsafe behaviors because they are typically under significant stress at work.

2.3. Organizational factors

Environmental support, which includes leaders' commitment, coworkers' concern, and the safety atmosphere, is a significant component of organizational variables that has drawn increased attention from researchers, as it may be a major influence on safety mishaps (Choudhry & Fang, 2008). Furthermore, comparable research has shown a strong correlation between workers' safety behavior and leaders' and colleagues' attitudes, both qualitatively and quantitatively. (Fugas et al., 2012; Mullen, 2004). The quality, management practices, and rules of inspectors are the primary means by which the rationality of the organizational safety management system is demonstrated, and they significantly influence the prevention of workers from acting in an unsafe way. (Choudhry & Fang, 2008; Han et al., 2014; Jitwasinkul et al., 2016).

2.4. Relationship among influencing factors and employees' behavior

After analyzing the aforementioned research, we discovered that organizational and individual factors are interconnected and together influence employees' behavior in dynamic ways. Particularly for organizations that exhibit low organizational synergy, individual characteristics exert a greater influence on workers' safety habits (Wen et al., 2023). It was shown that the primary risk factors for safety incidents are personnel with low levels of education or safety understanding in the transportation and construction sectors (Amponsah-Tawiah & Mensah, 2016). Concurrently, the significance of individual elements is also underscored, with the belief that these factors may have a more profound impact on safety (Choudhry & Fang, 2008). The coal mining sector possesses the two aforementioned qualities due to the variety of dangerous behaviors exhibited by miners, resulting from the intricate nature of their work. Therefore, when modeling, it is necessary to take into account both individual and organizational elements to explain the dynamic mechanisms linking influencing factors to miners' risky conduct.

3. Data and analysis

3.1. Study Design and Sample

This cross-sectional study was conducted at three adjacent underground coal mines operated by a large public-sector organization in central India. Data were obtained from a structured questionnaire and the organization's internal accident records over three years (2021–2023). Inclusion criteria were: full-time underground workers with at least six months of service and complete responses on all survey items. Exclusion criteria were: contractors, administrative staff, and workers with incomplete data. The final dataset comprised N = 1,539 valid observations.

3.2. Outcome Variable: Accident Severity

Accident severity was defined as a four-level categorical outcome based on established mining accident classification standards:

- Class 0 (Non-accidental): No injury or incident
- Class 1 (Minor accident): Minor injury requiring first aid or minor medical treatment
- Class 2 (Major accident): Major injury requiring hospitalization or resulting in temporary disability
- Class 3 (Serious accident): Serious injury, permanent disability, or fatality

This four-class variable was used consistently as the dependent variable in all models and evaluations.

3.3. Class Distribution and Imbalance Assessment

The distribution of accident severity across the four classes was as follows:

Table 1. Distribution of accident severity across the four classes.

Severity Class	Description	Count	Percentage
0	Non-accidental	261	17.0%
1	Minor accident	788	51.2%
2	Major accident	410	26.6%
3	Serious accident	80	5.2%
Total		1,539	100.0%

This distribution indicates a moderate class imbalance, with minor accidents most frequent (51.2%) and serious accidents least common (5.2%). No explicit resampling was applied; instead, stratified k-fold cross-validation was used to preserve the original severity distribution in each fold. Performance estimates for the rare serious-accident class (5.2% of cases) are considered less stable and should be interpreted with caution.

3.4. Independent Variables and Measurement Scales

Based on prior mining safety research and literature analysis, 14 independent variables were identified across five dimensions:

Table 2. Prior mining safety research and literature analysis.

Dimension	Variable Name	Description	Scale
Behavioral Factors	Risk Taking	Tendency to ignore safety rules and prioritize productivity	Likert 1–5
	Negative Affectivity	Frequency of negative emotions and distress at work	Likert 1–5
	Job Dissatisfaction	General dissatisfaction with job conditions and career	Likert 1–5
Unique Characteristics	Age	Age of worker (years)	Continuous
	Experience	Years of mining industry experience	Continuous
	Education Level	Highest education attained	Ordinal 1–5
	Worker Characteristics	Perceived physical fitness and suitability for mining	Likert 1–5
Personal Impression	Safety Perception	Perceived importance of safety procedures	Likert 1–5
	Working Pressure	Perceived time pressure and production demands	Likert 1–5
Enabling Surroundings (Social Support)	SE Family	Perceived safety support from family	Likert 1–5
	SE Relatives	Perceived safety support from relatives	Likert 1–5
	SE Co-workers	Perceived safety support from co-workers	Likert 1–5
Safety Management System	SE Leader	Leadership and supervisory safety support	Likert 1–5
	Inspectors Quality	Perceived quality of inspectors and the safety management system	Likert 1–5

All psychometric items were measured on a 1–5 Likert scale (1 = strongly disagree, 5 = strongly agree) and treated as continuous numerical inputs. Continuous demographic attributes (Age, Experience) were used as-is. Ordinal and categorical attributes (Education Level) were numerically encoded (1 = primary or below, 2 = secondary, 3 = higher secondary, 4 = diploma, 5 = graduate and above). For each construct (e.g., Risk Taking, Job Dissatisfaction), multiple questionnaire items were averaged to form composite scores, consistent with prior occupational safety climate scales.

3.5. Data Preprocessing

3.5.1. Data Quality and Integrity Assessment

A comprehensive data preprocessing procedure was conducted to ensure robustness in subsequent analyses. Missing value analysis confirmed that there were no missing values across all 1,539 cases. Duplicate detection with Python's pandas library found no duplicate rows, confirming data uniqueness. Outlier evaluation using standard deviation thresholds and boxplot visualization identified most variables with low skewness (range: −0.02 to 0.38) and moderate kurtosis (range: 0.20 to 1.26), indicating near-normal distributions. No extreme outliers warranted exclusion or transformation.

3.5.2. Feature Scaling

Feature scaling is essential for many machine learning algorithms sensitive to input magnitude. StandardScaler from sklearn. preprocessing was applied to implement z-score normalization (mean = 0, SD = 1). Critically, to prevent data leakage, Standard Scaler was fitted on the training data only; the fitted parameters were then applied to the test folds using the learned mean and standard deviation. This ensures test data remained truly unseen during preprocessing.

3.5.3. Train-Test Split and Cross-Validation Strategy

The dataset was divided into training and testing subsets using scikit-learn's train_test_split function with:

- Test size: 0.25 (25% of total data for evaluation; 75% for training)
- Random state: 42 (fixed for reproducibility)
- Stratification: Applied to the target variable (Accident Severity) to preserve class proportions in both training and test sets

Additionally, stratified k-fold cross-validation (k = 10) was employed to provide robust performance estimates. This approach ensures that each fold maintains the original four-class distribution, addresses class imbalance, and yields stable mean ± standard deviation estimates of key metrics across folds.

3.6. Machine Learning Models and Implementation

Eight machine learning algorithms were implemented in Python using scikit-learn and related libraries. For each algorithm, a unified scikit-learn Pipeline was constructed comprising feature scaling (StandardScaler), optional feature selection, and the classifier. All preprocessing steps were fit exclusively on training folds and applied to validation/test folds, avoiding data leakage.

3.6.1. Model Descriptions

- Decision Tree (DT): Non-parametric supervised learning algorithm that recursively splits data; interpretable but prone to overfitting without pruning.
- K-Nearest Neighbors (KNN): Instance-based learning using distance metrics (Euclidean or Manhattan) to classify based on k-nearest neighbors.
- Support Vector Machine (SVM): Supervised learning algorithm constructing optimal hyperplanes to maximize inter-class margin; handles non-linearity via kernel functions (RBF kernel used here).
- Random Forest (RF): Ensemble method using bagging and random feature selection to combine multiple decision trees; effective for high-dimensional and correlated features.
- Artificial Neural Network (ANN): Multi-layer perceptron with input, hidden, and output layers; uses backpropagation and gradient descent for optimization.
- Naive Bayes (NB): Probabilistic classifier based on Bayes' theorem; assumes conditional independence among predictors.
- Logistic Regression (LR): Generalized linear model for classification using the logistic sigmoid function; provides probabilistic predictions.

- Gradient Boosting (GB): Sequential ensemble method training weak learners iteratively on residual errors; uses regularization (subsampling, shrinkage) to reduce overfitting.

3.6.2. Hyperparameter Tuning

For the top-performing models (Random Forest, Gradient Boosting, SVM, and ANN), hyperparameter tuning was performed using a stratified 5-fold cross-validated grid search on the training data:

- Random Forest: n_estimators (100–500), max_depth (3–15), max_features ('sqrt', 'log2')
- Gradient Boosting**:** learning_rate (0.01–0.2), n_estimators (100–400), max_depth (3–7)
- SVM**:** C parameter (0.1–10), RBF kernel width gamma (1e-3 to 1e-1)
- ANN: 1–3 hidden layers with 32–128 neurons per layer, ReLU activations, L2 regularization (1e-4 to 1e-2)

Final hyperparameters were selected based on the highest mean macro-averaged F1-score on validation folds.

3.7. Performance Evaluation Metrics

Multiclass classification performance was evaluated using:

- Accuracy: Proportion of correctly classified instances across all four classes
- Macro-averaged Precision, Recall, F1-score: Average of class-specific metrics
- Macro-averaged ROC-AUC: Area under the Receiver Operating Characteristic curve, averaged across one-vs-rest classifiers for each class
- Specificity (per class): True negative rate for each severity class
- Confusion matrices: Detailed breakdown of classification accuracy across all class pairs

Results are reported as mean ± standard deviation across the 10 stratified cross-validation folds, providing robust estimates of generalization performance.

4. Results

4.1. Comparative Performance Metrics

Table 3 presents the comparative performance of all eight models evaluated. Gradient Boosting and Random Forest emerged as the top-performing models across most evaluation metrics.

Table 3. Comparative Performance Metrics of Machine Learning Models for Multiclass Accident Severity Prediction. Values are mean ± SD over 10 stratified cross-validation folds.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Specificity
Decision Tree	0.70 ± 0.04	0.68 ± 0.05	0.65 ± 0.06	0.66 ± 0.05	0.759 ± 0.05	0.75 ± 0.04
KNN	0.68 ± 0.05	0.62 ± 0.06	0.60 ± 0.07	0.61 ± 0.06	0.819 ± 0.04	0.71 ± 0.05
SVM	0.76 ± 0.03	0.74 ± 0.04	0.71 ± 0.05	0.72 ± 0.04	0.852 ± 0.03	0.78 ± 0.03
Random Forest	0.79 ± 0.02	0.78 ± 0.03	0.76 ± 0.04	0.77 ± 0.03	0.840 ± 0.03	0.81 ± 0.02
ANN	0.73 ± 0.04	0.71 ± 0.05	0.69 ± 0.06	0.70 ± 0.05	0.894 ± 0.04	0.76 ± 0.04
Naive Bayes	0.73 ± 0.03	0.65 ± 0.05	0.63 ± 0.06	0.64 ± 0.05	0.828 ± 0.04	0.77 ± 0.03

Logistic Regression	0.70 ± 0.04	0.64 ± 0.06	0.61 ± 0.07	0.62 ± 0.06	0.817 ± 0.05	0.74 ± 0.04
Gradient Boosting	0.81 ± 0.03	0.80 ± 0.04	0.79 ± 0.05	0.79 ± 0.04	0.914 ± 0.02	0.83 ± 0.03

Gradient Boosting achieved the highest overall performance: Accuracy 0.81, Precision 0.80, Recall 0.79, F1-score 0.79, and ROC-AUC 0.914. Random Forest followed closely: Accuracy 0.79, Precision 0.78, Recall 0.76, F1-score 0.77, and ROC-AUC 0.840. These ensemble methods' superior performance can be attributed to their inherent robustness, effective handling of non-linear relationships, and capacity to reduce both bias and variance through aggregation of multiple learners.

Support Vector Machines (SVM) achieved competitive performance (Accuracy 0.76, ROC-AUC 0.852), benefiting from their ability to find optimal separating hyperplanes in high-dimensional spaces. Artificial Neural Networks (ANNs) demonstrated reasonable performance (Accuracy: 0.73, ROC-AUC: 0.894), though they require extensive hyperparameter tuning.

Naive Bayes, Decision Trees, and Logistic Regression achieved moderate performance (Accuracy 0.70–0.73). At the same time, K-Nearest Neighbors exhibited the lowest performance (Accuracy: 0.68), suggesting that significant inter-feature dependencies exist in the dataset, which more sophisticated algorithms capture more effectively.

4.2. Multiclass Confusion Matrix Analysis

The confusion matrix for Gradient Boosting (the best-performing model) reveals important patterns. Most classification errors occur between *adjacent* severity levels (e.g., minor vs. major), whereas serious accidents (class 3) are rarely misclassified as non-accidental (class 0). This pattern indicates that the model captures the severity gradient well, even when it errs. The minority class (serious accidents, 5.2% of cases) shows relatively stable prediction rates across folds (approximately 68–72% recall), which is reasonable given its small size.

Table 5: Confusion Matrix for Gradient Boosting Model.

Predicted →	Class 0	Class 1	Class 2	Class 3
Actual ↓				
Class 0 (Non-acc.)	226	28	6	1
Class 1 (Minor)	35	712	38	3
Class 2 (Major)	12	62	322	14
Class 3 (Serious)	2	8	16	54

4.3. Feature Importance Analysis

4.3.1. Impurity-Based Feature Importance (Gini and Information Gain)

Tree-based models (Random Forest and Gradient Boosting) offer native feature importance via mean decrease in impurity (MDI). Both models consistently ranked features in similar order, though impurity-based importance can be biased toward high-cardinality features. Despite this limitation, the results provide a useful preliminary ranking.

4.3.2. Permutation Importance

Permutation importance, assessed on held-out test folds, offers a model-agnostic evaluation of feature influence. Features whose randomization substantially degrades model performance are deemed important. This approach poses less bias than impurity-based methods and provides a direct measure of each feature's impact on predictive accuracy.

4.3.3. SHAP (Shapley Additive exPlanations) Analysis

SHAP values, grounded in cooperative game theory, deconstruct each prediction into additive contributions from each feature, providing both local (instance-level) and global (dataset-level) insights. SHAP excels at illuminating feature contributions even in complex or "black-box" models such as ANNs or ensemble methods. Summary plots (beeswarm plots) and force plots reveal how specific feature values alter predictions.

4.3.4. Consolidated Feature Importance Rankings

Table 4 presents consolidated feature importance rankings across impurity-based (Gini), permutation, and SHAP methods for the top two models (Random Forest and Gradient Boosting):

Table 4. Feature Importance Rankings Across Multiple Methods.
Values represent normalized importance scores (0–1 scale). Consistent rankings across Gini, permutation, and SHAP indicate robust feature contributions.

Feature Name	Random Forest	Gradient Boosting	SHAP (Overall)
Risk Taking	0.19	0.20	0.19
Age	0.15	0.16	0.16
Experience	0.14	0.13	0.14
Negative Affectivity	0.12	0.11	0.12
Job Dissatisfaction	0.10	0.10	0.10
Education Level	0.09	0.08	0.08
SE Leader	0.07	0.07	0.06
SE Co-Worker	0.06	0.06	0.05
SE Family	0.05	0.05	0.05
SE Relatives	0.04	0.04	0.05

Risk Taking (importance ≈ 0.19–0.20), Age (≈ 0.15–0.16), and Experience (≈ 0.13–0.14) emerge as the most influential predictors across all three importance methods. Negative Affectivity and Job Dissatisfaction also exhibit substantial contributions (≈ 0.10–0.12). Social support variables (SE Leader, SE Co-Worker, SE Family, SE Relatives) collectively contribute approximately 0.20–0.27 combined importance, indicating that social dimensions collectively moderate accident severity.

4.3.5. Directional Interpretation from SHAP

SHAP summary plots (beeswarm) and partial dependence plots reveal directionality:

- Risk Taking: Higher Risk Taking scores *systematically shift predictions toward more severe accident classes* (major and serious), whereas lower scores are protective, associated with non-accidental and minor outcomes.
- Age and Experience: Both exhibit non-linear effects. Workers aged 25–45 years with 10–20 years of experience show lower predicted severity, while very young (<25 years) or older (>50 years) workers, combined with lower experience, exhibit elevated severity risk.

- Negative Affectivity and Job Dissatisfaction: Higher scores on these psychological factors consistently push predictions toward major and serious accidents, whereas low scores indicate non-accidental outcomes.
- Social Support (SE Leader, SE Co-Worker): Higher perceived support is strongly *protective*, reducing predicted severity gradients across all classes. The effect of leadership support is notably stronger than family or relative support, suggesting that organizational safety culture and supervisory commitment are particularly salient.

5. Discussion

5.1. Key Findings and Model Performance

This comprehensive investigation into accident severity prediction using machine learning has produced several pivotal insights. Eight distinct algorithms were systematically evaluated, with Gradient Boosting and Random Forest displaying superior predictive capability for multiclass accident severity. These ensemble methods demonstrated consistently high performance across multiple evaluation metrics (Accuracy, Precision, Recall, F1-score, ROC-AUC), highlighting their robustness and reliability in distinguishing between non-accidental, minor, major, and serious accident outcomes.

The successful prediction of accident severity has important implications for disaster risk reduction in occupational settings. By identifying conditions associated with escalation from minor to serious accidents, organizations can prioritize interventions to prevent high-severity outcomes, thereby reducing overall harm and supporting resilience objectives aligned with the Sendai Framework for Disaster Risk Reduction.

5.2. Feature Importance and Actionable Insights

In-depth feature importance analyses using multiple methods (impurity-based, permutation, SHAP) illuminated the determinants of accident severity. Risk-taking, Age, and Experience emerged as the most influential predictors across all three interpretability frameworks, with consistent rankings lending credibility to these findings.

5.2.1. Behavioral and Psychological Factors

The prominence of Risk Taking (importance ≈ 0.19) underscores that workers' willingness to ignore safety protocols and prioritize productivity is among the strongest drivers of escalation in accident severity. This suggests targeted behavioral safety interventions focusing on risk awareness, rule compliance, and the consequences of non-compliance could substantially reduce serious outcomes.

Negative Affectivity and Job Dissatisfaction (combined importance ≈ 0.22) indicate that psychological distress and workplace dissatisfaction meaningfully increase the risk of severity. These psychosocial factors warrant routine organizational screening through occupational health programs, coupled with targeted counseling, job redesign, or temporary reassignment for highly distressed workers.

5.2.2. Demographic Factors

Age and Experience (combined importance ≈ 0.29–0.30) demonstrate non-linear relationships with accident severity. While experienced workers (10–20 years) aged 25–45 years show lower predicted severity, very young or older workers, especially those with lower experience, face elevated risk. This pattern suggests that:

- Comprehensive induction and mentoring programs for newly hired or very young workers are critical.
- Older workers may require ergonomic assessments, health screenings, and potentially modified duty assignments to accommodate age-related changes in capability.
- Career progression and knowledge-transfer programs can harness the protective effects of experience.

5.2.3. Organizational and Social Support Factors

Social support dimensions (SE Leader, SE Co-Worker, SE Family, SE Relatives; combined importance ≈ 0.22) collectively demonstrate a protective effect on accident severity. Notably, leadership and supervisory support (SE Leader, importance ≈ 0.06–0.07) exerts a notably stronger protective influence than family or relative support, indicating that organizational safety culture and direct supervisory commitment are particularly salient in moderating severity.

These findings align with recent disaster risk management literature, which emphasizes integrating behavioral and organizational indicators into risk assessments rather than focusing solely on technical or physical hazards. This suggests that strengthening the following will reduce accident severity escalation:

- Safety leadership training: Equipping supervisors with skills to model safe behavior, provide constructive feedback, and foster a positive safety climate.
- Peer mentoring and co-worker support programs: Creating structured opportunities for experienced workers to guide newer colleagues on safe practices.
- Team-based safety initiatives: Building collective ownership of safety through peer accountability and group-level goal setting.

5.3. Practical Implications and Recommendations for Safety Management

The convergence of risk-taking, psychological factors, demographic patterns, and organizational support across multiple ML models and interpretability methods provides a robust, data-driven basis for prioritizing interventions in comparable mining environments:

1. Targeted Behavioral Risk Training: Develop and deliver role-specific safety training emphasizing the specific risks that high-risk-taking workers face, linking rule compliance directly to accident severity outcomes observed in real mining data.
2. Psychosocial Screening and Support: Implement routine screening (e.g., annual questionnaires) for negative affectivity, job dissatisfaction, and workplace stress. For workers who score highly, offer counseling, occupational health referral, or temporary reassignment to lower-risk tasks.
3. Enhanced Supervisory Safety Leadership: Invest in supervisor and manager training on safety communication, hazard observation, near-miss investigation, and supportive feedback. Supervisory commitment and modeling are demonstrated to be strong moderators of severity escalation.
4. Demographic-Sensitive Task Allocation: Tailor job assignments and duty schedules based on age-experience profiles. Provide additional mentoring and ergonomic support for very young or older workers, while leveraging the protective effects of experience through structured knowledge transfer and leadership roles.
5. Team-Based Safety Culture: Promote peer mentoring, buddy systems, and team safety discussions: Foster collective efficacy and mutual accountability for safety performance among co-workers.

While the observational study design does not establish direct causality, the convergent importance of these factors across multiple machine learning models and explainability methods provides robust evidence for their association with accident severity, supporting their consideration in evidence-based safety management strategies.

5.4. Limitations

This study has several important limitations that should be considered when interpreting and generalizing findings:

1. Geographic and Organizational Scope: Data originate from three mines within a single public-sector organization in central India. Generalizability to other mining regions, countries, mining methods (e.g., open-pit mining), and private-sector operators remains uncertain. Multi-site validation studies are needed.
2. Self-Report Bias: All behavioral and psychosocial predictors (Risk Taking, Negative Affectivity, Job Dissatisfaction, Social Support measures) are self-reported questionnaire items. Common-method bias and social desirability effects cannot be ruled out, potentially inflating or attenuating relationships.
3. Class Imbalance: While stratified cross-validation preserves class proportions, the serious-accident class comprises only 5.2% of cases (N = 80). Performance estimates for this minority class remain less stable than for majority classes. Future work should validate the findings on larger, multi-site datasets in which serious accidents are more frequent.
4. Temporal Validation**:** This study used a train-test split and cross-validation on historical data. Prospective validation against *future* accident outcomes would strengthen confidence in model generalization and provide evidence for real-world deployment.
5. Unmeasured Confounders: The study does not include technical/environmental hazard data (e.g., equipment condition, geological conditions, ventilation systems). While behavioral and organizational factors are important, their inclusion alone does not capture all relevant influences on accident severity.
6. Observational Design: The cross-sectional design precludes causal inference. The relationships identified warrant investigation through controlled studies or longitudinal tracking.

6. Conclusion

This comprehensive investigation into accident severity prediction using machine learning has substantiated the utility of ensemble methods (Gradient Boosting and Random Forest) in accurately classifying multiclass mining accident severity. The models achieved Accuracies of 0.81 and 0.79, respectively, with robust ROC-AUC scores of 0.914 and 0.840, demonstrating strong discriminative capability across four severity levels.

In-depth feature importance analyses—using impurity-based, permutation, and SHAP frameworks—consistently identified Risk Taking, Age, and Experience as the most influential predictors, alongside psychological factors (Negative Affectivity, Job Dissatisfaction) and organizational social support dimensions (leader and co-worker support). These findings translate into concrete recommendations for targeted interventions: behavioral risk training, psychosocial screening and support, enhanced supervisory safety leadership, demographic-sensitive task allocation, and team-based safety culture initiatives.

The study contributes a multiclass machine-learning framework that complements existing occupational disaster-risk reduction approaches. By shifting focus from accident *occurrence* to accident *severity*, this work enables mining organizations to prioritize resources toward preventing high-impact outcomes and building organizational resilience. Future multi-site validation and prospective testing of recommended interventions will further strengthen evidence for implementation in the mining industry and inform broader disaster risk reduction policy.

Author Contributions: Irshad Ahmad (author 1) conceived the study, designed the questionnaire, carried out data collection and preprocessing, implemented and compared the machine learning models, performed the statistical and explainability analyses, and drafted the manuscript. Dr. Ajay Kumar Gupta (author 2) provided conceptual guidance on study design, advised on the selection and interpretation of safety and behavioral factors, contributed to refining the methodology and discussion from a mining safety perspective, and critically reviewed and edited the manuscript. Both authors read and approved the final version.

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Appendix: Supplementary Materials

A.1 Confusion Matrix – Gradient Boosting Model

Table 5. Confusion Matrix for Gradient Boosting Model.
Diagonal entries represent correct classifications; off-diagonal entries represent misclassifications.
Note that errors predominantly occur between adjacent severity levels.

Predicted →	Class 0	Class 1	Class 2	Class 3
Actual ↓				
Class 0 (Non-acc.)	226	28	6	1
Class 1 (Minor)	35	712	38	3
Class 2 (Major)	12	62	322	14
Class 3 (Serious)	2	8	16	54

A.2 SHAP Interpretation Guidance

SHAP summary plots (beeswarm charts) for the best model (Gradient Boosting) display feature values (x-axis) against their SHAP values (y-axis), with red indicating higher feature values and blue indicating lower values. A rightward trend suggests the feature increases prediction toward higher severity, while a leftward trend indicates a protective effect. The width of the distribution reflects the range of SHAP values observed across the dataset, indicating variability in the feature's impact.

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