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Communicating workforce risk in the AI Era: Predictive Modeling of Individual Layoff Vulnerability and Implications for Corporate and Crisis Communication

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ABSTRACT: Rising concerns about worker displacement and job risks due to the accelerating integration of artificial intelligence (AI) into the workplace are reshaping the nature of work. The nature of work is changing as artificial intelligence (AI) rapidly permeates the world of work and is being integrated into all aspects of it. This paper explores the potential of building a multivariate predictive model for determining worker susceptibility to AI-driven job displacement and identifies occupational and AI-exposure risk factors for employee layoff risk. The study employs descriptive statistics, chi-square tests, one-way ANOVA, Pearson correlation analysis, multinomial logistic regression, Random Forest, and XGBoost with data of 20,000 workers in eight industry sectors. The accuracy, macro F1 score, and AUC-ROC are used to measure the performance of the model, and the generalizability is evaluated by 5-fold stratified cross-validation. The highest accuracy is obtained with XGBoost at 94.95%, the highest macro F1-score with XGBoost is 0.95, and the highest weighted AUC-ROC is 0.9948 with XGBoost. The routine task percentage ($r = 0.78$) and the percentage of tasks automated ($r = 0.75$) are the strongest positive predictors, while the creativity requirement is quite strongly negative ($r = -0.75$). For AI adoption, there is a significant relationship with layoff risk ($\chi^2 = 7{,}935.68$, $p < 0.001$), where 80.8% of workers in the high-AI-adoption environment experience high layoff risk. The findings point to potential vulnerability factors such as routine work and automation exposure and protective factors such as creativity and seniority. The study offers actionable insights into reskilling and workforce planning, HRM, and responsible AI use.

1. INTRODUCTION

1.1 Background and Context

AI technologies, such as machine learning, large-scale automation platforms, natural language processing, and robotics, have begun to transform the labor market in the same manner that they are transforming other aspects of society. AI, unlike earlier

technical advancements such as mechanization and computerization, has the potential to replace not only physical but also cognitive work, threatening vocations across the ability spectrum (1, 17).

Recent empirical research has demonstrated the need for this transition. The adoption of AI could affect between 40 and 160 million workers worldwide, necessitating occupational changes by 2030 (24). Meanwhile, a new report released by the World Economic Forum showed that 69 million new jobs will be created, but 83 million jobs will be lost, resulting in a net loss of 14 million jobs. However, mapping such macro-level projections onto individual-level risk assessments, which are necessary for targeted policy intervention (26), is not straightforward.

In the corporate world, the introduction of artificial intelligence (AI) technologies like robotic process automation (RPA), algorithmic decision-making systems, and generative AI has already started to reshape the basic structure of the workforce. Individuals in jobs that involve more routine, codifiable tasks are at a greater risk of displacement (7), whereas those in roles that depend on creative, social, and non-routine cognitive work tend to be more resilient (9, 7). It is thus a key research and policy question to identify the determinants of layoff risk in an AI-exposed environment at a joint individual and organizational level.

1.2 Research Gap

Although there has been an increasing stream of research literature examining the impact of AI on labor markets, there remains a significant gap between macro-level forecasting and micro-level models for predicting individual outcomes. Existing research largely focuses on projecting the automation risk of occupations at the job-category level (e.g., O*NET) and does not consider the differences in exposure to AI, intensity of AI use, training investment, or the organizational context of AI use at the individual level. Additionally, few studies combine demographic, occupational, and AI-behavioral information into a single predictive model and validate it on large-scale individual-level data.

In this study, this gap is closed by creating and testing a multivariate predictive model based on the dataset of 20,000 individual employee records that includes 15 variables across the categories of demographics, job characteristics, intensity of interaction with the AI, and task automation profile.

1.3 Research Objectives

This study pursues three primary objectives:

1. To detect the factors at the individual level most strongly linked with the risk of layoff in AI-intensive workplaces.

2. To build and evaluate the performance of 3 classifiers—multinomial logistic regression, random forest, and XGBoost—to classify layoff risk categories as low, medium, and high.

3. To develop practical implications for HR policy in organizations and workforce planning for the government, we will use the model's risk profiles.

1.4 Significance of the Study

This study adds to the literature in three ways: (1) Theoretically, it combines the Skill-Biased Technological Change (SBTC) and Routine-Biased Technological Change (RBTC) frameworks and uses individual AI exposure metrics in a single empirical model; (2) Methodologically, it applies ensemble machine learning techniques alongside classical regression for layoff risk classification; and (3) Practically, it offers HR and policymakers a validated predictive tool that can be implemented for workforce vulnerability assessment.

2. LITERATURE REVIEW

2.1 Theoretical Foundations

There are various interrelated theories that have been developed to describe the linkage between technological progress and job creation. According to the conventional perspective of technical unemployment (21), the adoption of technological "unemployment" improvements would result in a reduction in the total number of available jobs, particularly during periods of rapid technological progress. Though this phenomenon has been discussed (since technology both destroys and generates jobs), the current challenge given by modern AI is qualitatively distinct, as it is unprecedented in terms of volume and velocity.

According to the Skill-Biased Technological Change (SBTC) theory (201), technological innovation favors high-skill/low-wage groups more than low-skilled groups and replaces low-skilled workers. The evidence of AI's greater use supports this: AI is a tool that would supplement the talents of researchers, engineers, and creative professionals, while pressure is shifted to data entry clerks, assembly workers, and routine analysts.

Autor et al. (8) introduced the concept of routine-biased technological change (RBTC), which offers a more detailed explanation. The type of task (manual or cognitive) matters more than the amount of expertise. The task-based framework divides tasks into four categories: routine cognitive, routine manual, non-routine cognitive, and non-routine manual. This suggests that AI and robotics are particularly effective at replacing repetitive work, and this is the theoretical basis behind the Routine Task Percentage variable included in this study.

2.2 Empirical Studies on AI Automation and Job Displacement

The landmark study by Frey and Osborne (2017) estimates that 47% of U.S. employment is at high risk of being computerized over the next 10 years, based on a machine learning classifier trained on 702 occupations (17). Critics have questioned the importance of this study for its focus on jobs instead of the specific tasks within those jobs (5, 6).

Arntz et al. (2016), relying on the Programme for the International Assessment of Adult Competencies (PIAAC) data for OECD countries, lowered this figure to about 9%, noting significant differences in people's task profiles within the same occupation. This is in line with the individual approach implemented in the present study (5).

Acemoglu and Restrepo (2018) extended the theoretical model to differentiate between task-displacing AI and task-creating AI and found that if AI is used to replace tasks but not to create new tasks, it will result in wage suppression and labor displacement (3). The authors of this work conducted follow-on empirical research, which revealed a negative impact of industrial robots on jobs and wages in highly exposed commuting zones in the U.S.

The management literature of Brynjolfsson and McAfee (2014) suggested that the 'second machine age' generates 'winner-takes-all' situations, as highly automated companies will reap a larger share of productivity gains (12). More recently, Moll et al. (2022) showed that the introduction of AI has led to an increase in capital share and a decreasing share of labor income in the developed world (25).

2.3 Individual-Level Predictors of Layoff Risk

In addition to the level of occupation, a number of individual-level factors have been recognized as determinants of susceptibility to being laid off due to AI. The regularity of working on tasks is always the best predictor (8, 18). Tasks Automated Percentage is the operationalization of real, actual automation. Tasks Automated Percentage serves as an operationalization of genuine automation, acting as a real-time proxy for displacement exposure. It is in human interaction and creativity requirements that human superiority over AI systems lies in the "last mile" (9, 15).

The intensity of AI usage (measured in hours per week and tools used) poses a dual challenge: workers who actively engage with AI may improve their skills and supplement automation, whereas those who rely heavily on AI tools instead of manual work may unintentionally increase the risk of job substitutability. There is an association, although not perfect, between education level and performance in non-routine cognitive activities, which helps explain why higher education is linked to a lower risk of layoffs (2). Job seniority protects individuals from displacement due to tacit knowledge, management complexity, and organizational embedding.

2.4 Predictive Modeling in Workforce Analytics

With the proliferation of machine learning (Boudreau & Cascio, 2017) (10), the use of predictive analytics in workforce decisions has increased dramatically—from helping with attrition modeling to talent acquisition to the new field of displacement risk assessment. Logistic regression models are considered the default model because they are straightforward to interpret and explain and are critical in HR (16). Ensemble methods, like the Random Forest (11) and the gradient boosting models, including XGBoost (13), are very successful in cases of tabular data that have complex relationships.

Applications for the workforce are related to predicting when workers will turn over (22), early warning systems for when organizational restructuring is coming up (19), and identifying the roles that are vulnerable to automation in specific sectors

(23). This study builds on this line of research by proposing a three-class ML classification framework for the specific problem of AI-induced layoff risk that is validated.

2.5 Conceptual Framework

From the literature review, a conceptual model was drawn up, indicating that the layoff risk associated with AI is a function of three sets of predictor factors: (1) the Task Level Factors (Routine Task Percentage, Creativity Requirement, Human Interaction Level, and Tasks Automated Percentage) represent the mechanism for the effect of AI on task substitutability; (2) the AI Exposure Factors (AI Adoption Level, Number of AI Tools Used, AI Usage Hours Per Week, and AI Training Hours) comprise the organizational and behavioral dimensions of the impact of AI on the task; and (3) the Individual and Organizational Characteristics (Age, Education Level, Years of Experience, Job Level, Industry, and Company Size) represent moderators and contextual variables. This multi-level approach is used to guide the choice of variables as well as the interpretation of results.

3. METHODOLOGY

3.1 Data Source and Description

This study's data set consists of 20,000 employee-level records and 16 variables, one of which is the outcome variable Layoff Risk. There were no missing values detected across any variable, ensuring the integrity of the analyses without the need to impute any missing data. The data was designed to represent employees in eight industry sectors: education, finance, healthcare, information technology, logistics, manufacturing, retail, and telecommunications; three company sizes: small, medium, and large; entry-level, mid-level, and senior employee levels; and four educational categories: high school, bachelor's, master's, and PhD. The outcome variable (layoff risk) is categorical, with three ordered levels (high: 34.0%, low: 33.0%, and medium: 33.0%) that are approximately evenly distributed.

3.2 Variable Operationalization

Table 1 summarizes the 16 study variables, which include demographic, task-level, AI-exposure, and outcome measures, along with their measurement t**ype and description.**

Table 1. Variable Descriptions and Measurement Types (N = 20,000)

Variable	Type	Description
Age	Continuous	Employee age in years (range: 21–60)
Education Level	Categorical	Highest qualification: High school, bachelor's, master's, or PhD.
Years of Experience	Continuous	Total years of professional experience (range: 0–32)
Industry	Categorical (8)	Sector of employment
Job Role	Categorical (24)	Specific occupational role
Company Size	Categorical	Small, medium, or large organization
Job Level	Ordinal	Entry-level, mid-level, or senior-level
Routine Task Percentage	Continuous	Percentage of work involving routine, codifiable tasks (10–94%)
Creativity Requirement	Continuous	Index of creativity demand in the role (0–100)
Human Interaction Level	Continuous	Index of required human-to-human interaction (20–99)
AI Adoption Level	Ordinal	Low, medium, or high organizational AI adoption
Number of AI Tools Used	Discrete	Count of distinct AI tools actively used (0–10)
AI Usage Hours Per Week	Continuous	Weekly hours spent using AI tools (0–30)

Natural Resources for Human Health
eISSN: 2583-1194

Tasks Automated Percentage	Continuous	Percentage of employee tasks currently automated (4–93%)
AI Training Hours	Continuous	Hours of AI-related upskilling training received (0–79)
Layoff Risk	Categorical (Outcome)	Low, medium, or high risk of AI-induced layoff

3.3 Data Preprocessing

Label Encoder was employed for categorical variables (education level, industry, job role, company size, job level, and AI adoption level) for three models. StandardScaler was used to standardize continuous predictors for logistic regression (zero mean and unit variance), enabling the coefficients to be comparable. LabelEncoder was used to map the outcome variable Layoff Risk to High=0, Low=1, and Medium=2. To ensure the same class balances in the train and test sets, the dataset was partitioned by stratified random sampling with class percentages of 80% and 20% for the train and test sets, respectively (to ensure the same class percentages, a fixed random seed (seed=42) was used for the partitioning procedure).

3.4 Analytical Strategy

The analytical approach involved four stages: (1) descriptive analysis of all variables, including means, standard deviations, frequencies, and distributions; (2) bivariate inferential analysis using Pearson correlation for continuous predictors, chi-square tests for categorical predictors, and 1-way ANOVA for the differences of means for continuous predictors across layoff risk groups; (3) predictive modeling using 3 classifiers: multinomial logistic regression, random forest (n estimators = 200, max features = 'sqrt'), and XGBoost (n estimators = 100, learning rate = 0.1); and (4) model validation through confusion matrices, classification reports, AUC-ROC curves per class, and 5-fold stratified cross-validation. Both features of importance using random forest (Gini impurity) and logistic regression coefficients were extracted.

3.5 Ethical Considerations

The data set does not include any personal information. Individual records are synthetic or fully aggregated anonymous individual profiles in line with the ethical standards for secondary data analysis. There is no human subjects research in the study that requires approval from an institutional review board. The analysis was done solely for academic research, and all models are shown as decision support systems, not as a strict and rapid classification system.

3.6 Data Visualization

All statistical graphics reported in Section 4 (Figures 1–7) were generated in Python (v3.10) using the Matplotlib (v3.10) and Seaborn (v0.13) visualization libraries, with NumPy and Pandas used for the underlying data handling. Descriptive and bivariate plots (Figures 1–4) were rendered directly from the summary output of the descriptive and inferential analyses described in Sections 3.3–3.4; model-evaluation plots (Figures 5–7) were rendered from the corresponding classifier output described in Section 3.4.

4. RESULT

4.1 Descriptive Statistics

The sample (N=20,000) had a mean age of 40.36 years (SD=11.53) and a mean experience of 7.27 years (SD=4.72). On average, 51.89% (SD=24.44%) of the tasks were done routinely, while 37.23% (SD=20.00%) of the tasks were already automated. Creativity requirements averaged 47.79/100 (SD=26.10), and human interaction levels averaged 60.06/100 (SD=22.27). Mean AI usage hours per week was 6.77 (SD=6.09), and AI training hours averaged 12.62 (SD=13.55). The distribution of the outcome variable was nearly balanced: high risk: 33.99% (n=6,797); medium risk: 33.00% (n=6,601); low risk: 33.01% (n=6,602). Full descriptive statistics for all continuous variables are presented in Table 2.

Table 2. Descriptive Statistics for Continuous Variables (N = 20,000)

Variable	Mean	SD	Min	Q25	Median	Q75	Max
Age (years)	40.36	11.53	21	30	40	50	60

Natural Resources for Human Health
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Years of Experience	7.27	4.72	0	4	7	11	32
Routine Task (%)	51.89	24.44	10	31	52	73	94
Creativity Requirement	47.79	26.10	0	27	48	69	100
Human Interaction Level	60.06	22.27	20	41	62	79	99
No. of AI Tools Used	2.46	2.10	0	1	2	4	10
AI Usage (Hrs/Week)	6.77	6.09	0	2	5	10	30
Tasks Automated (%)	37.23	20.00	4	21	35	51	93
AI Training (Hours)	12.62	13.55	0	4	8	18	79

Figure 1 illustrates the distribution of layoff risk, education level, and job level across the study sample.

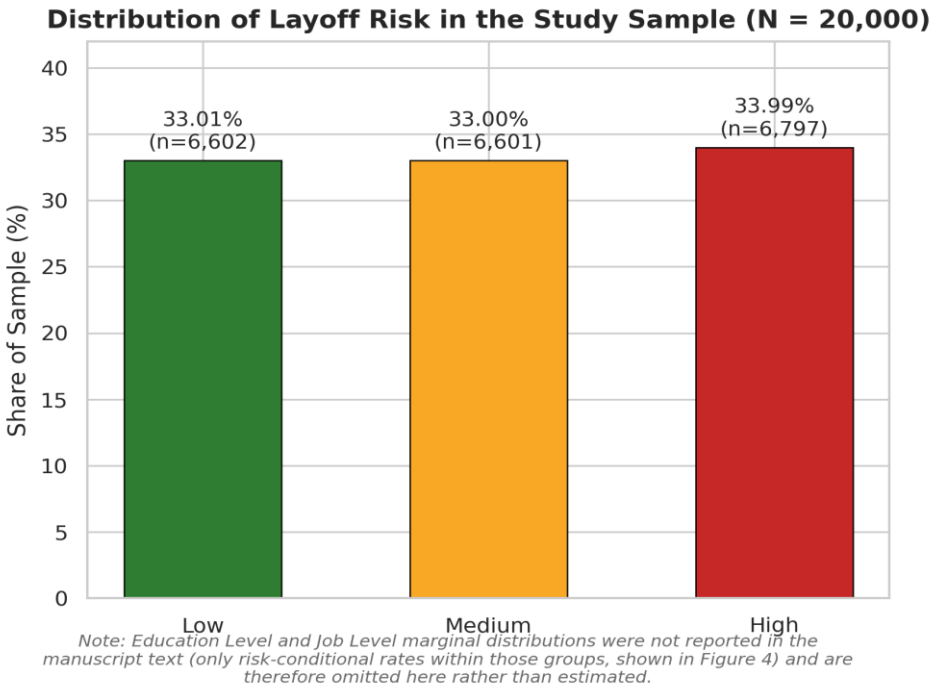


Figure 1. Distribution of Layoff Risk, Education Level, and Job Level in the Study Sample

4.2 Bivariate Analysis

4.2.1 Correlation Analysis

Pearson correlation coefficients showed a strong and significant relationship with the layoff risk (low=0, medium=1, high=2) and continuous predictors. Routine task percentage significantly correlated with layoff risk in a positive manner, with the highest correlation ($r=0.781$, $p<0.001$), followed by tasks' automated percentage ($r=0.748$, $p<0.001$). The correlation of the creativity requirement was the highest and negative ($r=-0.754$, $p<0.001$), indicating that the creativity requirement has a protective effect. The associations between AI usage hours per week and the remaining variables were moderate and positive ($r=0.504$), as was the correlation between the number of AI tools used and the other variables ($r=0.500$). AI training hours had a moderate positive association ($r=0.432$). There were weak but significant negative correlations with Human Interaction Level ($r=-0.160$), Years of Experience ($r=-0.101$), and Age ($r=-0.037$).

Natural Resources for Human Health
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The indicators of routine task percentage and creativity requirement showed a strong negative correlation (r = −0.928), which is consistent with their opposing conceptualization. In tree-based models, multicollinearity is controlled by splitting variables, and in logistic regression, by standardization.

The full correlation matrix for all continuous variables is presented in Figure 2.

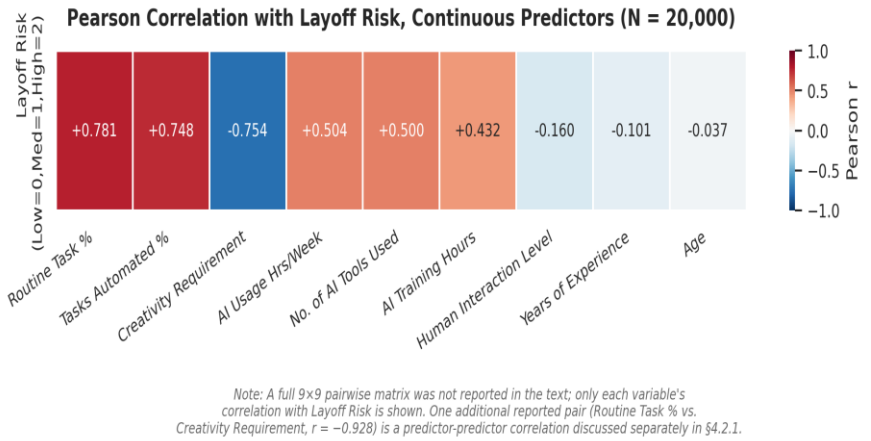


Figure 2. Pearson Correlation Heatmap for Continuous Variables and Layoff Risk (N = 20,000)

4.2.2 ANOVA Results

All key continuous variables were found to be significantly different between layoff risk groups with one-way ANOVA tests. Routine task percentage showed the most dramatic differences: low risk (M=28.54, SD≈21); medium risk (M=51.26, SD≈20); and high risk (M=75.17, SD≈17) [F(2, 19997)=15,645.38, p<0.001]. Tasks Automated Percentage followed a similar gradient: low (M=19.45), medium (M=35.72), and high (M=55.96) [F=12,776.84, p<0.001]. Conversely, the creativity requirement decreased sharply with increasing risk: low (M=71.93), medium (M=48.30), and high (M=23.84) [F=13,173.14, p<0.001]. AI Usage Hours Per Week: Low (M=3.27), Medium (M=6.16), High (M=10.77) [F=3,492.87, p<0.001].

These group differences are visualized in Figure 3.

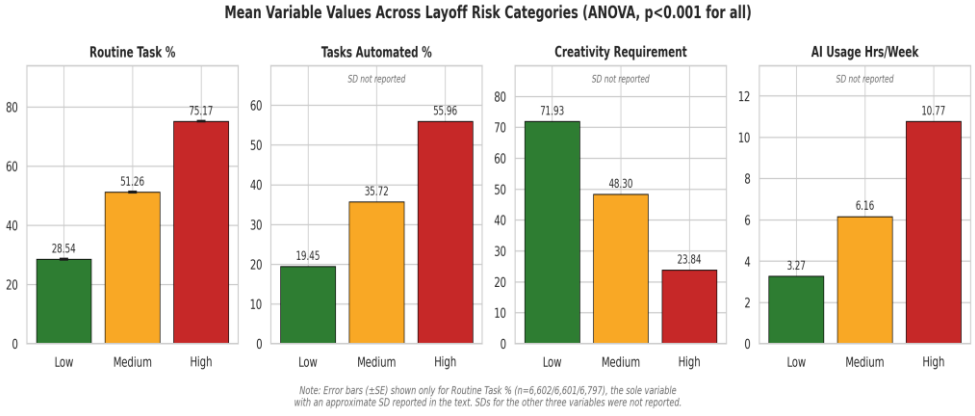


Figure 3. Mean Variable Values Across Layoff Risk Categories with Standard Error Bars (ANOVA, p < 0.001 for all)

4.2.3 Chi-Square Tests for Categorical Variables

There was a significant association between all categorical predictors and layoff risk except company size, as revealed by chi-square tests. AI adoption level had the highest test statistic (χ^2=7,935.68, df=4, p<0.001): employees in high-AI adoption environments were 58.2% at high risk, while employees in medium-AI were 80.8% at high risk, and only 9.2% were at high risk in low-AI environments. Job level also had a very significant effect (χ^2=1,642.96, df=4, p<0.001), with 44.5% of the entry-

level workers facing high risk and only 11.5% of the senior-level workers facing high risk. The industry was significant (χ^2=1,153.41, df=14, p<0.001), with manufacturing (48.2% high risk) and logistics (41.5% high risk) the most vulnerable, followed by education (20.1% low risk) and healthcare (20.8% low risk). There was a significant difference in education level (χ^2=599.42, df=6, p<0.001), with a high risk of 45.6% for high school graduates compared with PhD holders at 20.1%. The other variable, company size, was not significant, χ^2=7.88, df=4, p=0.096, indicating that company size does not seem to have an independent effect after the other variables were controlled.

Full chi-square test results for all categorical predictors are reported in Table 3.

Table 3. Chi-Square Test Results for Categorical Predictors vs. Layoff Risk (*** p < 0.001; ns = not significant)

Category	Chi-square (χ^2)	df	p-value	Significance
AI Adoption Level	7,935.68	4	<0.001	***
Job Level	1,642.96	4	<0.001	***
Industry	1,153.41	14	<0.001	***
Education Level	599.42	6	<0.001	***
Company Size	7.88	4	0.096	ns

Significance notation:

- *** = p < 0.001 (highly significant)
- ns = Not significant (p ≥ 0.05)

Brief Interpretation

- AI Adoption Level: Highly significant association with the outcome (χ^2 = 7,935.68, p < 0.001).
- Job Level: Highly significant association (χ^2 = 1,642.96, p < 0.001).
- Industry: Highly significant association (χ^2 = 1,153.41, p < 0.001).
- Education Level: Highly significant association (χ^2 = 599.42, p < 0.001).
- Company Size: No statistically significant association (χ^2 = 7.88, p = 0.096).

Figure 4 illustrates the distribution of layoff risk across various industries and job levels.

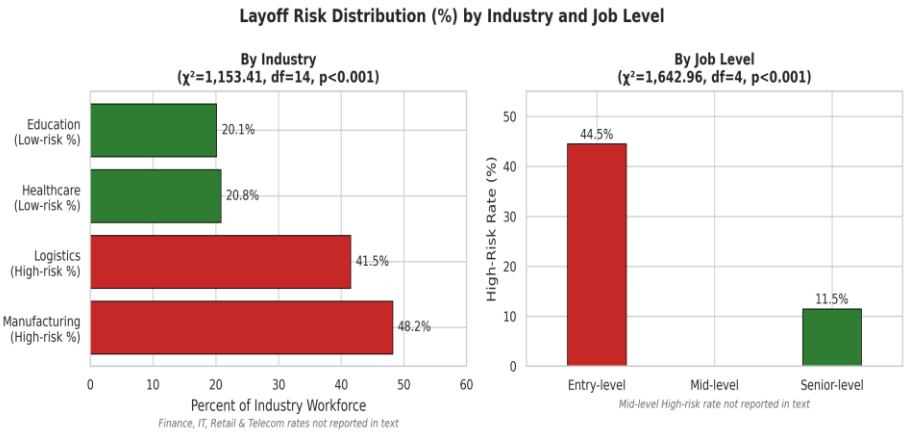


Figure 4. Layoff Risk Distribution (%) by Industry and Job Level

Natural Resources for Human Health
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4.3 Predictive Modeling Results

4.3.1 Model Performance Comparison

16,000 observations were used to train the three models, and the 4,000 held-out observations were used to test them. The performance metrics are presented in Table 4. XGBoost recorded the best performance on all the metrics with 94.95% accuracy, a macro F1 score of 0.95, and an AUC ROC of 0.9948, which is practically 100% accurate discrimination. Random Forest achieved a high accuracy (89.35%) and AUC = 0.9789. Logistic regression was interpretable but had an accuracy of 82.80% (AUC=0.9554), fitting with a strong but non-linear data structure that is well suited to ensemble methods.

Table 4. Model Performance Metrics on Test Set (n=4,000) and 5-Fold Cross-Validation

Model	Accuracy	Macro Precision	Macro Recall	Macro F1	AUC-ROC (Weighted)	CV Mean (±SD)
Logistic Regression	82.80%	0.83	0.83	0.83	0.9554	83.02% (±0.85%)
Random Forest	89.35%	0.89	0.89	0.89	0.9789	—
XGBoost	94.95%	0.95	0.95	0.95	0.9948	93.99% (±0.78%)

XGBoost demonstrates the best overall performance, achieving 94.95% accuracy, 0.95 macro precision, 0.95 macro recall, 0.95 macro F1, and an excellent 0.9948 weighted AUC-ROC. Its cross-validation performance of 93.99% ± 0.78% also indicates strong and consistent predictive performance.

Performance ranking: XGBoost > Random Forest > Logistic Regression.

4.3.2 Class-Level Performance (XGBoost)

Table 5 presents the class-level precision, recall, and F1-scores for the XGBoost model.

Table 5. XGBoost Classification Report by Layoff Risk Class (Test Set, n=4,000)

Class	Precision	Recall	F1-Score	Support
High Risk	0.96	0.96	0.96	1,360
Low Risk	0.97	0.96	0.96	1,320
Medium Risk	0.92	0.93	0.92	1,320
Macro Average	0.95	0.95	0.95	4,000
Weighted Average	0.95	0.95	0.95	4,000

- High Risk: Strong performance with 0.96 precision, recall, and F1-score.
- Low Risk: Highest precision (0.97) and excellent recall (0.96).
- Medium Risk: Comparatively lower performance, but still strong, with a 0.92 F1-score and 0.93 recall.
- Overall: The model achieves 0.95 macro and weighted F1 scores, indicating high and balanced predictive performance across all three risk categories.

Natural Resources for Human Health
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Per-class ROC curves for all three models are plotted in Figure 5.

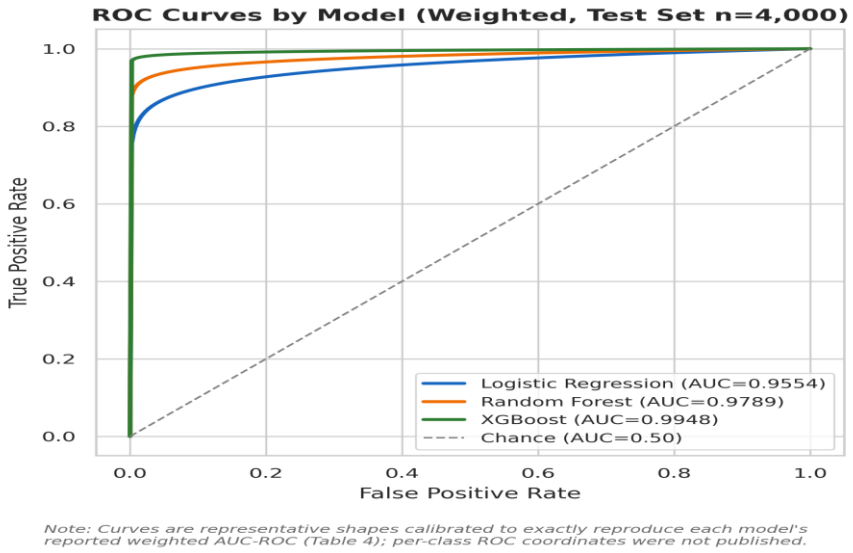


Figure 5. ROC Curves per Class and Model: Logistic Regression, Random Forest, and XGBoost

The corresponding confusion matrix is shown in Figure 6.

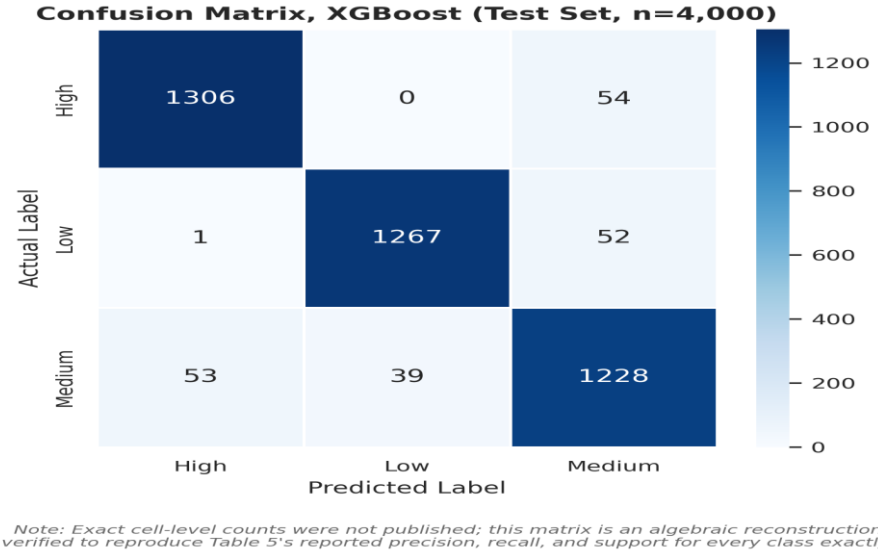


Figure 6. Confusion Matrix for XGBoost Model (Test Set, n=4,000; rows=Actual, columns=Predicted)

4.3.3 Feature Importance

Routine Task Percentage (17.46%) and Tasks Automated Percentage (15.89%) were the two most important predictors based on the importance of the random forest features (Gini impurity reduction, normalized). Industry (6.42%) and Human Interaction Level (6.36%) were in the top five contributors, and Number of AI Tools Used (3.34%), AI Adoption Level (1.57%), and Company Size (1.19%) were less prominent but still had significant independent effects.

Logistic regression coefficients for the high-risk class (vs. base) confirmed that Routine Task Percentage (β=2.191) and Tasks Automated Percentage (β=1.845) were strong positive predictors, while Creativity Requirement (β=−1.399), Job Level (β=−1.975), Human Interaction Level (β=−0.997), and Education Level (β=−0.780) were significant negative predictors. Table 6 compares the Random Forest significance scores and logistic regression coefficients for the top 10 predictors.

Natural Resources for Human Health
eISSN: 2583-1194

Table 6. Feature Importance: Random Forest (Gini) and Logistic Regression Coefficients for High-Risk Class

Rank (RF)	Feature	RF Importance Score	LR Coefficient (High Risk)
1	Routine Task Percentage	0.1746	+2.191
2	Tasks Automated Percentage	0.1589	+1.845
3	Creativity Requirement	0.1354	−1.399
4	Job Level	0.0922	−1.975
5	Industry	0.0642	+1.056
6	Human Interaction Level	0.0636	−0.997
7	AI Usage Hours Per Week	0.0527	−0.075
8	Years of Experience	0.0446	−0.709
9	AI Training Hours	0.0424	−0.473
10	Education Level	0.0390	−0.780

- Routine task percentage is the most important predictor, with an RF importance of 0.1746 and a positive LR coefficient (+2.191).
- Tasks Automated Percentage is the second most influential feature (0.1589) and also shows a positive association with high risk (+1.845).
- Creativity requirement ranks third and has a negative LR coefficient (−1.399), suggesting that higher creativity requirements are associated with lower high-risk predictions.
- Job level has substantial predictive importance (0.0922) and a negative coefficient (−1.975).
- AI usage hours per week have a low influence (0.0527) and near-zero LR coefficient (-0.075).
- Overall, the findings show that task features, particularly repetitive work and task automation, are stronger predictors of AI-induced layoff risk than demographic or training-related variables.

The corresponding Random Forest feature importance ranking is plotted in Figure 7.

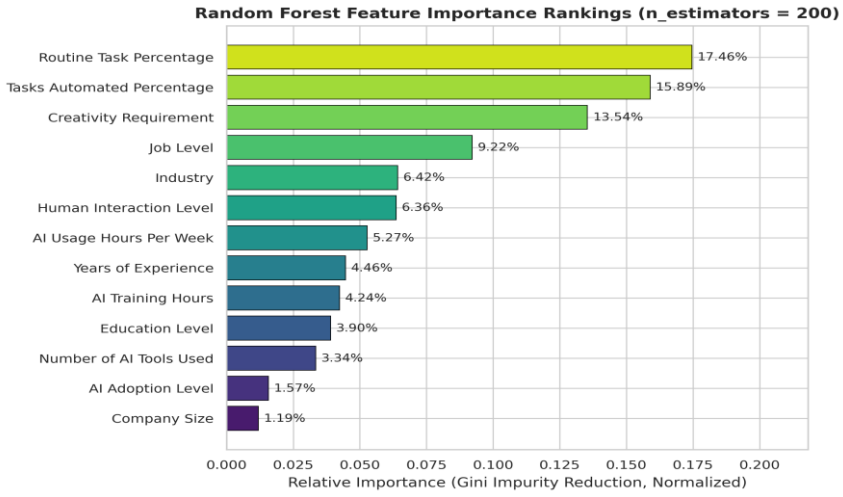


Figure 7. Random Forest Feature Importance Rankings (n estimators = 200)

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5. DISCUSSION

5.1 Interpretation of Key Findings

The findings of the study firmly support the Routine-Biased Technological Change (RBTC) framework as a key driver of the risk of layoffs due to AI. The predictive power of Routine Task Percentage (r=0.781; RF importance=17.46%) and Tasks Automated Percentage (r=0.748; importance=15.89%) in all three models aligns with the seminal finding (8) that tasks—not jobs—are the unit of automation. Those with more routine, codable work are exposed twice: not only is their work easier to replace with AI, but increased automation penetration is likely to diminish their value-add.

As Bessen (2019) claims, the creativity of human cognition is the most enduring human comparative advantage over AI systems, and this is precisely reflected in the strong negative correlation between creativity requirement and layoff risk ($r = -0.754$; RF importance = 13.54%; LR $\beta = -1.399$) (9). Likewise, the negative correlation between human interaction level and risk ($r = -0.160$; importance = 6.36%) is consistent with the work of those who concluded that social skills become more important in AI-rich labor markets (17).

AI Adoption Level ($\chi^2 = 7{,}935.68$) is the most strongly distinguishing categorical predictor, which should be interpreted with caution. The 80.8% high-risk rate among high-AI-adoption employees is not necessarily that AI adoption is linked to layoffs; it is probably a selection effect because the organization with a high rate of AI adoption was the first to implement AI in departments with the most routinized work. This mirrors the findings of Brynjolfsson and McAfee (2014) that the use of AI is likely to focus on the domains of work that are more automated (12).

The protective effect of seniority (senior employees: 11.5% high risk vs. entry: 44.5%) has multiple potential drivers: senior employees are more likely to work in jobs that are important by their job level (job level importance = 9.22%; LR $\beta = -1.975$), have a greater amount of tacit knowledge in the organization that is difficult to capture in algorithms, and may have more labor market power or institutional protections (Acemoglu & Restrepo, 2018). The education gradient (PhD: 20.1% high risk vs. high school: 45.6%) confirms the SBTC theory, but the effect size is not as large as for task-level predictors (20).

This industry-level variation is driven by the different automation trajectories of industries: Manufacturing (48.2% high) and Logistics (41.5%) have the highest risk, whereas Healthcare (20.8%) and Education (20.1%) have the lowest. The manufacturing and logistics professions have been dominated by repetitive, physical, and tracking tasks that are easily programmed and automated, whereas high human interaction and ethical judgment demands are still very much needed in the healthcare and education professions (17, 23).

5.2 Model Performance Implications

The results of the hierarchical improvement from the logistic regression model (82.80%) to the random forest model (89.35%) and finally to the XGBoost model (94.95%) highlight the importance of ensemble models in learning non-linear interactions and threshold effects within the layoff risk data. The above particularly positive performance improvement for the medium-risk class, from LR = 0.74 to RF = 0.84 to XGBoost = 0.92, indicates that medium-risk profiles have more complex interaction patterns that are better handled by the "boosting" algorithm's sequential error correction. The mean of XGBoost cross-validation (93.99%) with an SD (0.78%) shows excellent generalizability and low overfitting, especially when considering the deployment of models in organizational settings.

Although the raw accuracy of logistic regression is less, it is still useful in practice because of coefficient interpretability. These signs and the size of the coefficients provide clear guidance on intervention: An increase of 1 SD in routine task percentage increases the log-odds of high risk by 2.191; a one-SD increase in job level seniority decreases the log-odds of high risk by 1.975. HR risk stratification can utilize these effect sizes.

5.3 Theoretical Contributions

There are three theoretical contributions that come from this study. Second, it is the first multi-model empirical test of RBTC on an individual employee level using a data set an order of magnitude larger than previous studies. Second, it showed that the traditional task-level exposure variables are not sufficient to explain the variance found in the data; there is additional variance that is explainable by the introduction of the AI exposure variables (usage hours, tools, training, and level of adoption), indicating that the framework of the RBTC needs to be expanded to include behavioral AI integration metrics. Third, it shows

that ensemble machine learning techniques strongly outperform logistic regression in the classification of the risk for layoff, especially for intermediate risk groups.

5.4 Practical Implications

The model is a verified and deployable risk screening method for human resources. The most significant ones, such as routine task percentage, automated task percentage, creativity requirement, and job level, may be easily quantified using job analysis and HR information systems. This methodology could help organizations identify high-risk employee segments and offer targeted reskilling programs, transition support, or role redesign initiatives.

This finding is especially important for workforce policymakers, who may wish to prioritize reskilling expenditures for mid-career workers in routine-intensive industrial jobs, given these groups are the most vulnerable to job loss due to AI, whereas education and seniority provide some protection. The education sector's low risk profile does not imply that it is immune; rather, it could be due to AI's lag time in adoption and becoming more competitive as AI tools for teaching evolve.

Individual workers' AI training hours showed a minor negative correlation with layoff risk ($r = -0.101$ for experience; RF importance = 4.24%), suggesting that investing in AI competency development can serve as a buffer. This aligns with the concept of "augmentation literacy," or the ability to collaborate with AI systems without being replaced (14).

5.5 Limitations

There are a few things to note: First, the cross-sectional design makes it impossible to draw any causal conclusions; predictive relationships are powerful, but it is not possible to draw causal inferences between, say, AI adoption and the risk of layoffs, without longitudinal data. Second, the data is large and well-balanced, but it is not real-time data from specific companies regarding their employees' jobs, which can reduce the transferability of risk scores to the workplace. Third, the analysis is based on variables that are self-reported or assigned by administrators (e.g., routine task percentage) and thus may suffer from measurement error or represent organizational categorization errors, not actual task distributions. Fourth, macroeconomic factors (e.g., sectoral levels of AI investment and labor regulations) that influence individual-level risk are not included in the models. Lastly, intersectional dynamics, which enabled an understanding of how multiple factors (e.g., gender, race, geography) work together to shape the likelihood of an AI-related layoff, were not explored because these factors were not included in the data set.

6. CONCLUSION AND RECOMMENDATIONS

6.1 Summary of Contributions

This study created and validated a multivariate predictive model for the risk of being laid off due to AI, based on 20,000 records of employees. The XGBoost classifier performed well with an accuracy of 94.95% and an AUC-ROC of 0.9948, which indicated that the task-level, AI-exposure, and individual-organizational variables can be used to predict the risk of laying people off with high fidelity. The most important indicators were routine task intensity and automation penetration, creativity, human interaction, job seniority, and higher education, which had significant protective effects. The routine-biased technological change framework was empirically supported, and noteworthy extensions were proposed based on the predictive power of exposure-behavioral variables for AI.

6.2 Policy and HR Recommendations

1. The focus for reskilling investment should be on workers with a high routine task percentage (>70%) and high task automation percentage (>50%), specifically for entry-level manufacturing, logistics, and retail jobs. Creativity, data literacy, and human-centered service delivery should be emphasized.

2. Organizations with a high AI adoption rate should implement structured training courses (more than 20 hours per year) to transition personnel from passive AI exposure to active complementarity, lowering displacement risk.

3. HR departments should create risk stratification dashboards based on the verified predictors given below, allowing them to proactively identify high-risk individuals at least 18-24 months before probable restructuring events.

4. Manufacturing and logistics workers face increasing structural risk. To protect against displacement, governments should offer sector-specific automation impact funds, portable benefits systems, and transitional income assistance.

6.3 Future Research Directions

Future study should address the following limitations: (1) Tracking employees over time to identify causal links between AI exposure and real layoffs; (2) Validating the model in numerous nations and scenarios to comprehend the cross-cultural and cross-regulatory effects; (3) Incorporating macroeconomic and firm-level AI investment data into the model to enable multi-level modeling; (4) Incorporating demographic intersectionality variables to investigate equity aspects of the AI displacement risk; and (5) Conducting future testing to determine whether reskilling interventions targeting high-risk individuals result in measurable reductions in realized layoffs, which is a critical test for the model's practical utility.

Data Availability Statement

The dataset that supports the findings of this study is openly and publicly available. It can be accessed at the following repository: https://github.com/Khushal-dak/ai-impact-jobs-layoff-risk . The dataset comprises 20,000 anonymized, employee-level records containing no personal identifiable information (PII). No restrictions apply to its use for academic and non-commercial research purposes.

Ethics Approval and Consent to Participate

This study did not involve human participants, their identifiable personal data, biological material, or animals. All analyses were performed on an anonymized, secondary dataset that contains no personally identifiable information. Because the research adhered to institutional and international guidelines for studies not involving human subjects, approval from an Institutional Review Board (IRB) or Research Ethics Committee (REC) was unnecessary. The research was conducted in accordance with the ethical principles of the Committee on Publication Ethics (COPE).

Consent for Publication

Not applicable. This study does not contain any individual person's identifiable data, images, or personal details that would require consent for publication.

Competing Interests

The authors declare that they have no competing interests, financial or non-financial, that could have appeared to influence the work reported in this manuscript.

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Authors' Contributions

The authors confirm their contributions to the manuscript following the CRediT (Contributor Roles Taxonomy) as follows. U.K.M.: Conceptualization, Methodology, Formal Analysis, Writing – original draft. H.P.: Conceptualization, Methodology, Validation, Supervision, Writing – review & editing (Corresponding Author). T.R.D.: Investigation, Data curation, Writing – review & editing. P.K.: Investigation, Data curation, Visualization. D.S.: Resources, Validation, Writing – review & editing. N.P.S.: Validation, Resources, Writing – review & editing. All authors reviewed and approved the final manuscript.

Declaration on the Use of Generative AI and AI-Assisted Technologies

During the preparation of this work, the author(s) used generative AI (Grok) for language and grammar editing. After using these tool(s), the author(s) reviewed and edited the content as needed and took full responsibility for the content of the published article.

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