Decoding the Silent Resignation: How AI Spots At-Risk Employees Before They Leave

Mohammad Mahdi Ghaderi[1] **Vahid Torkzadeh**[2]

[1] *Department of Computer Engineering, Ma.C, Islamic Azad University, Mashhad, Iran*
[2] *Department of Computer Engineering, Ma.C, Islamic Azad University, Mashhad, Iran*

v.torkzadeh@iau.ac.ir

Abstract

Employee attrition poses a significant challenge for modern organizations, with the phenomenon of ”silent resignation”—where employees become disengaged long before formally resigning—exacerbating the problem. Late detection of at-risk employees leads to increased turnover costs, loss of institutional knowledge, and decreased team morale. This study presents an AI-driven solution to proactively identify employees who are likely looking for a new job. Using a public HR dataset, we developed and compared machine learning models, including Random Forest and XGBoost, to predict an employee’s intent to switch jobs based on demographic, experiential, and company-related features. Our results demonstrate that the XGBoost model achieved a strong predictive performance with a ROC-AUC score of 0.82, effectively identifying key indicators of disengagement. The most influential predictors were found to be the city’s development index, company size, and years of experience. This work contributes a robust framework for early attrition risk detection, enabling HR departments to implement targeted retention strategies before valuable talent is lost.

Keywords: Employee attrition, silent resignation, predictive analytics, AI in HR, machine learning, XGBoost, feature importance.

v.torkzadeh@iau.ac.ir

1 Introduction

Employee turnover is one of the most persistent and costly challenges facing modern organizations [7]. Beyond the direct financial costs of recruitment and training, high attrition rates can disrupt team dynamics, impact productivity, and lead to a loss of valuable institutional knowledge. A particularly insidious aspect of this problem is the "silent resignation" or "quiet quitting" phenomenon, where employees mentally and emotionally disengage from their roles long before they submit their notice [1]. This disengagement manifests as reduced productivity, lower participation in team activities, and a general lack of initiative. Recent research in the healthcare sector has shown how decision trees, random forests, support vector machines, and neural networks can be applied to predict quiet quitting behavior [7]. The Society for Human Resource Management (SHRM) estimates that the cost of replacing an employee can be as high as 50% to 200% of their annual salary, highlighting the financial imperative to address attrition proactively [4]. By the time these signs are noticed through traditional management channels, it is often too late to intervene effectively.

The business impact of late detection is substantial. Firms that fail to manage retention proactively face high turnover costs and reduced productivity [8]. Traditionally, the field of HR analytics relied on retrospective data, which, while insightful, failed to provide the predictive power needed for timely intervention [2]. The advent of artificial intelligence (AI) and machine learning (ML) offers a powerful new toolkit for Human Resources (HR) to shift from a reactive to a predictive stance. Modern machine learning models, including neural networks [3] and ensemble methods like gradient boosting [5], have proven highly effective in this domain, capable of capturing complex, non-linear relationships within employee data that traditional statistical methods often miss. Recent studies confirm that algorithms such as Random Forests and XGBoost perform particularly well in turnover prediction tasks [8, 7]. This data-driven approach is further enhanced by sophisticated feature engineering, which is critical for transforming raw HR data into meaningful predictors of behavior [6].

This study aims to leverage AI to decode the subtle signals of silent resignation. By analyzing a comprehensive set of employee data, we seek to build a predictive model that can identify employees who are actively looking for a new job opportunity. This goal aligns with recent HR analytics research that demonstrates the effectiveness of predictive models in anticipating employee attrition [9, 10]. The objective is to provide HR professionals with an early-warning system, enabling them to initiate timely and personalized interventions to retain their most valuable assets: their people.

2 Research Methodology

Our approach involved a structured process of data preparation, model development, and evaluation, with a strong emphasis on handling the practical challenges of real-world HR data. This section outlines the dataset used, the preprocessing steps taken, the models developed, and the metrics used for evaluation.

2.1 Data Source and Description

The analysis was conducted on the "HR Analytics: Job Change of Data Scientists" dataset, publicly available from Kaggle. The dataset contains 19,158 records of candidates enrolled in a data science training program. Each record includes 14 features, such as demographics (gender, city), professional background (experience, education, company type), and training details (training hours). The target variable, `target`, is a binary indicator where 1 signifies that the candidate is looking for a job change, and 0 signifies they are not. This dataset has been widely used in recent HR analytics studies to evaluate the predictive potential of ML models for turnover [10].

v.torkzadeh@iau.ac.ir

2.2 Data Preprocessing and Feature Engineering

The raw dataset contained missing values and categorical features that required careful handling before modeling.

- **Data Cleaning:** The `experience` and `last_new_job` columns contained non-numeric values (e.g., `>20`, `<1`, `never`). These were mapped to numerical equivalents (`21`, `0`, `0`, respectively) to facilitate analysis.

- **Handling Missing Values:** The machine learning models chosen for this study, particularly XGBoost, are capable of handling missing values internally. Therefore, no explicit imputation was performed, simplifying the preprocessing pipeline.

- **Feature Encoding:** To make the categorical data suitable for machine learning algorithms, a multi-strategy encoding approach was used:
  - **Ordinal Encoding** was applied to features with an inherent order, such as `education_level` (Primary School to PhD) and `company_size` (`<10` to `10000+`).
  - **Label Encoding** was used for binary categorical features like `relevent_experience`.
  - **One-Hot Encoding** was applied to nominal features with no intrinsic order, such as `gender`, `major_discipline`, and `company_type`. The `city` feature was also one-hot encoded, creating a high-dimensional feature space. The `enrollee_id` column was dropped as it serves only as an identifier.

These preprocessing steps follow best practices in HR predictive analytics, which emphasize the importance of careful feature engineering in improving model performance [6, 9].

2.3 AI/ML Models

Two powerful ensemble learning models were selected for this classification task, known for their high performance and ability to handle complex datasets [8, 7].

1. **Random Forest Classifier:** An ensemble of decision trees that operates by building multiple trees during training and outputting the mode of the classes. It is robust to overfitting and provides insights into feature importance.

2. **XGBoost (Extreme Gradient Boosting):** A highly optimized implementation of gradient boosting, renowned for its speed and predictive accuracy. It builds models sequentially, with each new model correcting the errors of the previous one.

To address the class imbalance observed in the target variable (approx. 75% "not looking" vs. 25% "looking"), specific parameters were used: `class_weight='balanced'` for Random Forest and `scale_pos_weight` for XGBoost. A standard 80/20 train-test split was performed, with stratification on the target variable to ensure the class distribution was maintained in both sets. Numerical features were scaled using `StandardScaler`. Similar modeling strategies have been validated in recent HR analytics studies [9, 10].

v.torkzadeh@iau.ac.ir

3 Results and Discussion

This section presents the findings from our exploratory data analysis and the performance of the predictive models. The results provide compelling evidence that AI can effectively identify employees at risk of silent resignation.

3.1 Exploratory Data Analysis Insights

Initial analysis revealed a significant class imbalance, with approximately 75% of individuals not looking for a job change, as shown in Figure 2. Further exploration highlighted key behavioral patterns. Figure 4 shows that employees with very little experience (<5 years) or a great deal of experience (>20 years) were more inclined to seek new opportunities. This suggests that early-career professionals seeking growth and senior experts looking for new challenges are key flight-risk segments.

Interestingly, Figure 3 indicates a subtle trend where individuals looking for a job change tend to undertake more training hours, possibly to upskill for a new role. The analysis of job tenure revealed that individuals who had switched jobs just one year prior were the largest group actively looking for another change, suggesting a potential mismatch in their previous move.

3.2 Model Performance and Evaluation

Both the Random Forest and XGBoost models demonstrated strong predictive capabilities. The XGBoost model slightly outperformed the Random Forest classifier across most key metrics, as summarized in Table 1.

The high recall of our models indicates that such a system can serve as a reliable early-warning tool for HR departments. The confusion matrices for both models (Figure 5) highlight their effectiveness. Both models achieve a high recall for the positive class ('Looking'), correctly identifying over 77% of employees who are at risk of leaving. This is a critical success for an early-warning system, as minimizing false negatives (missed at-risk employees) is paramount. While the precision for the 'Looking' class is moderate (around 55-56%), resulting in some false positives, this trade-off is often acceptable in retention contexts. It is generally less costly to engage with a content employee than to miss an at-risk one.

3.3 Key Predictive Features

The feature importance analysis from the superior XGBoost model revealed the primary drivers behind an employee's decision to look for a new job (Figure 6). The top 5 most predictive features were:

1. **City Development Index:** The socioeconomic status of an employee's city was the single most important predictor.
2. **Company Size:** The size of the current employer played a significant role.
3. **Education Level:** The level of an employee's formal education.
4. **City (Specific):** Being in specific cities (e.g., city_103, city_160) was highly predictive.
5. **Experience:** The total years of professional experience.

The prominence of the **city development index** suggests that external market conditions and opportunities heavily influence an employee's loyalty. Individuals in highly developed cities may have more exposure to alternative job opportunities, making them higher flight risks. **Company size** and **experience** align with established HR theories; employees in very small or very large companies, or those at the beginning or end of their careers, often have distinct motivations for seeking change.

The main limitation of this study is its reliance on data from candidates in a specific training program, which may not be fully representative of the general workforce. Furthermore, the dataset lacks dynamic, time-series data (e.g., performance trends over time) which could further enhance predictive accuracy.

v.torkzadeh@iau.ac.ir

4 Tables, Figures, and Charts

This section consolidates all the key visuals and tables generated during the analysis, providing a graphical and tabular summary of our findings.

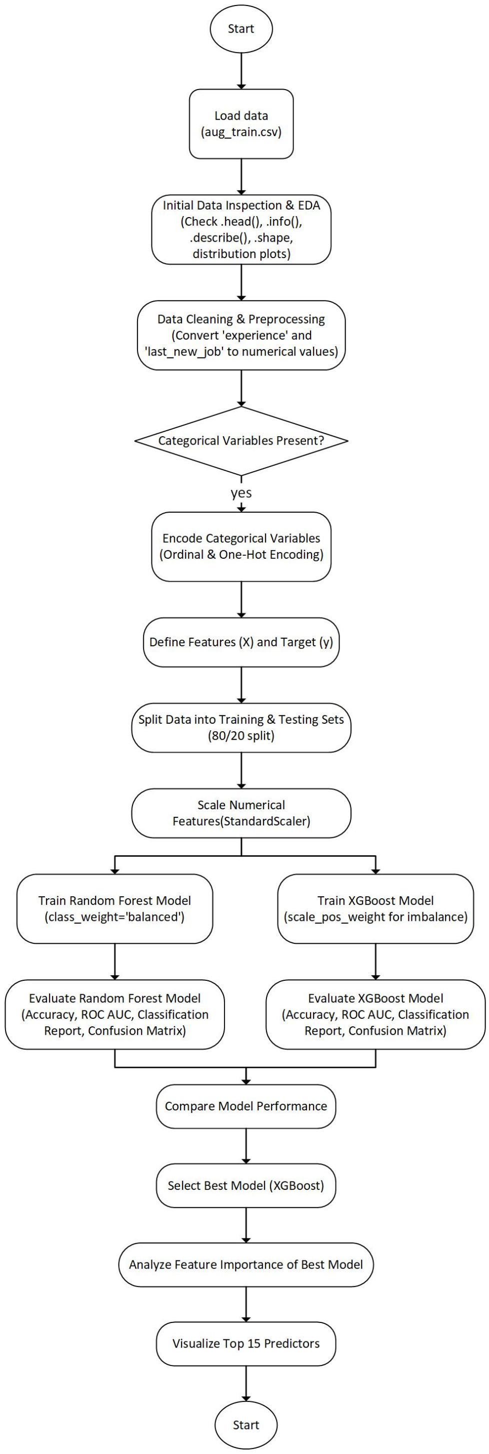


Figure 1: Flowchart detailing the end-to-end machine learning methodology, from data loading and preprocessing to model training, evaluation, and feature importance analysis.

v.torkzadeh@iau.ac.ir

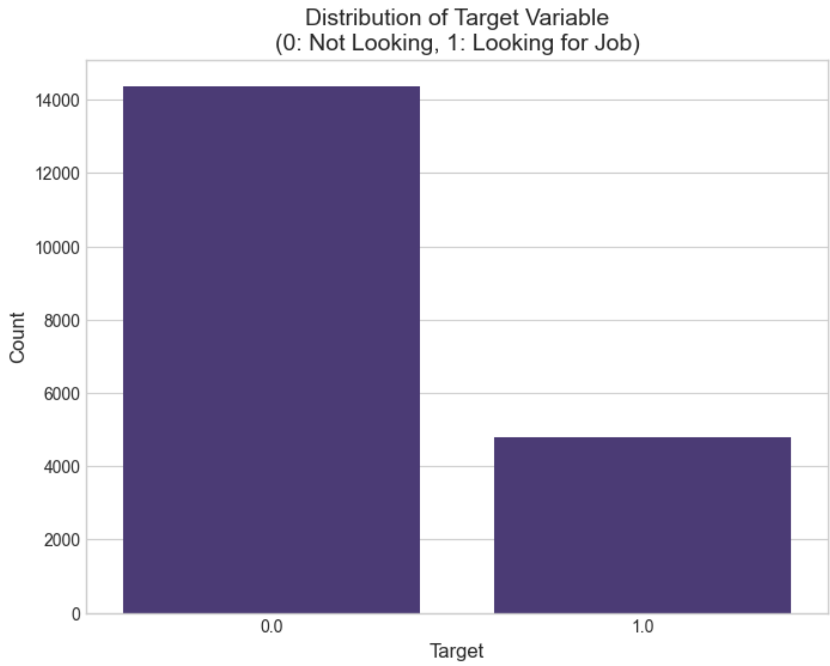


Figure 2: Distribution of the Target Variable, showing a significant class imbalance.

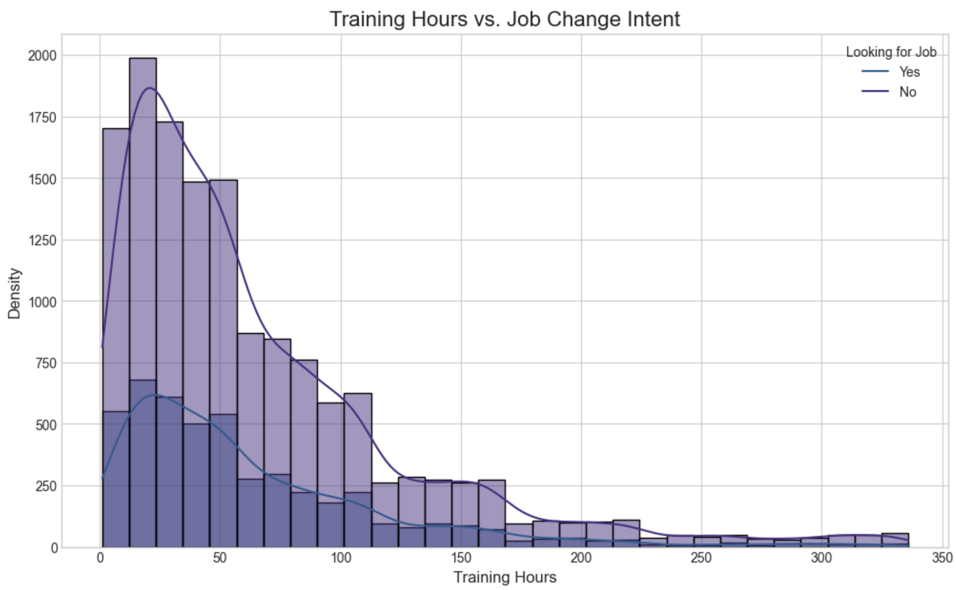


Figure 3: Distribution of Training Hours by Job Change Intent.

v.torkzadeh@iau.ac.ir

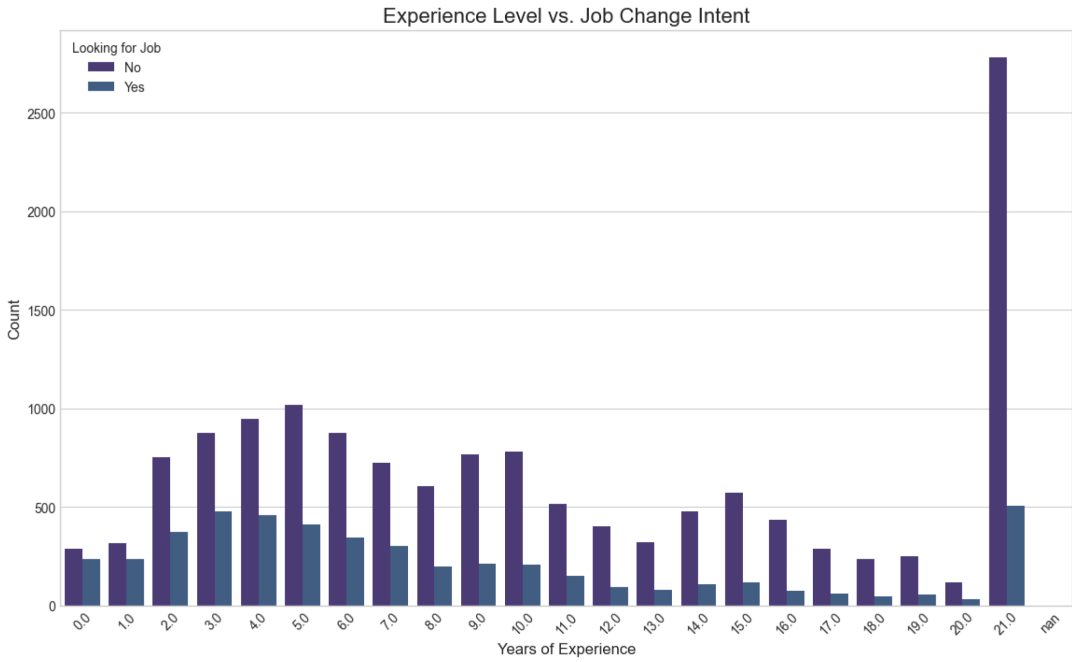
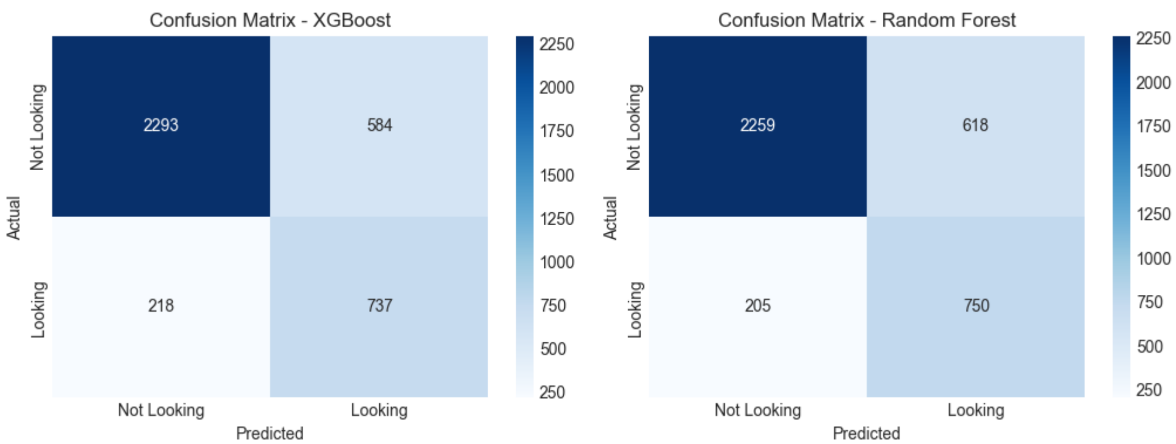


Figure 4: Experience Level vs. Job Change Intent.

Table 1: Comparison of Model Performance Metrics.

Model	Accuracy	ROC-AUC	Recall (Class 1)	F1-Score (Class 1)
Random Forest	0.7852	0.8125	0.79	0.65
XGBoost	0.7907	0.8179	0.77	0.65



XGBoost **Random Forest**

Figure 5: Confusion Matrices for XGBoost (Left) and Random Forest (Right) Models.

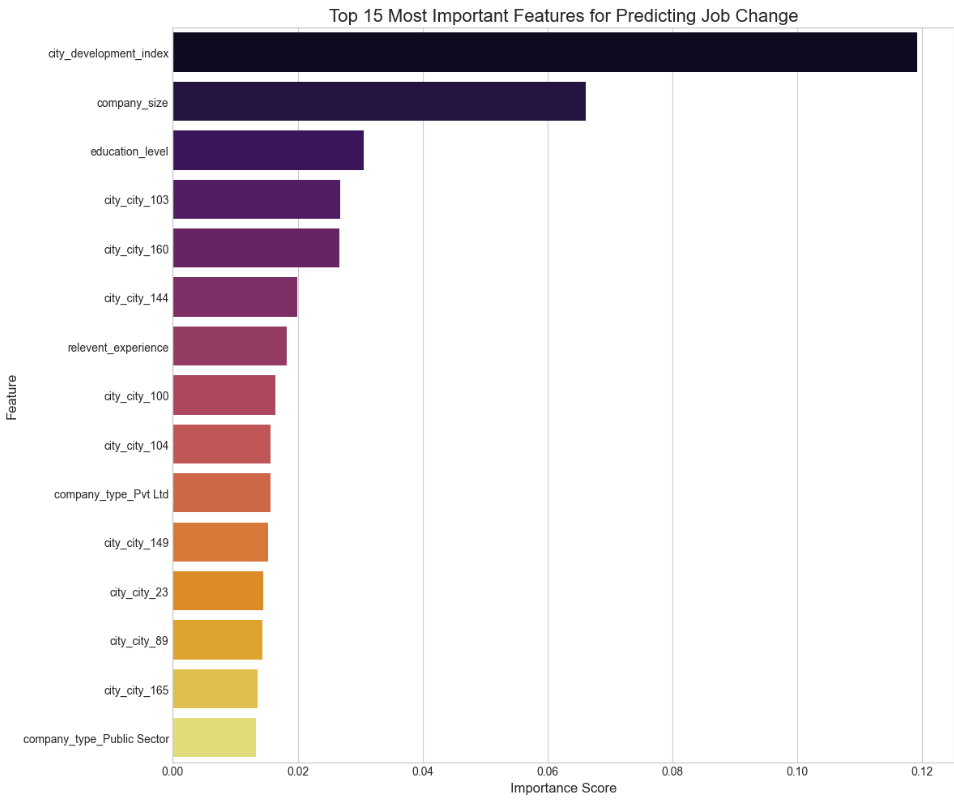


Figure 6: Top 15 Most Important Features from the XGBoost Model.

v.torkzadeh@iau.ac.ir

5 Formulas and Mathematical Equations

The evaluation of our classification models relied on several standard performance metrics. This section provides the mathematical formulas for these key metrics. In these formulas, TP, TN, FP, and FN represent True Positives, True Negatives, False Positives, and False Negatives, respectively.

5.1 Evaluation Metrics Formulas

1. **Accuracy:** Measures the proportion of total predictions that were correct.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

2. **Precision:** Measures the proportion of positive identifications that were actually correct. A high precision relates to a low false positive rate.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

3. **Recall (Sensitivity):** Measures the proportion of actual positives that were identified correctly. This metric is critical for our use case, as we want to identify as many at-risk employees as possible.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

4. **F1-Score:** The harmonic mean of Precision and Recall. It is a useful metric for comparing models, especially when there is a class imbalance.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

5.2 ROC-AUC Score

The Receiver Operating Characteristic (ROC) Area Under the Curve (AUC) score was also used. The ROC curve is a plot of the True Positive Rate (Recall) against the False Positive Rate at various threshold settings. The AUC represents the likelihood that the model will rank a randomly chosen positive instance higher than a randomly chosen negative one. A score of 1.0 represents a perfect model, while a score of 0.5 represents a model with no discriminative ability.

v.torkzadeh@iau.ac.ir

6 Conclusion

This project successfully demonstrates the value of applying AI to the complex challenge of employee retention. We developed a robust XGBoost model capable of identifying employees looking for a job change with a ROC-AUC score of 0.82, providing a practical tool for decoding silent resignation. Our analysis identified non-obvious yet powerful predictors, such as the city development index, that can help organizations refine their retention strategies.

The value of this approach lies in its ability to empower HR teams with proactive, data-driven insights. Instead of waiting for exit interviews, organizations can use these predictions to initiate supportive conversations, offer new growth opportunities, or address underlying issues before they lead to resignation.

6.1 Future Work

Future work will focus on enhancing the model's capabilities and applicability. Key next steps include:

- **Integrating Diverse Data Sources:** Incorporating data from performance reviews, internal communication platforms (using NLP for sentiment analysis), and project management tools to capture a more holistic view of employee engagement.
- **Developing a Real-Time Dashboard:** Creating an interactive dashboard for HR managers that displays flight risk scores and key contributing factors for each employee, while adhering to strict privacy and ethical guidelines.
- **Fairness and Bias Auditing:** Implementing advanced techniques to audit the model for any demographic bias and ensure its predictions are fair and equitable.

By continuing to refine these AI-driven tools, organizations can build a more resilient and engaged workforce, turning the tide on the costly problem of employee turnover.

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v.torkzadeh@iau.ac.ir