Predicting Employee Turnover Using Personality Assessment: A Data-Driven Approach

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Keywords: Machine Learning (ML), Artificial Intelligence, Employee Turnover, Predictive Analytic, Human Resources (HR), Behavioral Profiling, PACE Framework.

Abstract: Employee turnover represents a persistent challenge for organizations seeking to maintain stability, retain institutional knowledge, and control costs. Traditional predictive models often rely on static employee records and demographic variables, providing limited insight into the nuanced behavioral patterns that precede workforce attrition. This study leverages the PACE Behavioral Profile Mapping (BPM) framework to integrate behavioral features into a machine learning–based turnover prediction pipeline. Clustering techniques were employed to ensure model generalization for specific company clusters, and hyperparameter optimization was performed using Optuna. The resultant CatBoost models demonstrated notable improvements in predicting turnover risk, particularly for employees at higher risk of departure, when PACE-based behavioral indicators were incorporated. These findings suggest that a more comprehensive characterization of employee tendencies, beyond conventional demographic and historical measures, can enhance the identification of at-risk individuals. By adopting behaviorally informed analytics, organizations may achieve more targeted and effective retention strategies, ultimately supporting more stable workforce management.

1 INTRODUCTION

Employee turnover presents a persistent challenge for organizations, influencing productivity, operational continuity, and financial outcomes. Understanding and predicting turnover risk is crucial for Human Resource Management (HRM) to implement effective retention strategies. Despite the growing availability of employee data, predicting turnover remains complex, as it often involves multifaceted behavioral and contextual factors that are not easily quantifiable.

One approach that offers a structured basis for categorizing and evaluating employee behaviors is the PACE Behavioral Profile Mapping (BPM) framework (Vieira et al., 2023). By classifying individuals into four archetypes (Planner, Analyst, Communicator, and Executor) this framework provides an empirical foundation for examining complex behavioral patterns within organizational contexts. Given its relative novelty, PACE may serve as an underexplored reference point for systematically investigating subtle interactions and adaptive responses, thereby contributing to a more nuanced understanding of workplace dynamics.

While PACE provides a theoretically comprehensive framework, its practical effectiveness for predicting turnover has yet to be rigorously evaluated. Behavioral profiling is inherently complex, and the extent to which archetypal classifications and situational indicators – such as energy, morale, and flexibility – translate into actionable insights for turnover prediction remains an open question.

This study investigates the integration of the PACE Behavioral Profile Mapping (BPM) framework with machine learning techniques to predict employee turnover using real-world data. By carefully engineering features to address ethical concerns, grouping companies based on shared turnover patterns for enhanced model generalization, and prioritizing recall to effectively identify at-risk employees, this research seeks to assess the PACE framework's practical utility and limitations. The findings aim to inform HR practitioners and researchers on whether such behav-

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Mazo, R. N., Nogueira Júnior, M. P., Soares de Quadros, A. R., Vieira, A. and Brandão, W. C.
Predicting Employee Turnover Using Personality Assessment: A Data-Driven Approach.
DOI: 10.5220/0013436400003929
In *Proceedings of the 27th International Conference on Enterprise Information Systems (ICEIS 2025) - Volume 1*, pages 582-592
ISBN: 978-989-758-749-8; ISSN: 2184-4992

ioral profiling approaches can complement existing methods, ultimately supporting more proactive and targeted retention strategies.

Our contributions in this paper are as follows:

- We propose a methodology for predicting employee turnover using behavioral profiling, integrating the PACE framework with machine learning models.
- We explore clustering techniques to group companies based on turnover patterns, enhancing model scalability and generalizability.
- We provide insights into the challenges of turnover prediction and propose recommendations for improving data collection and model interpretability in future applications.

2 BACKGROUND

In this section, we specify terms related to this study, such as Employee Turnover, Machine Learning core concepts, and the features utilized in our methodology.

2.1 Employee Turnover

Employee turnover remains a critical concern for organizations worldwide due to its substantial impact on financial performance, operational efficiency, and overall effectiveness (Hancock et al., 2013). High turnover rates can lead to increased recruitment and training costs, loss of organizational knowledge, and decreased employee morale. Consequently, understanding the factors that influence employees' intentions to leave has become a paramount focus for academics and professionals in HRM. By exploring these elements, organizations can develop effective strategies to enhance employee retention, improve productivity, and maintain a competitive edge in their respective industries. However, to implement these strategies successfully, it is crucial to identify potential turnover risks early. Early identification of employees who may be considering departure allows organizations to proactively address underlying issues, tailor retention initiatives, and ultimately mitigate the adverse effects associated with high turnover rates.

2.2 Machine Learning

2.2.1 Supervised Machine Learning

Supervised learning is particularly suitable for turnover classification because it leverages labeled data to predict outcomes. This works in contrast to unsupervised machine learning, where it uses only the input features X without corresponding labels Y and is typically used for clustering or anomaly detection, which is less applicable in this context. In scenarios where labeled data is scarce, semi-supervised learning can be an alternative. This method uses a small portion of labeled data along with a larger set of unlabeled data to improve learning accuracy.

Our study focuses on supervised machine learning methods, specifically utilizing algorithms like Random Forest and Logistic Regression, which will be detailed in subsequent sections. Typically, the dataset is split into training and testing subsets, often in an 80-20 ratio. The model is trained on 80% of the data and tested on the remaining 20% to evaluate its performance. The supervised learning approach is advantageous when ample labeled data is available, allowing the model to learn intricate patterns that distinguish employees who are likely to leave from those who are not. This method is also adaptable for making predictions on new data, enabling organizations to identify at-risk employees proactively.

2.2.2 Training and Testing

In the realm of supervised machine learning, the fundamental concepts of training and testing data are pivotal for developing predictive models. These models learn from data pairs $\{X,Y\}$, where X represents the input features – such as employee demographics, job satisfaction scores, and performance metrics –, and Y denotes the target variable, in this case, the turnover status i.e., whether an employee stays or not.

The training dataset is employed to teach the model's underlying patterns and relationships between X and Y. Once trained, the model's efficacy is evaluated using the testing dataset, which assesses its ability to generalize and make accurate predictions on new, unseen data. This process ensures that the model is not merely memorizing the training data but is capable of predicting turnover intentions in a real-world setting.

2.3 Features for Turnover Classification

At the organizational level, subtle indicators related to the composition of the workforce, the structure of internal roles and units, the general patterns of staff tenure, the degree to which systematic behavioral assessments are embedded in the corporate routine, and the cumulative record of prior separations collectively offer a nuanced perspective on turnover dynamics. Analyzing these interconnected signals allows for a more comprehensive understanding of how organizational characteristics and embedded practices shape both retention outcomes and the likelihood of departures.

The PACE BPM framework (Vieira et al., 2023) offers a probabilistic approach to quantifying individual behavioral tendencies through four distinct archetypes: Planner, Analyst, Communicator, and Executor. These archetypes provide a structured framework for understanding employee behavior patterns in response to workplace stimuli, which makes them particularly useful for predicting turnover. Each archetype embodies a unique response rhythm, highlighting specific personality traits and work preferences. For example, “Planners” prioritize stability, meticulous preparation, and adherence to rules, while “Executors” excel in fast-paced, dynamic environments requiring decisive and energetic responses. Meanwhile, “Communicators” thrive in collaborative, socially engaging settings, and “Analysts” emphasize precision, organization, and methodical approaches within structured contexts.

This framework enables organizations to evaluate not only the dominant behavioral traits of employees but also situational indicators such as energy levels, morale, flexibility, and motivation. Such granular profiling provides valuable insights into how employees engage with their work environment and adapt to varying demands. By incorporating these behavioral insights as features together with the non-behavioral features into machine learning models, organizations could enhance their ability to predict turnover risks, ensuring alignment between employees’ behavioral tendencies and their roles within the workplace. This integration facilitates more proactive and targeted retention strategies, contributing to organizational stability and efficiency.

3 RELATED WORKS

Employee turnover remains a critical challenge for organizations, significantly affecting financial performance, operational stability, and long-term organizational growth. High turnover rates increase recruitment and training costs, leading to the loss of institutional knowledge, and lower employee morale. These impacts are particularly pronounced in industries such as manufacturing and services, where skilled labor is integral to maintaining productivity. (Veglio et al., 2024) highlight that turnover in multinational companies disrupts strategic continuity and operational efficiency, emphasizing the need for tailored retention strategies informed by predictive analytics.

Artificial intelligence (AI) and advanced analytics have become essential tools in addressing employee turnover. (Gopinath and Appavu alias Balamurugan, 2024) explore the role of human resource analytics, demonstrating how machine learning models can integrate behavioral, demographic, and organizational data to predict turnover risk. Their study shows that AI can provide actionable insights, enabling HR professionals to implement targeted interventions for at-risk employees. However, they also acknowledge challenges such as the potential for data bias and the need for transparent algorithms to maintain employee trust.

(Marín Díaz et al., 2023) examine the integration of traditional employee metrics with behavioral data for predicting turnover. Their work highlights the importance of incorporating factors like job satisfaction and career development opportunities into predictive models. Similarly, (Morelli et al., 2024) investigates clustering techniques to group employees based on turnover propensity, enhancing the interpretability of predictive models.

Moreover, probabilistic approaches to behavioral profiling are gaining attention in turnover research. (Gopinath and Appavu alias Balamurugan, 2024) emphasize that behavioral profiling frameworks, such as those mapping archetypes or response rhythms, can improve turnover predictions by integrating qualitative insights with quantitative metrics. This complements the findings of (Veglio et al., 2024), who stress the importance of blending behavioral insights with organizational data to address the complexities of turnover dynamics in multi-national contexts.

Studies on turnover prediction show results are highly dependent on the dataset used. (Park et al., 2024) achieved 78.5% accuracy using XGBoost on the Korean 2019 Graduate Occupation Mobility Survey. (Lim et al., 2024) achieved over 90% accuracy on the IBM Employee Attrition dataset using a hybrid KNN-based model. (Chakraborty et al., 2021) reached 90% with Random Forest and 80% with Naive Bayes. (Al Akasheh et al., 2024) achieved 92.5% on the same IBM dataset using Knowledge Convolutional Networks. Still on the IBM dataset, (Yiğit and Shourabizadeh, 2017) used data mining for over 80% average precision, and (Ozdemir et al., 2020) used various methods for 75% precision.

To our knowledge, no studies directly use BPM information for turnover prediction. (Tsaousoglou, 2021) argue that psychometric assessment is crucial to ensure employees can learn and maintain job performance. (Li et al., 2022) discuss how different profiles have varying motivations, requiring different retention strategies. Similarly, (Emerson et al., 2023) show how psychometric assessments of stress and burnout contribute to student dropout rates, suggesting different profiles respond differently to incentives.

All mentioned studies collectively underscore the value of AI-driven analytics in turnover prediction while highlighting key challenges, including data quality, ethical concerns, and model interpretability. This paper builds on prior work by integrating behavioral profiling through the PACE framework with machine learning models, prioritizing recall to enhance the identification of at-risk employees. By addressing these challenges, this study contributes to the development of scalable, actionable, and ethical solutions for managing employee turnover.

4 METHODOLOGY

This study investigates the application of machine learning techniques for employee turnover prediction using the PACE behavioral profiling framework. The methodology aims to balance predictive accuracy, ethical considerations, and practical applicability, while addressing challenges related to data variability across different organizations and ensuring generalizability across a wide range of enterprise contexts.

The methodology is outlined in Figure 1, which illustrates the key steps that guided the experimental process. Each step in the flowchart represents a critical phase in the development and evaluation of the proposed approach, ensuring a systematic and structured workflow.

4.1 Modeling Strategy

4.1.1 Feature Engineering and Selection

Feature engineering was guided by both practical and ethical considerations. In particular, features with potential ethical implications, such as those related to demographic attributes or hierarchical status, were purposefully excluded to maintain fairness and compliance with regulatory standards. Instead, derived features concentrated on organizational and behavioral metrics, including the proportional relationship between an individual's tenure and the average tenure within the company, the density of turnover occurrences over specified intervals, and aspects derived from the PACE framework. By favoring these constructs, the feature set aimed to retain predictive utility while mitigating biases and ethical concerns.

Correlation analysis was performed to identify and remove multicollinear features. Additionally, feature importance was evaluated using preliminary model tests, with preference given to interpretable features.

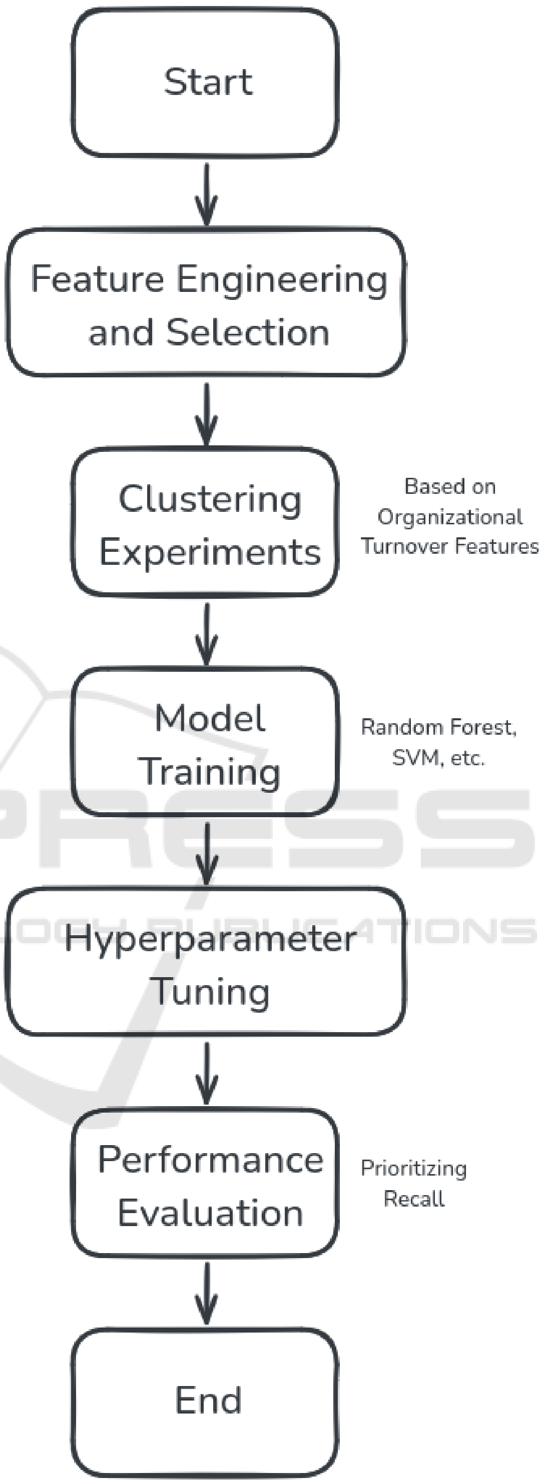

Figure 1: Methodology Flowchart. This diagram represents the steps and processes used in the proposed methodology.

4.1.2 Clustering Strategy

Initially, turnover prediction models were developed for individual companies or sectors, requiring a minimum volume of data to enable training, as shown in the study (Adeusi et al., 2024), which applies machine learning techniques to predict turnover in high-stress sectors. However, this approach proved impractical for smaller companies due to insufficient data and the recurring cost of tailoring models to each new organization. To overcome these limitations, a unified modeling approach was explored, grouping companies with shared characteristics to maintain individual-level relevance while reducing modeling costs.

The grouping was primarily driven by the score_company variable, which represents a turnover density rate adjusted for time, reflecting company-specific turnover characteristics. This approach aimed to achieve meaningful predictions, especially in contexts where the goal is proactive retention interventions, even if this means prioritizing recall over accuracy to capture a larger number of potential turnover cases.

The clustering strategy aimed to identify more uniform training subsets by grouping company's based on a combination of organizational-level metrics. Initially, a single metric served as a foundation, score_company, however, more balanced and representative groupings emerged when additional features were considered in conjunction. Integrating a broader range of features—encompassing organizational volume, indicators of workforce separations, temporal retention measures, and the original foundational score_company. To determine the optimal number of clusters, the Elbow Method was employed, allowing the selection of an appropriate partitioning threshold that minimized within-cluster variance while avoiding overfitting. The final clustering was performed using the k-means algorithm, which efficiently partitioned the data into meaningful, internally cohesive groups, thereby facilitating more robust and generalizable turnover prediction.

4.1.3 Machine Learning Models

Various ML models were tested, including neural networks as Long Short-Term Memory (LSTM) based, Support Vector Machine (SVM), Random Forest, XGBoost, and CatBoost. The following strategies were implemented:

- **Hyperparameter Tuning.** Optuna (Akiba et al., 2019) was used to optimize model hyperparameters.
- **Data Imbalance Management.** Oversampling technique Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2011) were combined with manually tuned class_weights to address imbalances and ensure meaningful predictions without overly passive or alarmist results.

4.2 Evaluation Metrics

Predictive performance was evaluated using the recall metric, which prioritizes the identification of true positives over precision and overall accuracy. Recall is calculated as follows:

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

This approach ensures the model captures the maximum number of employees at risk of turnover, aligning with the goal of enabling proactive retention strategies. While precision and overall accuracy were considered, the trade-off with recall was deemed appropriate for the specific application. Precision is calculated as follows:

$$\text{Prec.} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Additionally, the F1-score, which balances precision and recall, was also considered. It is defined as the harmonic mean of precision and recall:

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy, which measures the proportion of correctly predicted instances, is given by:

$$\text{Acc.} = \frac{\text{True Positives (TP)} + \text{True Negatives (TN)}}{\text{Total Predictions}}$$

Metrics were examined at the aggregate level for both experimental setups, incorporating class balancing and oversampling techniques. Following this initial assessment, the best-performing model was subjected to hyperparameter optimization (Akiba et al., 2019). Subsequently, metrics were re-evaluated to compare the model's performance when utilizing the complete set of features against the configuration excluding the PACE framework features.

5 RESULTS

5.1 Clustering Analysis

To improve the predictive accuracy of turnover models, a clustering strategy was implemented to group companies based on shared characteristics derived from key turnover metrics. The Elbow Method was used to determine the optimal number of clusters, balancing model complexity and performance. As shown in the Elbow Curve (Figure 2), the point of inflection occurs at $k = 6$, suggesting that six clusters provide an appropriate representation of the data while avoiding overfitting.

Each cluster was analyzed individually, with separate predictive models evaluated within these groups. This clustering strategy allowed the models to account for inter-company variations in turnover behavior and better adapt to specific organizational contexts. By tailoring the prediction models to clusters, the following advantages were observed:

1. **Increased Recall.** Models trained within clusters demonstrated higher recall for the minority class (class 1), indicating better identification of employees at high turnover risk.
2. **Balanced Metrics.** Accuracy and F1-scores were more evenly distributed across clusters, reflecting improved generalization compared to a single, non-clustered model.
3. **Interpretable Results.** Clustering enabled a better understanding of company-specific patterns, such as turnover density, regional impacts, and operational constraints.

The resulting performance metrics for the models (LSTM, SVM, XGBoost, and CatBoost) were summarized across all clusters, detailing precision, recall, and F1-scores for each class. This demonstrates the efficacy of leveraging clustering as a preprocessing step to improve the predictive power of machine learning models in turnover prediction tasks. Moreover, the tailored approach ensures actionable insights for companies with varying sizes and operational characteristics.

5.2 Experimentation with Weight Balancing

Weight balancing was employed to address the inherent class imbalance in turnover prediction, where the minority class (employees likely to leave) is often underrepresented. This approach aimed to enhance recall for the minority class (class 1) without significantly compromising precision for the majority class (class 0). Table 1 summarizes the performance metrics for LSTM, SVM, XGBoost, and CatBoost models across all clusters when weight balancing was applied.

The results demonstrate that weight balancing improved the recall and F1-scores for class 1 in all models, particularly in clusters with higher turnover density. This adjustment ensures the models can better identify employees at risk of leaving, supporting proactive retention strategies while maintaining adequate performance for class 0. The experimentation highlights the utility of weight balancing in mitigating class imbalance challenges in turnover prediction.

Among the models evaluated, CatBoost consistently achieved the best overall performance across clusters, with high precision and recall for both classes, balancing predictive accuracy and generalization effectively

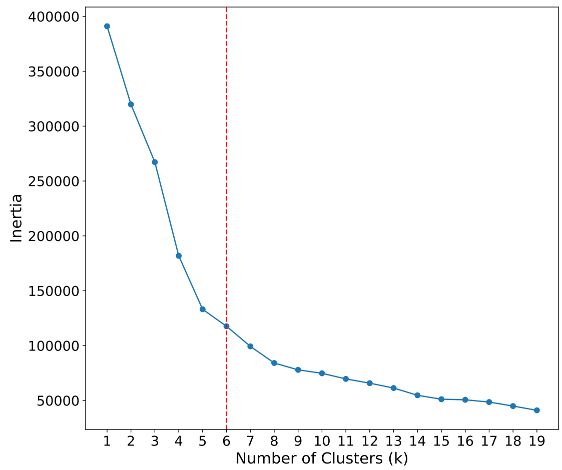

Figure 2: Elbow Method for KMeans Clustering.

5.3 Experimentation with SMOTE

SMOTE (Chawla et al., 2011) was applied to address class imbalance by generating synthetic samples for the minority class (employees likely to leave). The primary objective of using SMOTE was to enhance recall for class 1 while maintaining balanced performance across other metrics. Table 2 presents the performance metrics for LSTM, SVM, XGBoost, and CatBoost models across all clusters when SMOTE was employed.

Contrary to expectations, the use of SMOTE did not result in consistent improvements in recall for class 1. While some models, such as CatBoost, maintained relatively stable performance across clusters, the recall for class 1 generally decreased compared to models trained without SMOTE. For instance, CatBoost achieved a maximum recall of only 42% for class 1 in cluster 4, whereas recall for other models, such as XGBoost, dropped to as low as 24% in certain clusters. These results indicate that SMOTE's oversampling may have introduced noise or distorted the feature space, leading to suboptimal performance for the minority class.

Table 1: Combined Performance Metrics Across Clusters for Turnover Prediction using Weight Balance.

No.	Model	Cluster	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	LSTM	1	0	62.00	80.00	61.00	69.00
			1		39.00	62.00	48.00
		2	0	59.00	91.00	57.00	70.00
			1		23.00	69.00	34.00
		3	0	63.00	88.00	64.00	74.00
			1		28.00	62.00	39.00
		4	0	61.00	84.00	61.00	71.00
			1		31.00	59.00	41.00
		5	0	59.00	86.00	59.00	70.00
			1		28.00	61.00	38.00
		6	0	62.00	91.00	61.00	73.00
			1		23.00	67.00	34.00
2	SVM	1	0	58.00	81.00	54.00	65.00
			1		37.00	68.00	48.00
		2	0	61.00	91.00	60.00	72.00
			1		23.00	67.00	35.00
		3	0	61.00	88.00	61.00	72.00
			1		28.00	64.00	39.00
		4	0	63.00	85.00	63.00	72.00
			1		33.00	63.00	43.00
		5	0	58.00	87.00	56.00	68.00
			1		27.00	66.00	39.00
		6	0	63.00	91.00	62.00	74.00
			1		23.00	66.00	34.00
3	XGBoost	1	0	64.00	78.00	69.00	73.00
			1		40.00	51.00	45.00
		2	0	84.00	89.00	92.00	91.00
			1		48.00	40.00	43.00
		3	0	77.00	86.00	86.00	86.00
			1		40.00	41.00	41.00
		4	0	78.00	85.00	87.00	86.00
			1		51.00	48.00	50.00
		5	0	73.00	85.00	80.00	82.00
			1		36.00	45.00	40.00
		6	0	81.00	89.00	89.00	89.00
			1		37.00	37.00	37.00
4	CatBoost	1	0	63.00	81.00	62.00	70.00
			1		40.00	63.00	49.00
		2	0	70.00	93.00	70.00	80.00
			1		30.00	71.00	42.00
		3	0	72.00	89.00	76.00	82.00
			1		36.00	58.00	44.00
		4	0	72.00	86.00	76.00	81.00
			1		42.00	58.00	49.00
		5	0	68.00	87.00	70.00	77.00
			1		33.00	59.00	42.00
		6	0	73.00	91.00	76.00	83.00
			1		29.00	57.00	39.00

Although SMOTE did not meet its intended goal of improving recall for class 1, it slightly increased precision and F1-scores for class 0 in most models, indicating better representation of the majority class. This highlights a potential trade-off between oversampling and predictive accuracy, emphasizing the need for tailored strategies to handle imbalanced datasets in turnover prediction.

Our experiments showed that applying SMOTE to address class imbalance did not improve performance. This is likely due to the complex structure of the turnover dataset. The minority class (employees likely to leave) overlaps significantly with the majority class. SMOTE's synthetic samples did not accurately capture the data distribution, adding noise and increasing overfitting. The high dimensionality of our features also complicated SMOTE's interpolation, reducing the discriminative power of the augmented data. These findings suggest weight balancing may be more effective than SMOTE for this dataset's class imbalance.

5.4 Best Model Selection: CatBoost with Class Weights and Hyperparameter Tuning

Based on the results of previous experiments, the CatBoost model with class weight balancing emerged as the most suitable for turnover prediction. This model demonstrated consistent performance across clusters, excelling in recall for the minority class (class 1) while maintaining robust metrics for the majority class (class 0). To further enhance its predictive capability, hyperparameter tuning was performed using the Optuna framework, which systematically searches for the optimal combination of parameters to maximize performance.

5.4.1 Hyperparameter Tuning with Optuna

Optuna (Akiba et al., 2019) is a state-of-the-art framework for automated hyperparameter optimization. The tuning process focused on improving recall for class 1, a critical metric for turnover prediction. Key parameters optimized during the process included:

- **Learning Rate.** Controlled the step size at each iteration of model training.
- **Depth.** Defined the maximum depth of the decision trees in the model, impacting its ability to capture complex patterns.
- **L2 Regularization.** Mitigated overfitting by penalizing large weights, ensuring generalization.
- **Bagging Temperature.** Adjusted the variability in data subsampling during training to balance diversity and stability.

The optimization objective prioritized maximizing recall for class 1 while ensuring balanced performance across other metrics.

5.4.2 Performance Metrics of the Best Model

The final performance metrics of the CatBoost model, presented in Table 3, underscore the model's capacity to handle turnover prediction and lend support to the hypothesis that incorporating the PACE behavioral features enhances predictive performance. When compared to the configuration excluding PACE features, the full feature set consistently achieved higher accuracy and improved F1-scores for the positive (turnover) class across all examined clusters. This pattern suggests that behavioral indicators captured by the PACE framework provide actionable information that augments traditional organizational metrics, ultimately contributing to more robust and nuanced turnover predictions.

Key observations for the best model when utilizing the complete feature set include:

- **Class 0 (Majority Class).** The model consistently achieved high precision and recall across all clusters, with F1-scores ranging from approximately 75% to 81%.
- **Class 1 (Minority Class).** Recall values improved notably, reaching up to 76% in certain clusters, while F1-scores varied between 42% and 56%. These results indicate a substantive increase in the detection of actual turnover cases.

These findings emphasize the potential value of incorporating behavioral features derived from profiling frameworks like PACE into turnover prediction efforts. The CatBoost model, especially after hyperparameter tuning, performed better when these PACE-based inputs were included, underscoring their added value over configurations relying solely on traditional organizational metrics. Although overall improvements in minority class detection were moderate, the inclusion of behavioral indicators contributed to more nuanced insights and enhanced recall rates, ultimately supporting more informed and targeted retention strategies.

5.4.3 Insights and Implications

The CatBoost model, with its tuned parameters and the integration of behavioral features derived from the PACE framework, not only achieved robust performance for the majority class but also demonstrated improved recall for the minority class. This balanced performance is particularly valuable for actionable turnover predictions, as it enables HR professionals to more accurately identify at-risk employees while preserving precision for those likely to remain.

The experiment highlights the importance of combining class weighting strategies, advanced hyperparameter optimization frameworks such as Optuna, and the incorporation of behavioral profiling features to achieve superior results in complex predictive tasks. These findings underscore the potential of tailored, behaviorally-informed machine learning approaches for addressing organizational challenges, ensuring that models remain both interpretable and actionable for HR decision-making.

Table 2: Combined Performance Metrics Across Clusters for Turnover Prediction using SMOTE.

No.	Model	Cluster	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	LSTM	1	0	58.00	79.00	58.00	66.00
			1		36.00	60.00	45.00
		2	0	70.00	88.00	76.00	81.00
			1		23.00	40.00	29.00
		3	0	65.00	87.00	67.00	75.00
			1		28.00	56.00	37.00
		4	0	62.00	83.00	65.00	73.00
			1		31.00	54.00	39.00
		5	0	60.00	84.00	62.00	71.00
			1		27.00	55.00	36.00
		6	0	69.00	89.00	72.00	80.00
			1		24.00	49.00	32.00
2	SVM	1	0	62.00	78.00	66.00	71.00
			1		38.00	53.00	44.00
		2	0	68.00	88.00	72.00	79.00
			1		23.00	46.00	30.00
		3	0	66.00	86.00	70.00	77.00
			1		28.00	50.00	36.00
		4	0	66.00	83.00	70.00	76.00
			1		33.00	50.00	40.00
		5	0	66.00	84.00	70.00	77.00
			1		29.00	48.00	36.00
		6	0	71.00	90.00	74.00	81.00
			1		25.00	50.00	34.00
3	XGBoost	1	0	69.00	75.00	84.00	79.00
			1		43.00	31.00	36.00
		2	0	83.00	89.00	92.00	90.00
			1		45.00	34.00	39.00
		3	0	80.00	84.00	93.00	88.00
			1		43.00	24.00	31.00
		4	0	75.00	83.00	85.00	84.00
			1		44.00	40.00	42.00
		5	0	78.00	83.00	92.00	87.00
			1		44.00	24.00	31.00
		6	0	83.00	88.00	93.00	90.00
			1		40.00	27.00	32.00
4	CatBoost	1	0	72.00	75.00	90.00	82.00
			1		51.00	25.00	34.00
		2	0	83.00	88.00	93.00	90.00
			1		43.00	29.00	34.00
		3	0	81.00	84.00	94.00	89.00
			1		49.00	23.00	32.00
		4	0	78.00	84.00	88.00	86.00
			1		51.00	42.00	46.00
		5	0	80.00	82.00	95.00	88.00
			1		52.00	20.00	29.00
		6	0	84.00	88.00	94.00	91.00
			1		43.00	27.00	33.00

5.5 Discussions About PACE

5.5.1 Limitations for Turnover Prediction

While the PACE framework effectively assesses individual responses in specific situations, Profiler reports alone cannot directly measure performance. This limitation can be addressed by analyzing changes in previous test results, evaluating environmental demands, and measuring individual adaptation. Poor adaptation could suggest performance issues.

Since PACE is a self-report tool, accurate self-assessment is crucial. If an individual cannot accurately assess environmental demands or their own personality traits, the resulting data may not reflect true performance, leading to inaccurate conclusions.

Table 3: Performance Metrics Across Clusters for Turnover Prediction Best Model CatBoost.

No.	Model	Cluster	Class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	All features - CatBoost	1	0	68.00	86.00	66.00	75.00
			1		46.00	72.00	56.00
		2	0	71.00	96.00	69.00	80.00
			1		33.00	84.00	47.00
		3	0	73.00	92.00	73.00	81.00
			1		38.00	73.00	50.00
		4	0	71.00	89.00	71.00	79.00
			1		41.00	69.00	52.00
		5	0	72.00	92.00	71.00	80.00
			1		39.00	76.00	52.00
		6	0	72.00	93.00	72.00	81.00
			1		30.00	70.00	42.00
2	Non PACE Features-CatBoost	1	0	65.00	84.00	63.00	72.00
			1		43.00	71.00	53.00
		2	0	67.00	96.00	63.00	76.00
			1		30.00	87.00	44.00
		3	0	69.00	92.00	68.00	78.00
			1		35.00	75.00	48.00
		4	0	67.00	85.00	70.00	77.00
			1		36.00	58.00	45.00
		5	0	69.00	91.00	68.00	78.00
			1		37.00	74.00	49.00
		6	0	70.00	93.00	70.00	80.00
			1		29.00	69.00	41.00

5.5.2 PACE-Based Retention Strategies

HR can use PACE results to develop targeted retention strategies. Profiler results reveal how individuals respond to specific situations, allowing HR to place employees in preferred environments and minimize conflict. For example, assigning an Analyst to a communication-focused role could cause stress, forcing them into undesired situations. While such assignments might be necessary at times, Profiler data helps HR to avoid unsuitable reassignments that could lead to employee attrition.

6 CONCLUSIONS AND FUTURE WORKS

One of the key challenges and considerations in turnover prediction is addressing ethical concerns. To mitigate the risk of biased predictions, features with potential ethical implications were excluded. For instance, while state-level data (UF) was initially considered, it ultimately proved both resource-intensive and inconsistent to collect, resulting in its removal.

Another challenge lies in the data limitations themselves. A significant hindrance to model development was the incomplete and inconsistent logging of employee turnover data by organizations. Encouraging companies to maintain continuous and accurate data recording practices could substantially enhance the quality of future predictive models. By improving data reliability, these efforts would not only refine the accuracy and robustness of turnover predictions but also facilitate their broader application across varied organizational settings.

Turnover prediction is inherently complex due to the multifaceted and evolving factors influencing employee decisions. Evaluating the effectiveness of such models poses a particular challenge: successful retention strategies may, by design, lower turnover rates, thus diminishing the apparent predictive accuracy. To address this, subsequent rounds of profiling after retention interventions can provide a more reliable gauge of their true impact. Moreover, presenting results as probability intervals rather than categorical outcomes facilitates a more consultative, analytics-driven approach, allowing HR professionals to interpret these predictions as indicative trends rather than definitive forecasts.

For future improvements, the focus should be on enhancing the predictive capabilities of turnover models by integrating temporal data and expanding the range of features. Incorporating time-based information can reveal critical patterns and trends preceding turnover events. Key avenues for improvement include:

- **Temporal Data Integration.** Incorporating time-series data such as changes in employee performance metrics, tenure progression, and fluctuations in workload can provide deeper insights into the dynamics influencing turnover.

- **Additional Features.** Introducing new variables like employee engagement scores, satisfaction surveys, training participation, and career development opportunities can enrich the dataset and enhance model accuracy.
- **Longitudinal Analysis.** Employing longitudinal studies to track employee behavior over extended periods may uncover latent factors contributing to turnover, enabling more proactive interventions.
- **External Factors.** Including external data such as economic indicators, industry trends, and regional employment rates can help contextualize turnover patterns within the broader market environment.

By expanding the feature set and integrating temporal aspects, future models can achieve improved generalization and predictive performance. These enhancements would allow organizations to identify at-risk employees more accurately and implement targeted retention strategies, ultimately reducing turnover rates and associated costs.

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