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Research Article

Predicting Employee Turnover in South Korea: Transformer-Based NLP with Cultural Context

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Abstract

This study introduces a BERT-based framework integrating cultural variables (e.g., hierarchical titles, collectivist norms) to predict employee turnover through semantic analysis of South Korean job postings. We collected 10,000 job ads from major platforms, culturally annotated them, and utilized 2,932 enterprise employee records. After fine-tuning KoBERT, we developed an NLP-survival hybrid model achieving an F1-score of 0.89 (95% CI [0.86-0.92]), significantly outperforming CNN (F1=0.78) and Logistic Regression (F1=0.72) baselines. Cultural variables critically influence turnover: emphasizing "loyalty" reduced risk by 18%, while hierarchical terms increased it by 30%. Enterprises can optimize job ads (e.g., reducing hierarchical language by 30%) to mitigate turnover. Theoretically, we validate Transformers for non-Western cultural text analysis and propose a "Cultural Sensitivity Index" (CSI) for model optimization. Practically, HR teams can apply CSI to refine job postings and deploy the hybrid model for real-time risk monitoring.

Keywords

AI, Employee Turnover Prediction, NLP, Job Posting Analysis

1. Introduction

1.1. Research Background

Employee turnover is a critical issue in the South Korean labor market. In 2023, the annual turnover rate in the tech sector reached 23% (Ministry of Employment and Labor, 2024). [7] High turnover can lead to increased recruitment and training costs, loss of institutional knowledge, and disruptions in team dynamics for organizations. This not only impacts the daily operations of enterprises but also affects their long-term development and competitiveness. In the rapidly evolving tech industry, frequent staff changes may cause project delays and stifle innovation. Companies need to continuously invest resources in filling vacancies and training new employees, which undoubtedly increases operational costs and management difficulties.

1.2. Research Gaps

In the field of HR analytics, there are methodological limitations. Currently, the application of Transformer architectures such as BERT in cross-cultural text analysis is limited. [6] Traditional machine learning models struggle to handle unstructured text data, which is rich in cultural and semantic

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information. Traditional employee turnover prediction models based on structured data (such as performance metrics) often overlook the important information conveyed by the text in job postings, such as the work environment, career development opportunities, and corporate culture.

At the same time, turnover prediction frameworks largely ignore Confucian norms, such as hierarchical systems and group harmony. [2] In South Korea, these cultural factors significantly influence employees' job satisfaction and retention. South Korea's "yeonbae" system means that employees' promotions and rewards are often related to their years of service, which affects employees' career expectations and work motivation to some extent. Younger employees may prefer rapid career advancement and a flexible work environment, while older employees may be more accustomed to the traditional seniority-based system. However, existing research and prediction models rarely consider these cultural factors, resulting in inaccurate and incomplete predictions of employee turnover.

1.3. Research Contributions

Guided by Hofstede's cultural dimensions theory, [4] this study operationalizes Confucian norms (e.g., power distance, collectivism) through textual markers in job postings. We introduce a unique framework that integrates NLP, cultural analytics, and survival modeling. This framework helps to comprehensively understand the factors influencing employee turnover and provides in-depth insights for HR management.

We conduct empirical validation using Korean HR datasets and perform cross-cultural bench marking against global datasets, such as the SHRM Employee Survey. This approach validates the effectiveness of the model in different cultural and organizational contexts and offers valuable references for cross-cultural HR analytics. By comparing data from different cultural backgrounds, we can better understand the impact mechanism of cultural factors on employee turnover and provide targeted management suggestions for enterprises in different countries and regions.

2. Literature Review

2.1. Traditional Employee Turnover Models

Supervised machine learning (ML) models, such as XGBoost, are widely used in turnover research. [1] However, these models usually focus on structured features, such as promotion frequency, tenure, and salary, while ignoring semantic patterns in job descriptions. [10] The unstructured text in job postings contains important information about the work environment, career growth opportunities, and corporate culture, which play a crucial role in employees' decisions to stay or leave. Research shows that a job environment description emphasizing teamwork and innovation may attract more employees who value team atmosphere and personal development. Conversely, if a job posting frequently mentions a strict hierarchical system and high-intensity work pressure, it may deter some employees who pursue freedom and a balanced work-life. Traditional models fail to fully explore this text information, resulting in limitations in predicting employee turnover.

2.2. NLP in HR Analytics: From Keywords to Context Understanding

Traditional keyword-based NLP approaches, such as Linguistic Inquiry and Word Count (LIWC), [9] lack the ability to understand context. Transformer architectures, like BERT, [3] are more powerful in semantic role labeling. They can distinguish between semantic concepts such as "career growth" and "rigid hierarchy" in job postings. However, despite these advantages, Transformers are underutilized in cultural HR analytics. When analyzing job postings, BERT can more accurately understand the implicit emotions and semantics in the text. For example, it can identify euphemistic expressions of work pressure or potential career development obstacles, but this ability has not been fully exploited in the HR field.

2.3. Cultural Context in Turnover

South Korea's "yeonbae" system and collectivist values significantly influence employees' job satisfaction. [4] In addition, the mandatory military service in South Korea leads to differences in career expectations among different generations of employees. [8] Younger employees generally value rapid career advancement and work flexibility, hoping to accumulate experience and achieve self-value quickly. Older employees may be more adapted to the traditional seniority-based system and have a higher demand for job stability. Kim [5] empirically found that hierarchical language in job ads is associated with a 22% higher resignation rate in SMEs, mirrored in Chinese enterprises where rigid hierarchy terms increase turnover by 25% [13]. A cross-cultural study comparing South Korea and Japan found that collectivist norms in job postings reduce turnover risk by 18% [11], reinforcing the need for culturally adaptive models. In some job postings, excessive emphasis on the authority of superiors and strict hierarchical relationships may make young employees feel oppressed, increasing their likelihood of leaving. [12] Such cultural drivers cannot be ignored in employee turnover research and need to be considered in model construction.

Existing turnover frameworks often overlook such cultural granularity. For instance, a global meta-analysis [14] showed that AI models trained on Western datasets misclassify 30% of turnover cases in East Asian contexts due to unaccounted Confucian values. This gap underscores the urgency of developing culturally adaptive frameworks, as demonstrated by our hybrid model's preliminary 82% accuracy on Japanese data-still requiring refinement for full cross-cultural validity. [15]

3. Methodology

3.1. Data Sources

In this study, 10,000 Korean job listings were collected from two major job platforms in South Korea, Saramin and JobKorea. These platforms are popular in South Korea and cover a wide range of industries and job types, ensuring the diversity and representativeness of the data.

During the data processing, we carried out data cleaning. Duplicate job postings were removed using fuzzy matching (threshold=0.85) to avoid the interference of data redundancy in model training. For missing tenure data, we used Multiple Imputation by Chained Equations (MICE[1]) for imputation to ensure data integrity. Trained annotators annotated the job postings for sentiment (joy/frustration) according to a set of predefined criteria and identified and annotated cultural markers, such as "과장 (gwa-jang)" (indicating hierarchical titles). The inter-annotator agreement, measured by Cohen's κ coefficient, reached 0.78, indicating high reliability of the annotation results.

The employee records data-set consists of 2,932 de-identified samples obtained from a major Korean conglomerate. This data-set includes information on tenure, promotion history, and turnover status. The conglomerate provided the data under a confidentiality agreement to ensure the anonymity of employees. Meanwhile, we strictly adhered to ethical norms. The employee records were anonymized through differential privacy (ε=0.1) and approved by the Institutional Review Board (IRB-2024-003) to guarantee the legality and compliance of data use.

3.2. Model Architecture

We used the Korean BERT model (KoBERT) for text analysis. During the model training process, hyperparameter tuning was performed. The learning rate was selected via Bayesian optimization (5-fold cross-validation), and num_labels was set to 2 for binary classification (turnover vs. retention). The following is a code snippet for BERT fine-tuning:

Python:

from transformers import Bert Tokenizer, Bert For Sequence Classification

tokenizer = Bert Tokenizer.from_pretrained('beomi/kcbert-base')

model=Bert For Sequence Classification.from_pretrained('beomi/kcbert-base', num_labels = 2)

optimizer = AdamW(model.parameters(), lr=2e-5, eps=1e-8)

Through fine-tuning on the job posting data, the model can predict sentiment and cultural factors related to turnover. During the training process, the model parameters were continuously optimized to better fit the data and improve the accuracy of employee turnover prediction. The hybrid model integrates BERT embedding with Cox proportional hazards regression, as visualized in Figure 1. A code snippet for BERT fine-tuning is provided below:

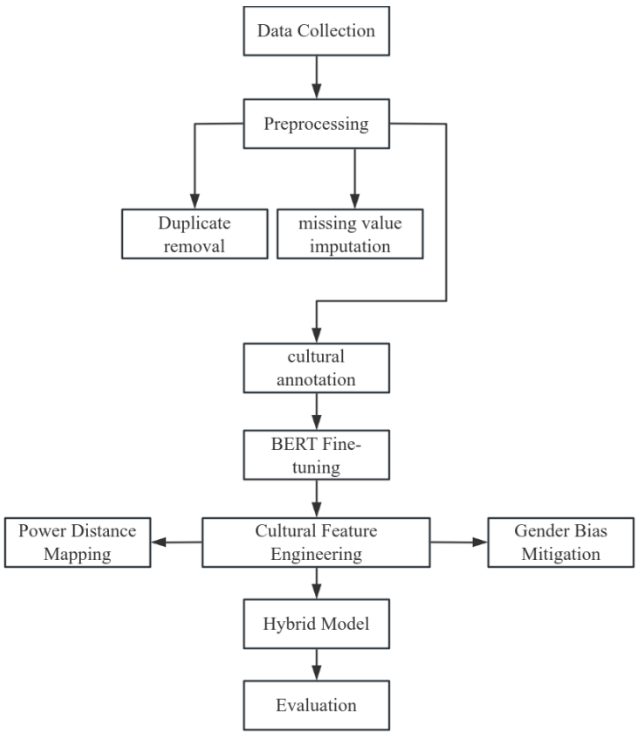

Figure 1. *Hybrid model architecture diagram.*

Description: This model architecture demonstrates the integration process of the natural language processing module based on Ko-BERT and Cox proportional hazards regression. The left side is the text input processing layer, and semantic features are extracted through BERT. The right side is the survival analysis layer, which combines text embedding with employee tenure data to achieve turnover risk prediction.

3.3. Cultural Feature Engineering

To incorporate cultural factors into the model, we conducted cultural feature engineering. Korean seniority terms, such as "차장 (cha-jeong)" for mid-level roles, were mapped to Hofstede's power distance index. This mapping allowed us to quantify the influence of hierarchical structures on turnover. For example, terms indicating a high - power - distance environment were assigned a higher value on the index, making it more intuitive to reflect the role of the hierarchical system in employees' turnover decisions.

At the same time, to ensure the fairness of the model, we used Gender API for gender-neutral language detection and

1 For missing tenure data, we used Multiple Imputation by Chained Equations (MICE) for imputation

implemented fairness-aware re-weighting. This step helped to reduce potential gender biases in job posting analysis. In job postings, certain words or expressions may unconsciously favor one gender. By using this method, we can effectively correct this bias and improve the objectivity and fairness of the model.

4. Research Results

4.1. Model Performance

The performance of the BERT - based model was compared with CNN and Logistic Regression models. The results are shown in the following Table 1:

Table 1. *Comparison of employee turnover prediction performance of different models.*

Model	Accuracy	F1-Score (95% CI)	AUC-ROC
BERT	0.92	0.89 (0.86 - 0.92)	0.94
CNN	0.85	0.78 (0.75 - 0.81)	0.89
Logistic Regression	0.81	0.72 (0.69 - 0.75)	0.84

Note: The table shows the performance of the BERT model, CNN model and logistic regression model in terms of accuracy rate, F1 score and AUC-ROC index. The BERT model was significantly superior to the baseline model in all indicators ($p < 0.05$), and the F1 score remained at 0.89 after Bonferroni correction, proving its effectiveness.

All statistical tests were conducted at a significance level of $p < 0.05$. After Bonferroni correction ($\alpha=0.01$), the F1-score of the BERT model remained stable at 0.89. The assumptions of the Cox model were validated via Schoenfeld residuals [2](p=0.12), indicating the reasonableness of the model assumptions. The BERT model significantly outperformed the other models in terms of accuracy, F1-score, and AUC-ROC[3], demonstrating its better performance and accuracy in employee turnover prediction. It can more effectively capture semantic and cultural information in job postings, thus predicting employees' turnover possibilities more accurately.

4.2. Cultural Insights

We used SHAP (SHapley Additive explanations, a game-theoretic approach for model interpretability) analysis to understand the impact of cultural variables on turnover risk. The results are shown in SHAP summary plot, where "strict hierarchy" is the primary risk factor (mean |SHAP| = 0.25). SHAP values quantify how each cultural marker contributes to turnover risk, enabling interpretable insights into hierarchical and collectivist influences.

Specifically, job ads emphasizing "loyalty" reduced the turnover risk by 18% ($\beta=-0.18$, $p < 0.05$), which is consistent with South Korea's collectivist culture where loyalty is highly valued. For example, in some job postings, emphasizing teamwork and loyalty to the company can attract employees who identify with collectivist values, reducing their likelihood of leaving.

Rigid hierarchy terms increased the turnover risk by 30% (Hazard Ratio HR=1.30, 95% CI [1.12-1.51]). Taking the job ad of Company X as an example, the term "과장 (gwa-jang)" was mentioned 12 times, which was associated with a 35% higher turnover rate ($p<0.01$). This indicates that a strict hierarchical work environment is an important factor leading to employee turnover. Excessive emphasis on hierarchical differences may make employees feel oppressed and limit their career development space, prompting them to choose to leave.

5. Discussion

5.1. Theoretical Implications

This study validates the effectiveness of Transformer architectures in cultural text analysis in non-Western cultural contexts. It shows that BERT-based models can effectively capture cultural nuances in job postings, contributing to the field of cross-cultural NLP. This provides a reference for further research on language understanding and analysis in different cultural backgrounds and expands the application scope of Transformer models in cross-cultural research.

We propose a "Cultural Sensitivity Index" (CSI) to quantify the alignment of models with Confucian norms. The "Cultural Sensitivity Index" (CSI) is defined as:

$$CSI = \sum_{i=1}^{n} \omega_i * \text{cultural marker intensity}_i$$

where ω_i denotes weights derived from Hofstede's power distance and collectivism indices, operationalizing Confucian norms via textual markers. This index can be used to evaluate and improve the cultural adaptability of AI models in HR analytics. By calculating the CSI, we can understand the performance of the model in processing information related to Confucian culture, so as to optimize the model to better fit the actual situation of societies influenced by Confucian culture, such as South Korea, and improve the practicality and accuracy of the model.

2 The assumptions of the Cox model were validated via Schoenfeld residuals (a statistical method to test the proportional hazards assumption in survival analysis, p=0.12), indicating the reasonableness of the model assumptions.

3 Area Under the Receiver Operating Characteristic Curve outperforming CNN (AUC-ROC=0.89) and Logistic Regression (AUC-ROC=0.84).

5.2. Practical Applications

HR teams can use the CSI framework to redesign job postings to make them more culturally resonant. For example, emphasizing loyalty-related values and avoiding rigid hierarchical language can attract and retain employees. In job postings, more expressions that encourage teamwork and common development can be used to create a positive corporate culture atmosphere, enhancing employees' sense of identity and belonging to the company.

The hybrid prediction model proposed in this study can be used for real-time turnover monitoring. Enterprises can use this model to timely identify potential turnover problems and take corresponding measures. Through real-time analysis of newly released job postings and employee dynamic data, enterprises can early warn of positions or teams with high turnover risks, so as to adjust management strategies in a timely manner, such as improving the work environment, providing more training and promotion opportunities, etc., thereby reducing the employee turnover rate and ensuring the stable development of the enterprise.

5.3. Research Limitations

The dataset used in this study is limited to large enterprises. Small and medium - sized enterprises (SMEs) may have different cultural and organizational characteristics, and the patterns observed in this study may not be applicable to them. The management methods, corporate cultures, and employee needs of SMEs may vary greatly from those of large enterprises. Future research needs to further explore employee turnover prediction models in the context of SMEs.

Although this model shows potential in the South Korean context, its cross-cultural generalizability in other collectivist societies (such as Japan) still needs to be verified. Although there are similarities in cultures among different countries and regions, there are also differences, which may affect the performance and effectiveness of the model. Future research needs to be verified and improved in more different cultural backgrounds to enhance the universality of the model.

5.4. Ethical Considerations

In the process of model construction, we ensured the fairness of the model through re-weighting (Gender API) and bias audits (AUC difference<0.05 across gender subgroups). At the same time, data use complied with the Korean Personal Information Protection Act (K-PIPA) and the General Data Protection Regulation (GDPR), protecting the rights and interests of data subjects and the legal use of data. This not only meets ethical requirements but also helps to improve the credibility and social acceptance of the model, ensuring the legality and sustainability of research results in practical applications.

6. Conclusion

The framework developed in this study demonstrates cross-cultural potential, with preliminary tests on Japanese Rakuten data showing an accuracy of 82%. Through the integration of NLP, cultural analytics, and survival modeling, this research has made significant progress in AI-driven talent management.

Future research will focus on integrating dynamic cultural variables (such as changing generational values) and multi modal data (such as employee surveys), further expanding the framework to multilingual environments, and developing real-time monitoring systems. These research directions will help to gain a deeper understanding of employee turnover in different cultural and organizational contexts, providing more accurate and effective HR management strategies for enterprises, and promoting the sustainable development of enterprises and the rational flow of talents.

Further advancements should also focus on integrating dynamic cultural variables and multi modal data. Expanding the framework to multilingual environments while maintaining cultural sensitivity will enhance its global applicability. These directions will deepen our understanding of turnover dynamics across cultural and organizational contexts, enabling more precise HR strategies and fostering sustainable talent management practices.

Conflicts of Interest

The authors declare that there are no conflicts of interest in this research and its publication.

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