The Impact of AI-Based Employee Analytics on Predicting Turnover in Labor Intensive Organizations: A Case of a Tobacco-Related Foreign Organization

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Abstract: Employee turnover is a major challenge for labor-intensive industries, affecting productivity, operational efficiency, and organizational stability. Traditional HR methods often fail to predict turnover proactively. This study examines the impact of Artificial Intelligence (AI)–based employee data analytics on predicting employee turnover in a tobacco-related foreign organization. Using quantitative research design, employee data—including job satisfaction, performance, compensation, overtime, and tenure—was analyzed through machine learning algorithms such as logistic regression, decision trees, and random forests. Findings indicate that AI-driven predictive analytics significantly enhances turnover prediction. The study highlights that AI integration in HR enables proactive workforce management, supports targeted retention strategies, and improves organizational performance. Implications for HR professionals include leveraging AI insights for timely interventions, optimizing working conditions, and ensuring ethical implementation of predictive technologies.

Keywords: *Artificial Intelligence, Employee Turnover, HR Analytics, Labor-Intensive Industries, Predictive Analytics*

Background

Employee turnover is one of the most critical challenges faced by organizations across various industries, as it directly influences organizational sustainability and competitiveness. High turnover rates can disrupt organizational productivity, increase operational costs, and reduce overall workforce stability (Hom et al., 2017). Beyond these immediate effects, persistent turnover can weaken institutional knowledge, reduce employee morale, and place additional strain on remaining staff, thereby creating a cycle of disengagement and further attrition. In labor-intensive industries, where production processes rely heavily on human labour, employee turnover can significantly affect operational efficiency and overall organizational performance (Jain, 2024).

Labour-intensive industries such as manufacturing, agriculture, and tobacco production require a substantial workforce to carry out routine and physically demanding operational tasks. These industries often experience elevated levels of employee turnover due to challenging working conditions, limited opportunities for career advancement, and relatively lower wage structures compared to knowledge-intensive sectors (Hausknecht & Holwerda, 2013). However, attributing turnover solely to these factors may oversimplify the issue, as organizational culture, leadership practices, and employee engagement levels also play a crucial role in shaping turnover intentions. Consequently, organizations operating in these sectors must adopt comprehensive and evidence-based strategies to effectively manage and reduce employee turnover.

Employee turnover refers to the rate at which employees leave an organization and are subsequently replaced by new hires. While a certain level of turnover is considered natural and can even be beneficial in introducing new perspectives, excessive turnover can result in significant financial and operational consequences (Mobley, 2011). These consequences include direct costs such as recruitment, selection, and training expenses, as well as indirect costs such as reduced productivity, loss of experienced employees, and disruptions to team cohesion (Allen et al., 2010). Moreover, high turnover rates can damage an organization's employer brand, making it more difficult to attract and retain skilled employees in the future.

Traditional approaches used by human resource (HR) departments to analyze employee turnover include exit interviews, employee satisfaction surveys, and descriptive HR reports. While these methods provide valuable insights into employee perceptions and experiences, they are largely reactive in nature and often fail to identify potential turnover risks before they materialize (Minbaeva, 2018). Additionally, these approaches are subject to various limitations, including response bias, incomplete data, and a lack of real-time analysis, which can hinder effective decision-making. As a result, organizations may struggle to implement timely and targeted interventions to address turnover issues.

Recent advancements in Artificial Intelligence (AI) and predictive analytics have significantly transformed the field of human resource management by enabling more sophisticated and proactive approaches to workforce analysis. AI technologies allow organizations to process large volumes of structured and unstructured employee data, uncover hidden patterns, and generate insights related to employee behavior, engagement, and retention (Davenport & Ronanki, 2018). Through the application of machine learning algorithms, AI systems can analyze historical HR data and develop predictive models capable of forecasting employee turnover with a higher degree of accuracy (Patil & Kadam, 2025).

Predictive analytics is increasingly being utilized by organizations to support data-driven decision-making in HR management. By examining key variables such as job satisfaction, compensation, workload, organizational commitment, and performance metrics, predictive models can estimate the likelihood of employee attrition and assist HR professionals in designing targeted retention strategies (Marler & Boudreau, 2017). However, despite its potential benefits, the use of predictive analytics also raises important concerns related to data quality, model transparency, and ethical considerations, particularly in relation to employee privacy and algorithmic bias.

The adoption of AI-based employee data analytics is especially important in labour-intensive industries, where workforce stability is closely linked to operational efficiency and productivity. Predictive analytics enables organizations to identify employees who are at risk of leaving and implement proactive measures, such as targeted training programs, improved compensation structures, and enhanced employee engagement initiatives, to improve retention (Basnet, 2024). Nevertheless, the successful implementation of such technologies depends on the availability of reliable data, organizational readiness, and the ability of HR professionals to interpret and apply analytical insights effectively.

Therefore, the objective of this study is to examine the impact of Artificial Intelligence–based employee data analytics on predicting employee turnover in a labour-intensive tobacco-related foreign organization. By addressing these aspects, the research intends to contribute to a deeper understanding of how analytics can be leveraged to enhance employee retention.

Research Objectives

General Objective

- To examine the impact of AI-based employee data analytics on predicting employee turnover in a labor-intensive organization within the tobacco industry.

Specific Objectives

- To examine the impact of long absenteeism on employee turnover in the selected tobacco-related foreign organization.
- To examine the impact of work–life balance on employee turnover in the selected tobacco-related foreign organization.
- To examine the impact of organizational culture on employee turnover in the selected tobacco-related foreign organization.
- To examine the impact of distance from home on employee turnover in the selected tobacco-related foreign organization.

Literature Review

Employee Turnover

Employee turnover has long been recognized as a critical issue in human resource management research. According to Hom et al. (2017), employee turnover refers to the voluntary or involuntary movement of employees out of an organization. High levels of turnover can negatively affect organizational productivity, employee morale, and operational continuity (Allen et al., 2010). Predictive analytics applies statistical and machine learning techniques to analyze historical employee data and forecast future turnover, enabling HR to shift from reactive to proactive workforce management (Shmueli and Koppius, 2011). This process typically involves collecting data from HR systems, performance records, attendance logs, surveys, and exit interviews, followed by preprocessing, model development, and evaluation to ensure accuracy (Marler and Boudreau, 2017). Common machine learning algorithms often achieve high predictive accuracy in turnover prediction (Patil and Kadam, 2025).

Several factors influence employee turnover. Long absenteeism refers to extended or frequent employee absences due to health issues, personal obligations, stress, or disengagement. In labor-intensive organizations, absenteeism directly affects productivity and operational efficiency and often signals underlying dissatisfaction or poor job fit. It is frequently considered an early warning sign of voluntary turnover, enabling HR professionals to implement targeted retention strategies such as workload adjustments, wellness programs, and flexible scheduling (Allen et al., 2010).

Work–life balance refers to the ability of employees to effectively manage professional and personal responsibilities. Poor work–life balance—often caused by excessive working hours or rigid schedules—can result in stress, burnout, reduced motivation, and lower job satisfaction. In labor-intensive sectors, maintaining a healthy balance is essential for reducing attrition. Employees who perceive organizational support for work–life balance are more likely to remain engaged and committed (Bakker and Demerouti, 2007).

Organizational culture encompasses shared values, beliefs, and norms that influence employee behavior and workplace interactions. A strong and positive culture enhances employee engagement, satisfaction, and commitment, whereas a negative or misaligned culture contributes to dissatisfaction and turnover. In labor-intensive environments, cultivating a supportive and inclusive culture is particularly important for employee retention (Schein, 2004; Robbins, 2003).

Distance from home refers to the commuting time or distance between an employee's residence and workplace. Long commutes can increase fatigue, stress, and work–life imbalance, ultimately reducing job satisfaction and organizational commitment. Employees facing excessive commuting burdens are more likely to seek alternative employment opportunities closer to home. This factor is especially significant in labor-intensive industries where consistent attendance is essential for operations (Mitchell et al., 2001).

The Mobley turnover model posits that job dissatisfaction initiates a sequence of withdrawal behaviors, including reduced effort, absenteeism, and disengagement, which eventually lead to employee resignation (Mobley, 2011). This model emphasizes the importance of understanding antecedents of dissatisfaction—such as job satisfaction, workload, compensation, and leadership style—since these factors directly influence employees' decisions to leave. By identifying early stages of withdrawal, organizations can implement proactive interventions to mitigate dissatisfaction before it results in turnover, which is particularly crucial in labor-intensive settings where employee retention significantly impacts productivity and operational efficiency.

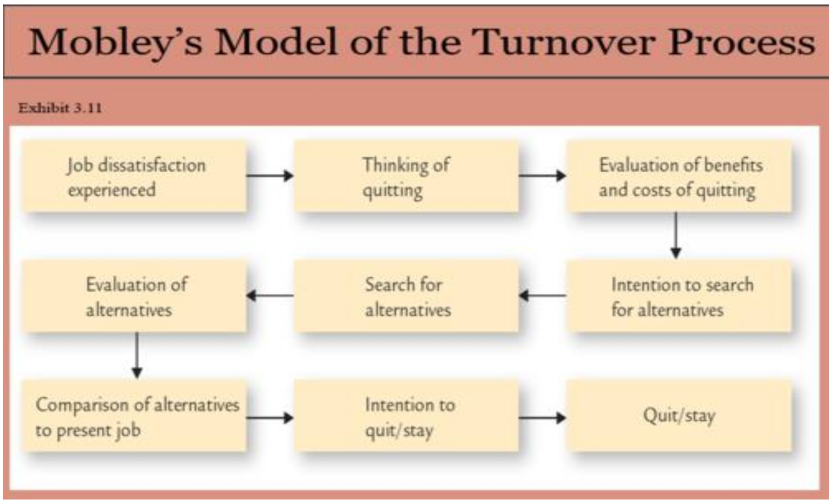


Figure 1: Mobley's Model of the Turnover Process

Source: Mobley, 1977

The Job Embeddedness Model explains employee retention by focusing on the factors that keep employees attached to their organizations rather than solely examining the reasons for leaving. The model was developed by Terence R. Mitchell, Thomas W. Lee, Brooks C. Holtom, Chris J. Sablynski, and Miriam Erez, who argued that employee turnover is influenced by the extent to which individuals are embedded in their work and community environments (Mitchell et al., 2001).

According to this model, job embeddedness consists of three key dimensions: links, fit, and sacrifice. Links refer to the formal and informal connections employees establish with colleagues, teams, and the broader community. Fit describes the compatibility between employees' personal values, career goals, and lifestyle and the organization’s culture and work environment. Sacrifice refers to the perceived cost associated with leaving the organization, such as the loss of benefits, relationships, and career opportunities.

The model further distinguishes between on-the-job embeddedness, which relates to organizational factors such as workplace relationships and culture, and off-the-job embeddedness, which includes community and personal life influences. When employees experience strong links, high levels of fit, and significant sacrifices associated with leaving, they are more likely to remain with the organization, thereby reducing turnover intentions (Mitchell et al., 2001).

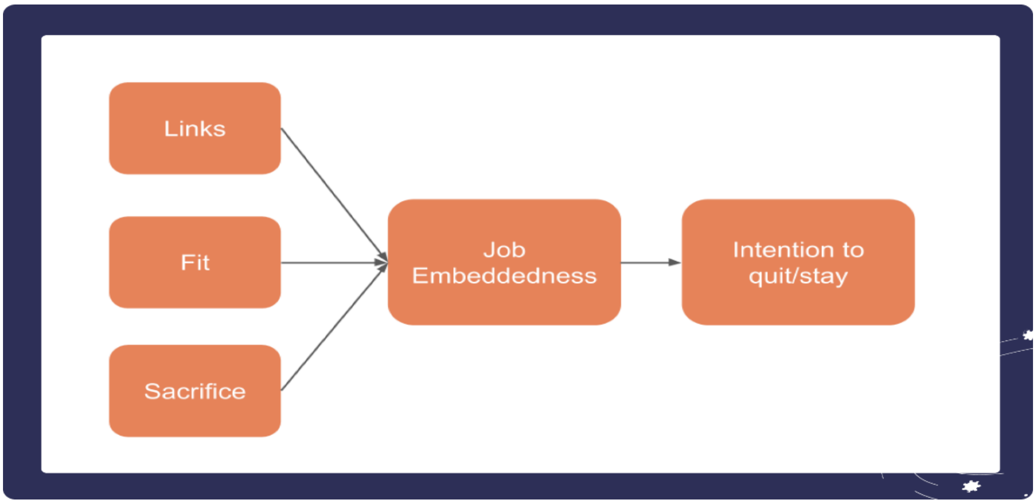


Figure 2: Job Embeddedness Model

Source: Mitchell et al., 2001

Herzberg’s Two-Factor Theory explains employee satisfaction and turnover through two categories of factors: hygiene factors and motivators (Herzberg et al., 1959). Hygiene factors include basic job conditions such as salary, benefits, working conditions, supervision, and company policies. When these factors are inadequate, employees become dissatisfied and are more likely to leave; however, improving them alone does not necessarily increase motivation.

Motivators, on the other hand, are related to the nature of the work itself and include achievement, recognition, responsibility, and opportunities for career growth. These factors enhance job satisfaction, engagement, and organizational commitment, thereby reducing turnover.

In the context of AI-based employee analytics, organizations can track both hygiene and motivator indicators—such as pay levels, promotions, recognition, workload, and training participation—to predict employees who may be at risk of leaving. This enables HR departments to take timely and targeted interventions, such as adjusting compensation, providing recognition, or offering career development opportunities, to improve retention and maintain workforce stability.

Methodology

A deductive research approach with a quantitative design was adopted for this study, as it enables the objective measurement of relationships between variables (Saunders et al., 2009). The population consisted of 250 machine operators employed at the selected manufacturing organization. A sample of 152 employees was selected using simple random sampling to ensure equal representation and minimize sampling bias (Wilson, 2010).

This study adopted a quantitative research design to examine the impact of Artificial Intelligence–based employee data analytics on predicting employee turnover in a tobacco-related foreign organization operating in a labor-intensive environment. Employee data were collected from the organization’s Human Resource Information System (HRIS). The dataset included variables such as age, gender, job role, salary level, job satisfaction, performance ratings, overtime status, and years of service. These variables were selected based on previous research indicating their importance in predicting employee turnover (Jain, 2024; Hom et al., 2017).All variables were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Secondary data on employee turnover were obtained from the organization's human resource information system (HRIS).

The study employed a stratified sampling method to ensure proportional representation of employees across different operational departments and job levels. Several machine learning algorithms Gradient Boosting/ K-Nearest Neighbors were applied to develop predictive models for employee turnover. These algorithms are widely used in predictive human resource analytics due to their ability to identify patterns in complex datasets (Patil & Kadam, 2025).

Model performance was evaluated using accuracy, precision, recall, and F1-score as key performance metrics.

Hypothesis Development

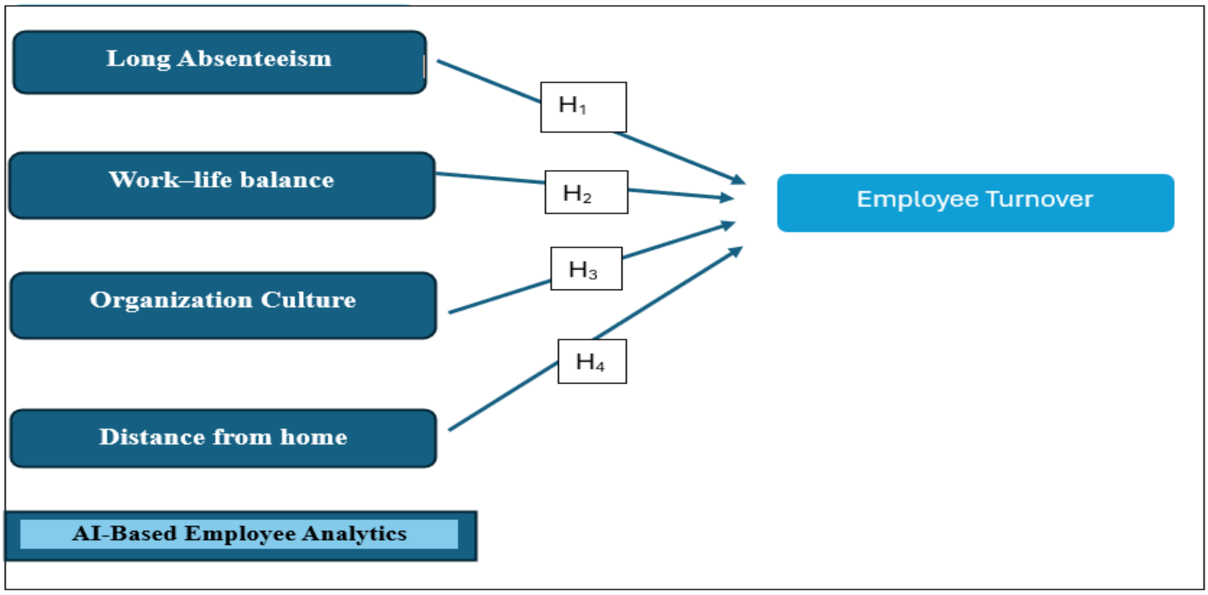
A hypothesis is a tentative statement about the relationship between two or more variables.

H1 – Long absenteeism has a significant impact on employee turnover of selected Tobacco-related foreign Organization

H2 – Work–life balance has a significant impact on employee turnover of selected Tobacco-related foreign Organization

H3 – Organizational culture has a significant impact on employee turnover of Selected Tobacco-related foreign Organization.

H4 – Distance from home has a significant impact on employee turnover of Selected Tobacco-related foreign Organization



Author's own work (2026)

Reliability Analysis

Reliability of the measurement scales was tested using **Cronbach's alpha** to determine the internal consistency of the constructs. All variables recorded alpha values above the acceptable threshold of 0.6, indicating satisfactory reliability of the measurement scales (Wilson, 2010).

Variables	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	No of Items
Long absenteeism	.636	.635	4
Work–life balance	.689	.687	4
Organizational culture	.786	.785	4
Distance from home	.654	.653	4
Employee Turnover	.782	.779	4

Descriptive Statistics

Descriptive analysis revealed that employee turnover recorded a high mean value (M = 4.15, SD = 0.56), indicating that turnover is a significant concern within the organization. Long absenteeism recorded a mean of 3.73 (SD = 0.55) Work–life balance recorded a mean of 3.98 (SD = 0.72), while organizational culture recorded a mean of 4.08 (SD = 0.49). Distance from home recorded a mean score of 3.65 (SD = 0.54), and long absenteeism recorded a mean of 3.73 (SD = 0.56). These results suggest moderate employee perceptions of work environment and organizational factors.

	N	Minimum	Maximum	Mean	Std Deviation
Long absenteeism	152	2.67	4.67	3.7333	0.5577
Work–life balance	152	2.50	5.00	3.9750	0.7158
Organizational culture	152	2.67	5.00	4.0750	0.4940
Distance from home	152	3.25	4.37	3.6500	0.5363
Employee Turnover	152	2.05	5.00	4.1525	0.5599

Correlation Analysis

Pearson correlation analysis indicated significant positive relationships between organizational turnover and work-related factors and **long absenteeism** at the 0.05 significance level. **Organizational culture** ($r = 0.648$, $p < 0.01$), followed by **work–life balance** ($r = 0.654$, $p < 0.01$), **employee turnover** ($r = 0.689$, $p < 0.01$), and **distance from home** ($r = 0.605$, $p < 0.01$). These findings suggest that both organizational practices and personal work circumstances significantly influence employee absenteeism.

Regression Analysis

Multiple regression analysis revealed that organizational and work-related factors jointly explained 38.8% of the variance in long absenteeism ($R^2 = 0.388$, $p < .01$). Among the predictors, long absenteeism emerged as the most significant contributor to turnover ($\beta = 0.609$, $p < .01$), while work–life balance and organizational culture demonstrated moderate predictive power. Distance from home showed a weaker, though still statistically significant, influence. These results indicate that organizational factors, personal circumstances, and cultural elements play a substantial role in shaping absenteeism behavior among employees.

Prior to analysis, the dataset underwent preprocessing procedures, including removal of missing values, encoding of categorical variables, and normalization of numerical variables to improve model performance (Shmueli and Koppius, 2011).

Findings and Discussion

The findings of this study reveal that employee turnover in labour-intensive organizations is strongly influenced by a combination of organizational conditions and individual employee circumstances. The analysis highlights that factors such as long absenteeism, work–life balance, organizational culture, and distance from home play a significant role in shaping employee behaviour and retention outcomes (Hausknecht & Holwerda, 2013).

Among these factors, **long absenteeism** emerged as the most critical indicator of employee turnover. Employees who frequently or consistently remain absent from work are more likely to experience disengagement, reduced commitment, and eventual withdrawal from the organization. This supports prior research indicating that absenteeism serves as an early warning sign of turnover intentions (Allen et al., 2010).

Prior research has consistently demonstrated that absenteeism is a strong behavioral precursor to voluntary turnover, as it reflects employee withdrawal cognition, reduced engagement, and declining job satisfaction (Steers & Mowday, 1981; Harrison & Martocchio, 1998). Employees with higher levels of absenteeism are more likely to exhibit lower organizational commitment and stronger turnover intentions (Sagie, 1998).

In addition, absenteeism is widely recognized as an early withdrawal behavior that often precedes actual resignation decisions, particularly in stressful or labor-intensive work environments (Johns, 2003). Contemporary workforce studies further support this relationship, indicating that absenteeism patterns can serve as a reliable predictive signal for identifying employees at risk of leaving the organization (Hausknecht & Holwerda, 2013).

Work–life balance was identified as another key factor influencing employee retention. Employees experiencing excessive workload, long working hours, and limited personal time are more likely to face stress and burnout, increasing their likelihood of leaving the organization (Bakker & Demerouti, 2007).

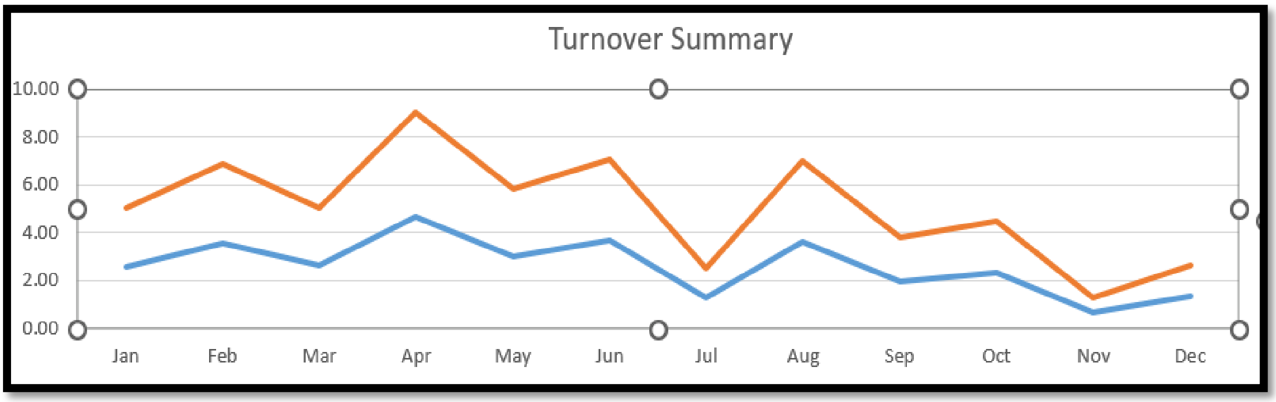
The findings also demonstrate that **organizational culture plays a vital role in retaining employees**. A supportive and positive work environment enhances employee engagement and commitment, whereas a weak organizational culture contributes to dissatisfaction and higher turnover intentions (Schein, 2004; Robbins, 2003).

In addition, **distance from home was found to influence employee turnover**, although to a lesser extent compared with other factors. Long commuting distances create physical fatigue and reduce overall job satisfaction, thereby increasing the likelihood of employee attrition (Mitchell et al., 2001).

Overall, the findings confirm that employee turnover is driven by multiple interconnected factors rather than a single cause. Importantly, the application of AI-based employee data analytics enabled the identification of these patterns and provided deeper insights into employee behaviour (Marler & Boudreau, 2017).

OVERALL TURNOVER SUMMARY -2025

	Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
Ops Only (Bmm+Leaf)	Ops %	2.61	3.58	2.62	4.70	3.02	3.69	1.32	3.65	1.97	2.34	0.69	1.38	2.63
All Staff	All Staff %	2.42	3.33	2.43	4.36	2.80	3.41	1.21	3.38	1.82	2.16	0.63	1.27	2.44



Source: HSENID System

By effectively managing key organizational factors through AI-based employee analytics—such as reducing long absenteeism, improving work–life balance, strengthening organizational culture, and addressing distance from home—management can enhance employee commitment and workplace satisfaction, which in turn helps to monitor and sustain lower turnover rates.

Conclusion

This study examined the impact of Artificial Intelligence (AI)–based employee data analytics on predicting employee turnover in a labour-intensive, tobacco-related foreign organization. The findings demonstrate that AI-driven predictive analytics can significantly enhance an organization's ability to forecast turnover and implement proactive retention strategies. By leveraging machine learning algorithms, organizations can analyze large volumes of employee data and uncover patterns linked to attrition, enabling timely identification of at-risk employees. The integration of AI-based HR analytics supports better workforce planning, reduces turnover, and improves overall organizational performance. However, successful implementation requires careful attention to ethical considerations, including data privacy, transparency, and algorithmic bias. Organizations must ensure that AI systems are used responsibly and that employee data is handled fairly and securely. In conclusion, AI-based employee data analytics is not merely a technological advancement but a strategic necessity. It provides a powerful framework for understanding employee behaviour, predicting turnover, and executing targeted retention strategies, allowing organizations to achieve workforce stability, enhance operational performance, and secure long-term sustainability in labour-intensive environments.

Practical Implications for HR Professionals

The findings of this study highlight several important implications for HR professionals in an increasingly AI-driven workplace.

By leveraging AI technologies, HR professionals can proactively address key factors that influence employee retention and workplace satisfaction. Long absenteeism can be monitored and predicted using AI-powered attendance tracking and predictive analytics, enabling timely interventions such as wellness programs or flexible schedules to support employees and reduce unplanned absences.

Work–life balance can be enhanced through AI-driven sentiment analysis and feedback platforms, allowing HR to implement personalized flexible work arrangements that align with employees' needs.

Organizational culture can be continuously assessed using AI tools that analyze communication patterns, collaboration networks, and engagement data, helping HR design targeted initiatives to strengthen employee engagement and foster a positive work environment.

Finally, in labour-intensive organizations, challenges related to distance from home can be addressed through AI-enabled workforce planning systems that optimize shift schedules, minimize travel time, and coordinate transportation or shuttle services for employees. By using AI to match workforce availability with operational needs and commuting constraints, HR can ensure smoother operations while reducing employee fatigue and absenteeism.

Collectively, these AI-driven strategies enable HR professionals to make data-informed decisions that enhance employee commitment, satisfaction, and retention, even in settings where remote work is not feasible.

References

Allen, D. G., Bryant, P. C., & Vardaman, J. M. (2010). Retaining talent: Replacing misconceptions with evidence-based strategies. *Academy of Management Perspectives, 24*(2), 48–64.

Bakker, A. B., & Demerouti, E. (2007). The job demands–resources model: State of the art. *Journal of Managerial Psychology, 22*(3), 309–328.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Harrison, D. A., & Martocchio, J. J. (1998). Time for absenteeism: A 20-year review of origins, offshoots, and outcomes. *Journal of Management, 24*(3), 305–350.

Hausknecht, J. P., & Holwerda, J. A. (2013). When does employee turnover matter? Dynamic member configurations, productivity, and collective performance. *Organization Science, 24*(1), 210–225.

Herzberg, F., Mausner, B., & Snyderman, B. B. (1959). *The motivation to work*. John Wiley & Sons.

Hom, P. W., Lee, T. W., Shaw, J. D., & Hausknecht, J. P. (2017). One hundred years of employee turnover theory and research. *Journal of Applied Psychology, 102*(3), 530–545.

Jain. (2024). Details not fully provided in manuscript (labor-intensive industry turnover study).

Johns, G. (2003). How methodological diversity has improved our understanding of absenteeism from work. *Human Resource Management Review, 13*(2), 157–184.

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. *The International Journal of Human Resource Management, 28*(1), 3–26.

Mitchell, T. R., Holtom, B. C., Lee, T. W., Sablynski, C. J., & Erez, M. (2001). Why people stay: Using job embeddedness to predict voluntary turnover. *Academy of Management Journal, 44*(6), 1102–1122.

Mobley, W. H. (1977). Intermediate linkages in the relationship between job satisfaction and employee turnover. *Journal of Applied Psychology, 62*(2), 237–240.

Mobley, W. H. (2011). *Employee turnover: Causes, consequences, and control* (2nd ed.). Routledge.

Minbaeva, D. (2018). Building credible HR analytics: Evidence-based insights for better HR decisions. *Human Resource Management Journal, 28*(1), 3–12.

Patil, & Kadam. (2025). Details not fully provided in manuscript (AI predictive analytics in HR).

Robbins, S. P. (2003). *Organizational behavior* (10th ed.). Prentice Hall.

Sagie, A. (1998). Employee absenteeism, organizational commitment, and turnover intention. *Journal of Vocational Behavior, 52*(2), 154–170.

Schein, E. H. (2004). *Organizational culture and leadership* (3rd ed.). Jossey-Bass.

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly, 35*(3), 553–579.

Steers, R. M., & Mowday, R. T. (1981). Employee turnover and post-decision accommodation processes. *Research in Organizational Behavior, 3*, 235–281.

Wilson, J. (2010). Details not fully provided in manuscript (reliability/Cronbach's alpha reference source).