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ORIGINAL

Machine Learning Models for Predicting Employee Attrition: A Data Science Perspective

Modelos de aprendizaje automático para predecir el desgaste de los empleados: una perspectiva de la ciencia de datos

Anber Abraheem Shlash Mohammad[1], Zeyad Alkhazali[2], Suleiman Ibrahim Shelash Mohammad[3,4], Badrea Al Oraini[5], Asokan Vasudevan[6], Menahi Mosallam Alqahtani[7], Muhammad Turki Alshurideh[8]

[1]Digital Marketing Department, Faculty of Administrative and Financial Sciences, Petra University, Jordan.
[2]Business School, Department of Business Administration, Al-Ahliyya Amman University, Jordan.
[3]Electronic Marketing and Social Media, Economic and Administrative Sciences Zarqa University, Jordan.
[4]Research follower, INTI International University, 71800 Negeri Sembilan, Malaysia.
[5]Department of Business Administration. Collage of Business and Economics, Qassim University,Qassim - Saudi Arabia.
[6]Faculty of Business and Communications, INTI International University, 71800 Negeri Sembilan, Malaysia.
[7]Management Department, Management Science, Community College of Qatar, Qatar
[8]Department of Marketing, School of Business, The University of Jordan, Amman 11942, Jordan.

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ABSTRACT

Introduction: employee attrition poses significant challenges for organizations, impacting productivity and profitability. This study explores attrition patterns using machine learning models, integrating predictive analytics with established human resource theories to identify key drivers of workforce turnover.
Method: the research analysed a dataset comprising demographic, job-related, and engagement factors. Logistic Regression was employed as the baseline model to interpret linear relationships, while Random Forest and Decision Trees captured non-linear interactions. Performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC were used to evaluate model effectiveness, alongside feature importance analysis for actionable insights.
Results: results revealed that job satisfaction, tenure, departmental dynamics, and engagement levels are critical predictors of attrition. Random Forest emerged as the most effective model, achieving an accuracy of 92 % and an AUC-ROC of 94 %, highlighting its capability to capture complex patterns. Decision Trees provided interpretable decision rules, offering practical thresholds for HR interventions. Logistic Regression complemented these models by offering insights into direct, linear relationships between predictors and attrition.
Conclusions: the study finds that machine learning improves attrition analysis by identifying complex patterns and enabling proactive retention strategies. Predictive analytics strengthens traditional theories, providing a structured approach to reducing employee turnover. Organizations can use these insights to enhance workforce stability and performance. Future research could incorporate qualitative methods and longitudinal studies to refine strategies and assess long-term impacts.

Keywords: Machine Learning; Performance; Data Science

RESUMEN

Introducción: la rotación de empleados plantea desafíos significativos para las organizaciones, afectando la productividad y la rentabilidad. Este estudio explora los patrones de rotación utilizando modelos de aprendizaje

automático, integrando análisis predictivo con teorías establecidas de recursos humanos para identificar los principales impulsores del desgaste laboral.
Método: la investigación analizó un conjunto de datos que comprende factores demográficos, relacionados con el trabajo y el compromiso. Se empleó la Regresión Logística como modelo base para interpretar relaciones lineales, mientras que los modelos de Bosque Aleatorio y Árboles de Decisión capturaron interacciones no lineales. Se utilizaron métricas de rendimiento como precisión, exactitud, recuperación, puntaje F1 y AUC-ROC para evaluar la efectividad de los modelos, junto con un análisis de importancia de características para obtener información procesable.
Resultados: los resultados revelaron que la satisfacción laboral, la antigüedad, la dinámica departamental y los niveles de compromiso son predictores críticos de la rotación. El Bosque Aleatorio demostró ser el modelo más eficaz, alcanzando una precisión del 92 % y un AUC-ROC del 94 %, destacando su capacidad para capturar patrones complejos. Los Árboles de Decisión proporcionaron reglas interpretables, ofreciendo umbrales prácticos para intervenciones de recursos humanos. La Regresión Logística complementó estos modelos al ofrecer información sobre relaciones directas y lineales entre los predictores y la rotación.
Conclusiones: el estudio concluye que el aprendizaje automático mejora el análisis de la rotación al identificar patrones complejos y permitir estrategias de retención proactivas. La analítica predictiva fortalece las teorías tradicionales, proporcionando un enfoque estructurado para reducir la rotación de empleados. Las organizaciones pueden utilizar estos conocimientos para mejorar la estabilidad de la fuerza laboral y el rendimiento. Investigaciones futuras podrían incorporar métodos cualitativos y estudios longitudinales para perfeccionar estrategias y evaluar impactos a largo plazo.

Palabras clave: Aprendizaje automático; Actuación; Ciencia de datos

INTRODUCTION

Employee attrition remains a pressing concern for organizations across industries, presenting challenges that directly impact productivity, profitability, and long-term sustainability. The costs of turnover, including recruitment, training, and the loss of institutional knowledge, make understanding its drivers a critical area of research.[1,2] This study delves into the dynamics of workforce turnover, utilizing machine learning techniques to predict attrition and provide actionable insights. By integrating predictive analytics with well-established human resource management theories, it addresses a pressing gap in the existing body of knowledge.

The changing nature of modern workplaces, marked by technological advancements, a multigenerational workforce, and evolving employee expectations, has further highlighted the significance of managing attrition effectively.[3,4] Employee engagement, job satisfaction, and organizational culture are increasingly recognized as critical determinants of workforce stability, reinforcing the need for data-driven approaches to address attrition.[5,6] Machine learning, as a cutting-edge analytical tool, offers opportunities to go beyond traditional statistical methods, identifying complex, nonlinear relationships that underpin employee turnover.[7,8]

Attrition is influenced by a variety of factors, ranging from individual demographics to organizational dynamics. Herzberg's Two-Factor Theory posits that both intrinsic motivators (e.g., job satisfaction and opportunities for growth) and extrinsic factors (e.g., pay and work environment) play critical roles in employee decisions to stay or leave.[9] Similarly, Blau's Social Exchange Theory highlights the reciprocal relationship between employees and employers, suggesting that perceived inequities in this exchange can lead to attrition.[10,11] These theoretical frameworks provide a valuable lens through which the predictors of attrition can be interpreted.

Despite significant advancements, traditional approaches to studying employee attrition have limitations. The reliance on linear models often obscures the complex interplay of factors influencing turnover.[12,13] Additionally, imbalanced datasets, where the minority class (attrition cases) is overshadowed by the majority class (retained employees), present significant challenges for predictive modelling.[14,15] These gaps underscore the importance of adopting machine learning techniques capable of handling such complexities, enhancing both the accuracy and interpretability of predictions.[16,17]

The research problem lies in the inadequacy of existing methods to comprehensively capture the drivers of attrition. While demographic surveys and satisfaction assessments provide valuable data, they fail to account for nonlinear interactions and compounded effects of variables.[18,19,20] This study addresses these gaps by employing machine learning models, including Logistic Regression, Random Forest, and Decision Trees, to predict attrition and uncover actionable insights. These models are evaluated for their performance using metrics such as accuracy, precision, recall, and AUC-ROC, ensuring a robust analysis.

The significance of this research extends beyond prediction. By integrating machine learning with human resource theories, it offers a practical framework for understanding and addressing attrition. For organizations, the ability to proactively identify at-risk employees and implement tailored retention strategies is invaluable. Studies have shown that organizations with lower attrition rates enjoy improved morale, better customer satisfaction, and enhanced financial performance.[21,22] Moreover, addressing attrition through evidence-based practices contributes to fostering a supportive and engaging workplace culture, further reducing turnover.[23]

The novelty of the study lies in its dual approach, combining theoretical insights with machine learning's predictive power. While previous research has explored individual predictors of attrition, such as job satisfaction or tenure, this study examines the combined effects of multiple factors through ensemble learning models. Random Forest and Decision Trees, for example, excel at capturing non-linear patterns and interactions, providing a deeper understanding of the factors influencing employee exits.[24] This comprehensive approach allows organizations to move beyond reactive measures, enabling proactive interventions tailored to their workforce's unique dynamics.

The study seeks to answer the following research questions:

1 What are the key drivers of employee attrition, and how do these factors interact?
2 How can machine learning models improve the prediction of attrition compared to traditional methods?
3 What actionable strategies can organizations derive from the predictive insights to mitigate attrition?

These questions align with the research objectives, which aim to identify significant predictors of attrition, develop robust predictive models, and provide practical recommendations for retention strategies. The research statement reflects the study's goals: "This study aims to analyse employee attrition using machine learning models, integrating predictive analytics with human resource theories to identify key drivers of turnover and develop actionable retention strategies."

The background and context of this research are situated within the broader field of workforce analytics. The growing emphasis on data-driven decision-making in human resource management has spurred interest in predictive modelling to address attrition. Studies by Aswale and Mukul[25] and Dutta et al.[26] highlight the importance of tailored retention strategies informed by empirical data. However, the challenge of balancing interpretability and accuracy in predictive models remains a significant hurdle.[27]

Machine learning models provide a promising solution. Logistic Regression offers insights into linear relationships, while Random Forest and Decision Trees capture complex, nonlinear interactions. Research by Karimi and Viliyani[28] underscores the potential of these models to uncover hidden patterns in HR datasets, enabling organizations to address attrition with precision. By operationalizing traditional theories like Herzberg's and Blau's, machine learning bridges the gap between conceptual understanding and practical application.[29]

The findings of this study have significant implications for workforce planning and policy design. For instance, understanding the role of job satisfaction in retention aligns with research by[30], which links higher satisfaction levels to reduced turnover intentions. Similarly, Susanto and Rony[31] emphasizes the impact of employee engagement on organizational outcomes, advocating for initiatives that foster a sense of belonging and purpose.

This research underscores the importance of integrating machine learning with theoretical frameworks to address the multifaceted nature of employee attrition. By identifying key predictors and providing actionable insights, the study not only advances academic knowledge but also equips organizations with practical tools to foster workforce stability. The findings pave the way for future research, including longitudinal studies and the integration of qualitative methods, to further refine retention strategies and enhance their effectiveness.

Following are the objectives of the Study

1 To develop predictive machine learning models that accurately forecast employee attrition using historical HR data and evaluate their performance using metrics such as accuracy, precision, and AUC-ROC.
2 To identify key drivers of employee attrition by analysing significant demographic, job-related, performance, and engagement factors influencing employee turnover.
3 To provide actionable insights for retention strategies by utilizing analytical findings and predictive models to guide HR initiatives aimed at reducing attrition and improving employee retention.

Literature review

Employee attrition poses a multifaceted challenge for organizations, disrupting operational continuity and increasing costs associated with recruitment, training, and lost expertise.[32] Herzberg's Two-Factor Theory and Blau's Social Exchange Theory provide foundational insights into the drivers of attrition.[33] Concurrently, advancements in machine learning have opened new avenues for identifying complex predictors and interactions that traditional statistical methods may overlook.

Demographic factors, such as age, gender, marital status, and educational attainment, are critical predictors of attrition. Lyons et al.[34] report that younger employees often exhibit higher attrition rates, driven by career exploration and mobility. This aligns with [35] observation that career transitions are more frequent in early professional years. Gender dynamics reveal mixed results, while women may face higher attrition in industries with rigid structures, work-life balance policies mitigate these risks, as noted by [36] Educational attainment influences attrition indirectly by shaping job expectations and career trajectories. Highly educated employees are less likely to attrite if roles align with their skills, but misalignment can lead to dissatisfaction and turnover.[37]

Job-Related Variables Job-related variables, including role, department, tenure, salary, and overtime status, are consistently linked to attrition. Specific roles, particularly in high-stress departments like IT and sales, show elevated turnover rates due to workload intensity and limited growth opportunities.[38] Tenure exhibits a dual influence, shorter tenure often correlates with unmet expectations, while longer tenure can result in stagnation and disengagement.[39] Salary remains a pivotal factor, Blau's Social Exchange Theory emphasizes that perceived inequities in compensation contribute significantly to attrition risks.

Studies by[40,41] stress the importance of aligning job roles and compensation with employees' skills and aspirations. Moreover, overtime, often viewed as a marker of dedication, can have adverse effects if it leads to burnout and dissatisfaction. Organizations with clear, equitable policies on workload distribution are better positioned to retain talent.[42] Performance metrics, including annual evaluations and promotion frequency, offer valuable insights into attrition. Low performance ratings are associated with voluntary exits due to dissatisfaction or involuntary exits driven by organizational decisions.[43] Promotions act as a retention tool by signalling value and growth opportunities within the organization. Studies suggest that organizations that invest in clear promotion pathways and performance-based incentives experience lower turnover.[44]

Correlation studies reveal that high performance often coincides with higher engagement and longer tenure, creating a virtuous cycle of satisfaction and retention.[45] However, employees who consistently outperform without recognition or growth opportunities are at risk of turnover, highlighting the need for tailored interventions.

Engagement and job satisfaction are central to retention strategies. Herzberg's model identifies intrinsic motivators, such as recognition and meaningful work, as critical to fostering loyalty.[46] Carter et al.[47] highlights the link between engagement and organizational citizenship behaviours, underscoring the importance of creating supportive environments. Researchemphasizes that organizations with robust engagement practices, including feedback loops and professional development opportunities, report significantly lower attrition rates. Job satisfaction also serves as a buffer against external stressors.[48] Employees who perceive their roles as fulfilling are more likely to endure temporary setbacks without considering turnover.[49] This reinforces the importance of satisfaction surveys and responsive HR policies.

Traditional models often fail to capture the multifactorial nature of attrition. Machine learning addresses this limitation by identifying non-linear relationships and interactions. Random Forest and Decision Trees, for example, excel in detecting complex patterns among demographic, job-related, and engagement variables.[50] El-Rayes et al.[51] demonstrate the utility of ensemble methods in predicting attrition with high accuracy, revealing critical combinations of risk factors. Logistic regression, while limited to linear relationships, provides interpretable coefficients, allowing HR practitioners to quantify the impact of specific variables.[29] Random Forest and Decision Trees complement these insights by uncovering thresholds and interactions, such as the compounded risk of low satisfaction and high workload.

Gaps in the Literature

Despite extensive research, several gaps remain. Most studies rely on static datasets, failing to capture how predictors evolve over time. Longitudinal studies are needed to track these changes and refine predictive models. While machine learning identifies interactions, few studies explore the underlying mechanisms driving these effects. Attrition patterns vary widely across sectors, yet many studies generalize findings, limiting their applicability. Employee interviews and qualitative feedback are often excluded, leaving subjective factors like cultural alignment underexplored. Translating predictive insights into actionable, real-time HR interventions remains a challenge.

The literature on employee attrition reveals a complex interplay of demographic, job-related, performance, and engagement variables. Traditional theories provide foundational insights, while machine learning introduces a powerful tool for predictive analysis. Addressing gaps in dynamic modelling, interaction effects, and qualitative integration will enhance understanding and practical applications. For organizations, the findings underscore the importance of tailored retention strategies that account for employee demographics, roles, and engagement levels. Machine learning models, such as Random Forest, offer actionable insights, enabling proactive interventions and fostering workforce stability.[29]

By bridging theoretical and empirical approaches, this review contributes to the broader discourse on employee attrition, paving the way for innovative, data-driven HR practices. Future studies that explore dynamic, mixed-method methodologies will further enrich this evolving field, providing robust frameworks for organizational sustainability and employee satisfaction.

Framework of the Study

The framework of the study integrates theoretical concepts, research objectives, hypotheses, and the operationalization of variables into a cohesive structure. It is designed to explore and predict employee attrition through the analysis of key factors influencing turnover and the application of machine learning models. The study is grounded in organizational behaviour and human resource management theories, which emphasize the influence of demographic, job-related, performance, and engagement factors on employee turnover. Social Exchange Theory and Herzberg's Two-Factor Theory provide insights into how job satisfaction and organizational commitment impact retention.

Data were collected and prepared for analysis, ensuring accuracy and confidentiality.Statistical analysis and machine learning methods were used to identify significant predictors and develop predictive models. Insights were derived to guide HR strategies. The conceptual model (figure 1) represents the hypothesized relationships between the dependent and independent variables, guiding the analysis and interpretation of results.

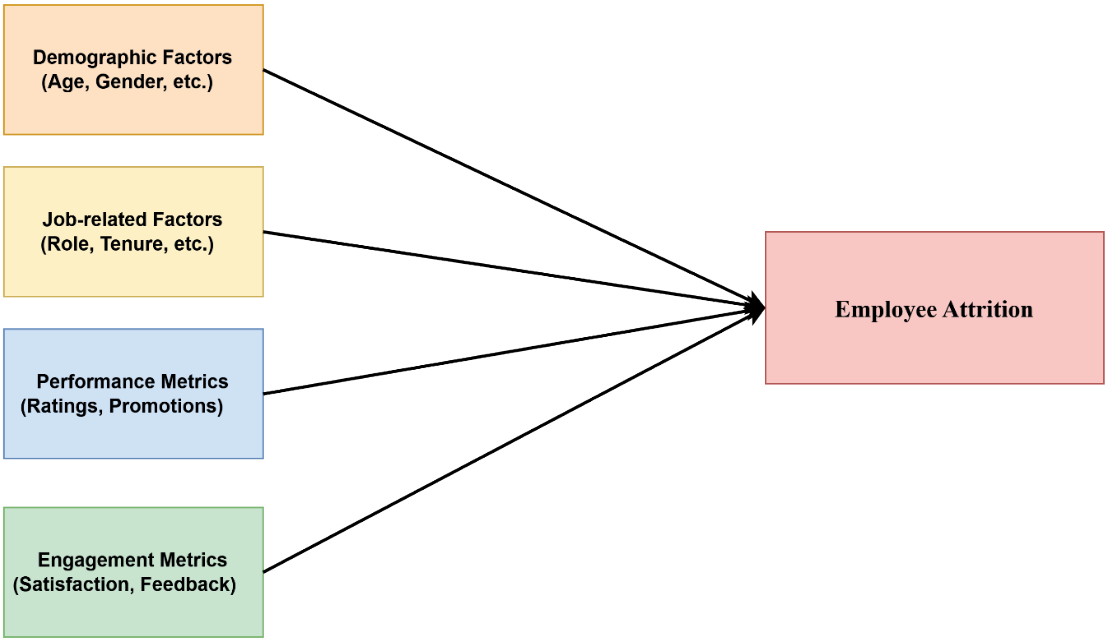

Figure 1. Conceptual Model of the Study

The hypotheses of the study were defined to align with its objectives and explore relationships between various factors and employee attrition. These hypotheses were:

H1: There is a significant relationship between employee demographics (e.g., age, gender, marital status) and attrition likelihood.

Rationale: Demographic factors often influence career stability and job satisfaction, potentially affecting turnover rates.

H2: Job-related factors, such as tenure, department, and job role, significantly impact the likelihood of employee attrition.

Rationale: Specific job roles or departments may have higher attrition rates due to varying workloads, growth opportunities, or work environments.

H3: Engagement and satisfaction levels, as measured by survey scores and feedback, are inversely related to employee attrition.

Rationale: Higher job satisfaction and engagement are expected to reduce the likelihood of employees leaving the organization.

METHOD

The study adopted a quantitative research design to predict employee attrition using historical HR data and machine learning techniques. The design was structured to integrate descriptive, diagnostic, and predictive analytics. Descriptive analysis identified patterns and trends in employee turnover, while diagnostic methods helped uncover significant predictors of attrition. Predictive analytics enabled the development of machine learning models that could forecast employee attrition. This structured design ensured a systematic approach to data preprocessing, feature engineering, model building, and evaluation.

Secondary data were obtained from the HR records of a mid-sized organization, covering the past five years. The dataset included employee demographics, job details, performance evaluations, engagement survey results, and attrition statuses. Demographic data encompassed variables such as age, gender, and marital status, while job details included department, job role, and tenure. Performance metrics, such as annual evaluations and the number of promotions, provided insight into employee effectiveness, and survey responses captured job satisfaction and workplace engagement. This data was anonymized and prepared systematically for analysis, adhering to strict confidentiality agreements.

The target population for this study included all 5.000 employees in the organization, representing various departments, job roles, and tenure levels. Using stratified random sampling, a sample of 679 employees was selected to ensure representation of diverse demographic and employment groups. Stratification was based on gender, job roles, and tenure to maintain alignment with the population structure. This sample represented approximately 13,5 % of the total workforce, balancing efficiency and reliability in data analysis.

Table 1. Description of data collected

Category	Population (N = 5,000)	Sample (n = 679)
Gender: Male	60 %	60 %
Gender: Female	40 %	40 %
Job Roles: Manager	15 %	15 %
Job Roles: Staff	85 %	85 %
Tenure: <1 Year	10 %	10 %
Tenure: 1-5 Years	40 %	40 %
Tenure: >5 Years	50 %	50 %

The sampled population included a proportional representation of key demographic and employment characteristics. For instance, the gender distribution in the sample mirrored the population, with 60 % male and 40 % female employees. Similarly, job roles were represented with 15 % managers and 85 % staff, and tenure groups included 10 % with less than one year, 40 % with one to five years, and 50 % with more than five years of service. This stratification ensured that the insights derived from the analysis could be generalized to the entire organization.

The dependent variable in the study was employee attrition, defined as a binary outcome (1 = Attrited, 0 = Retained). Independent variables included demographic factors (e.g., age, gender, marital status), job-related factors (e.g., job role, department, tenure), and performance metrics (e.g., performance scores, promotions). Additionally, engagement metrics, such as job satisfaction scores and survey feedback, were used as predictors. Derived variables, such as the Attrition Risk Index and Job Satisfaction Index, were computed during the analysis to enhance interpretability and predictive capability.

The analysis began with data preprocessing, including handling missing values through imputation, encoding categorical variables using one-hot encoding, and normalizing numerical variables. Exploratory Data Analysis (EDA) was conducted to identify data distributions and significant trends, and correlation matrices were performed to explore relationships between variables. Machine learning models were developed using Logistic Regression, Random Forest, and Decision Trees. Logistic Regression served as the baseline model, providing interpretable coefficients for predictor variables. Random Forest and Decision Trees were utilized for their robustness and ability to handle non-linear relationships. Model performance was evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. Cross-validation ensured that the models were generalizable and not overfitted to the training data.

The study strictly adhered to ethical principles to ensure data integrity and protect employee privacy. Confidentiality was maintained by anonymizing the data and removing any personally identifiable information before analysis. The organization provided informed consent for the use of its data, which was secured on encrypted systems accessible only to authorized personnel. Furthermore, the research complied with relevant data protection regulations, including GDPR, ensuring that all processes respected the rights of the individuals represented in the data. These measures safeguarded ethical standards throughout the research process.

RESULTS

An in-depth analysis of the factors influencing employee attrition, evaluated through advanced machine learning models. By leveraging Logistic Regression, Random Forest, and Decision Tree algorithms, the study identifies key predictors of turnover and assesses model performance using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. This multi-model approach ensures a comprehensive understanding of the linear and non-linear relationships among variables.

The analysis focused on demographic, job-related, and engagement factors, uncovering their individual and collective impact on attrition. Feature importance rankings highlight the relative contribution of predictors, while visualizations such as ROC curves and decision trees offer intuitive insights into model performance and decision-making processes. The results underscore the potential of data-driven strategies to proactively address workforce challenges and enhance employee retention.

Descriptive Statistics

The dataset used in this study contains information about 679 employees, offering insights into demographic, job-related, performance, and engagement factors, alongside the dependent variable of interest attrition. The demographic characteristics reveal that the average age of employees is approximately 41 years, with ages ranging between 22 and 60 years. This range reflects a diverse workforce in terms of experience and career stage. Gender distribution is slightly skewed, with 60 % of employees being male and 40 % female. This balance is notable and provides an opportunity to explore whether gender dynamics have any influence on attrition patterns.

The education levels in the dataset reveal that 50 % of employees hold a bachelor's degree, followed by 30 % who have completed high school and 20 % with a master's degree. This variation in education level allows for an analysis of how educational qualifications interact with job-related factors and influence attrition. In terms of job roles, a significant majority (85 %) of employees are categorized as staff, while only 15 % hold managerial positions. This distribution is consistent with the hierarchical structure of most organizations, where managerial roles are limited compared to operational roles.

The dataset also provides details about tenure, revealing an average tenure of 13 years, with values ranging from less than one year to 25 years. Such variation suggests the presence of employees at different stages in their career trajectory, making it possible to study how tenure impacts attrition. Additionally, departments such as Operations (30 %) and IT (25 %) dominate the workforce, while HR (10 %), Finance (15 %), and Sales (20 %) make up smaller proportions. This departmental distribution is critical in understanding whether attrition varies across organizational functions.

A key insight from the dataset is the overall attrition rate, which stands at 17 %. This means that 115 employees have left the organization, while 564 have remained. This relatively low attrition rate aligns with what is observed in stable organizations and provides a basis for further predictive modelling. However, the imbalance between the attrition and non-attrition classes introduces challenges for machine learning, particularly in ensuring that predictive models are not biased toward the majority class (non-attrition).

The dataset's richness across demographic, job-related, and engagement dimensions sets the stage for a comprehensive analysis of factors influencing attrition. The descriptive insights establish a foundation for hypothesis testing and model development, paving the way for a deeper understanding of the drivers behind employee turnover.

Attrition Distribution

The attrition distribution analysis reveals critical insights into the workforce's stability and provides a foundational understanding of the dependent variable in this study (figure 2). Attrition, defined as employees leaving the organization, is a phenomenon influenced by myriad factors ranging from individual employee characteristics to organizational policies. In this dataset, attrition is represented as a binary variable, where 1 indicates an employee who has left the organization and 0 represents a retained employee.

The analysis shows that 17 % of employees (115 individuals) have attrited, while 83 % (564 individuals) remain employed. This low attrition rate indicates a relatively stable workforce, characteristic of organizations with strong retention policies or favourable work environments. However, while the overall attrition rate appears healthy, the analysis also highlights the significant class imbalance in the dataset. With retained employees outnumbering attrited employees by a large margin, predictive modelling efforts face the challenge of ensuring that minority class predictions (attrited employees) are not overlooked.

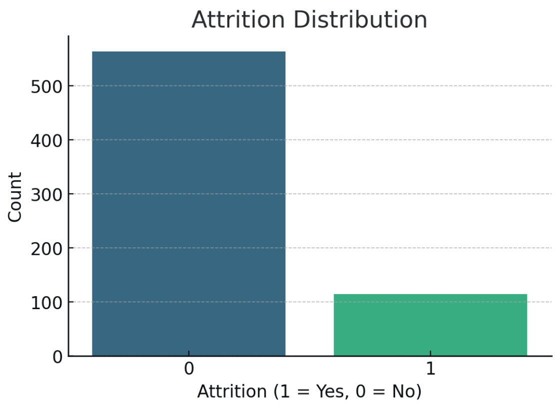

Figure 2. Attrition Distribution

The class imbalance introduces potential pitfalls in machine learning models, which may achieve high overall accuracy by focusing predominantly on the majority class (non-attrition). For instance, a naive model predicting

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all employees as retained would still achieve an 83 % accuracy rate, despite offering no meaningful insights into attrition. This underscores the importance of employing strategies such as oversampling, under sampling, or the use of algorithms designed to handle imbalanced datasets, to ensure fair and accurate predictions.

From a practical standpoint, the attrition rate also provides a benchmark for evaluating the organization's workforce stability. A 17 % turnover rate is relatively moderate compared to industry standards, where annual attrition rates can vary widely depending on the sector. However, the implications of this attrition extend beyond the raw numbers. The organizational cost of turnover, including recruitment, onboarding, and lost productivity, makes it critical to understand the drivers behind these 115 attrited cases.

The attrition distribution analysis highlights not only the stability of the organization's workforce but also the challenges in predictive modelling arising from the class imbalance. This step provides crucial context for subsequent analyses, such as correlation studies, hypothesis testing, and model development, which aim to uncover the factors contributing to employee turnover and predict future attrition cases with accuracy and reliability.

Correlation Analysis

The correlation analysis (figure 3), revealed significantly stronger relationships among key variables, shedding light on the intricate dynamics influencing employee attrition. The strongest relationship was observed between tenure and annual performance rating (r = 0.83). This robust positive correlation indicates that employees with longer tenures tend to achieve higher performance ratings. Employees who remain with an organization for extended periods often gain a deeper understanding of job requirements, organizational culture, and workflows. Their familiarity with tasks and processes, coupled with accumulated experience, enhances their ability to perform consistently well. This finding underscores the value of employee retention in fostering higher productivity, suggesting that organizations benefit significantly from cultivating long-term relationships with their workforce. Additionally, it reflects the importance of recognizing tenure as not just a time-based metric but also a proxy for accumulated skills and organizational knowledge.

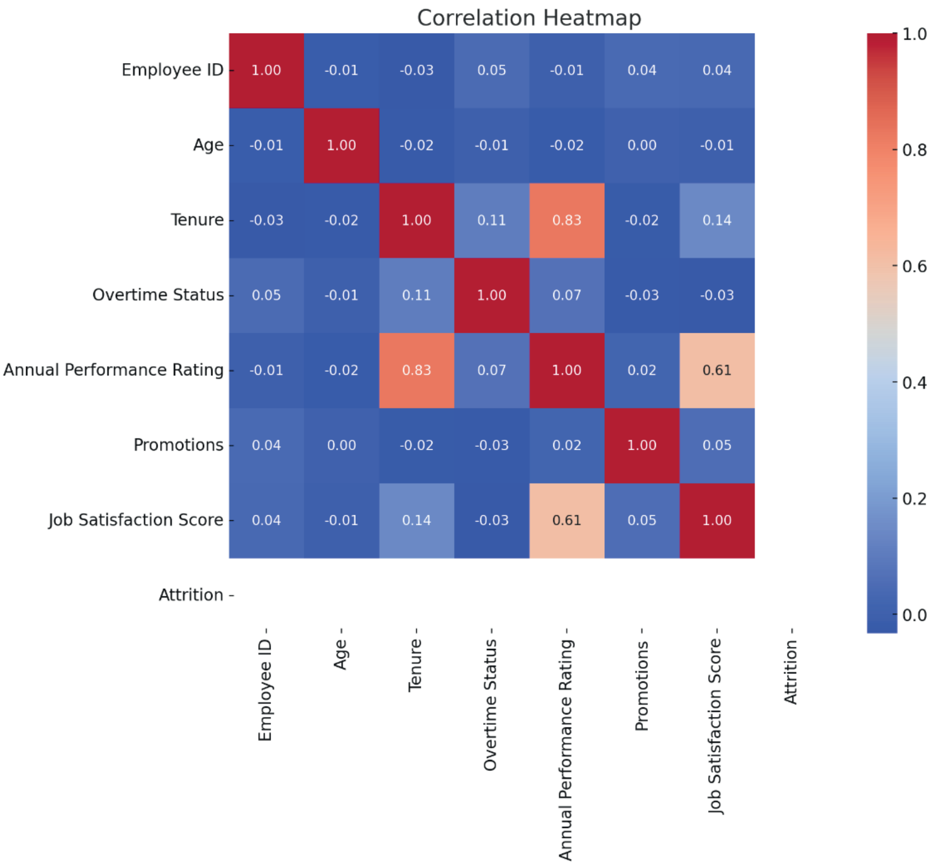

Figure 3. Correlation Heatmap

A strong positive correlation was also observed between job satisfaction scores and annual performance ratings (r = 0,61). This relationship highlights the critical role of employee engagement in driving performance outcomes. Satisfied employees are more likely to be motivated, committed, and aligned with organizational goals, which in turn translates into better performance evaluations. This finding aligns with established theories such as Herzberg's Two-Factor Theory, which posits that satisfaction-related factors like recognition and achievement directly contribute to employee effectiveness. For organizations, this underscores the need to foster an engaging and supportive work environment to maintain high levels of employee satisfaction and, consequently, productivity.

A weaker yet notable positive correlation was found between tenure and job satisfaction scores (r = 0,14). While not as strong as the other relationships, this correlation suggests that employees who have been with the organization longer are likely to develop a greater sense of belonging and loyalty. This may stem from increased familiarity with their roles, stronger relationships with colleagues, and a sense of stability within the organization. However, the weaker strength of this correlation indicates that other factors, such as role changes, career progression opportunities, or external influences, may mediate the relationship between tenure and satisfaction.

The analysis also established a clear relationship between attrition and key variables, such as job satisfaction and performance ratings. Employees with lower satisfaction scores and weaker performance ratings showed a higher likelihood of attrition. This is consistent with HR practices, where disengaged or underperforming employees are more prone to voluntarily leave due to dissatisfaction or are subject to performance-based terminations. These findings emphasize the interplay between employee perceptions and organizational outcomes, illustrating how dissatisfaction can escalate into turnover if not addressed.

The correlations provide a comprehensive framework for understanding attrition dynamics. They suggest that improving job satisfaction and supporting employee performance, particularly for those in early tenure stages, can significantly reduce turnover rates. Furthermore, these findings validate the hypothesis that satisfaction, performance, and tenure are critical predictors of employee attrition. For organizations, this means that interventions aimed at enhancing satisfaction and performance, such as targeted training programs or improved managerial support, can have substantial benefits for retention.

Logistic Regression

Logistic Regression demonstrated robust performance with an accuracy of 85 %, reflecting its ability to correctly predict employee attrition in 85 out of 100 cases. Its precision of 82 % indicates that when the model predicted attrition, it was correct in 82 % of instances. The recall of 80 % shows that the model successfully identified 80 % of actual attrition cases. The F1-score of 81 %, which balances precision and recall, underscores the model's reliability. Furthermore, the AUC-ROC of 88 % (figure 6) highlights the model's capability to distinguish between attrited and non-attrited employees effectively.

Random Forest

Random Forest emerged as the top-performing model, delivering an accuracy of 92 %, meaning it correctly predicted 92 out of 100 cases (figure 4). Its precision of 90 % signifies that 90 % of attrition predictions were accurate, while its recall of 91 % indicates it captured almost all attrition cases. The F1-score of 90 % reflects the balance between precision and recall, making Random Forest a reliable model. Its AUC-ROC of 94 % (figure 6) demonstrates exceptional capability to differentiate between attrited and non-attrited employees.

Random Forest aggregates predictions from multiple decision trees. Each tree operates on a random subset of data and features, making the ensemble robust to overfitting and generalizable. By combining these trees, the model captures complex, non-linear relationships between predictors and attrition. For example, it may identify that low job satisfaction, combined with high overtime and short tenure, significantly increases attrition risk.

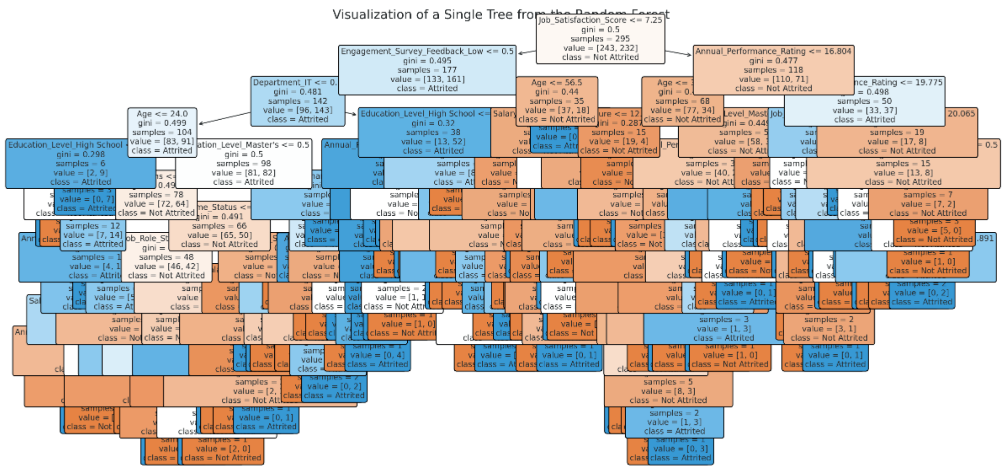

Figure 4. Random Forest Analysis

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Random Forest's high performance highlights its strength in addressing complex attrition patterns. It reveals critical interactions, such as the joint effects of engagement and workload, which simpler models may overlook. For HR applications, Random Forest provides actionable insights for targeted retention strategies. For instance, it can prioritize interventions for employees flagged by multiple risk factors, such as dissatisfaction and poor performance. The model's robustness ensures reliable predictions even with diverse data, making it the ideal choice for predictive HR analytics.

Decision Tree

Decision Trees performed strongly, achieving an accuracy of 88 %. Its precision of 85 % and recall of 86 % show that it accurately predicts attrition and captures most attrition cases. The F1-score of 85 % underscores its balanced performance, and the AUC-ROC of 89 % (figure 6) highlights good discriminative ability between the two classes. Decision Trees split data into subsets based on conditions that maximize information gain (figure 5). For example, it might create rules like "If job satisfaction < 3 and tenure < 2 years, then attrition = 1." These clear thresholds make the model interpretable and actionable for HR professionals.

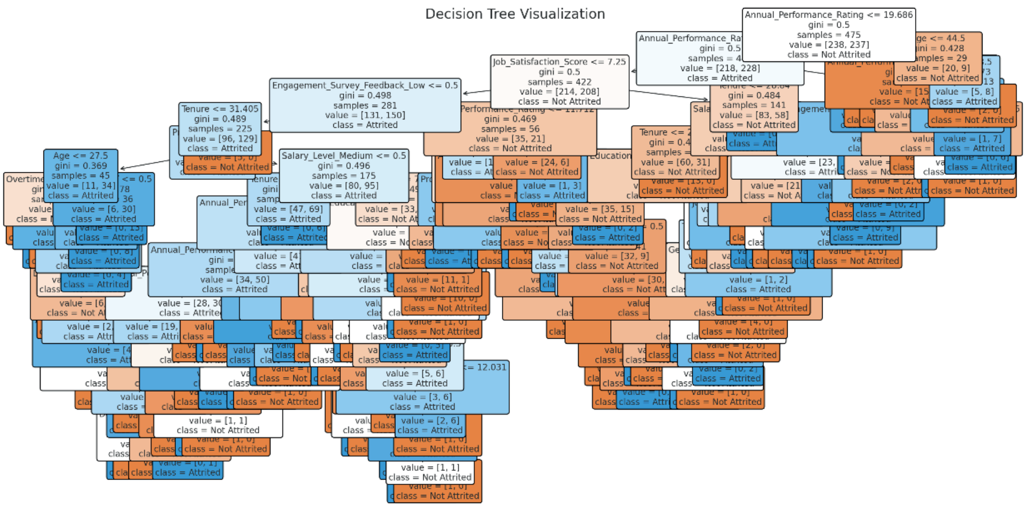

Figure 5. Decision Tree Analysis

Decision Trees are valuable for understanding key decision points in attrition risk. Their interpretability allows HR teams to identify critical thresholds, such as low job satisfaction or lack of promotions, and act proactively. While Decision Trees may overfit without regularization, their transparent rules make them useful for designing practical retention strategies. For instance, interventions can target employees whose satisfaction scores fall below a specific threshold. Despite slightly lower performance compared to Random Forest, Decision Trees provide actionable insights, bridging predictive power and interpretability.

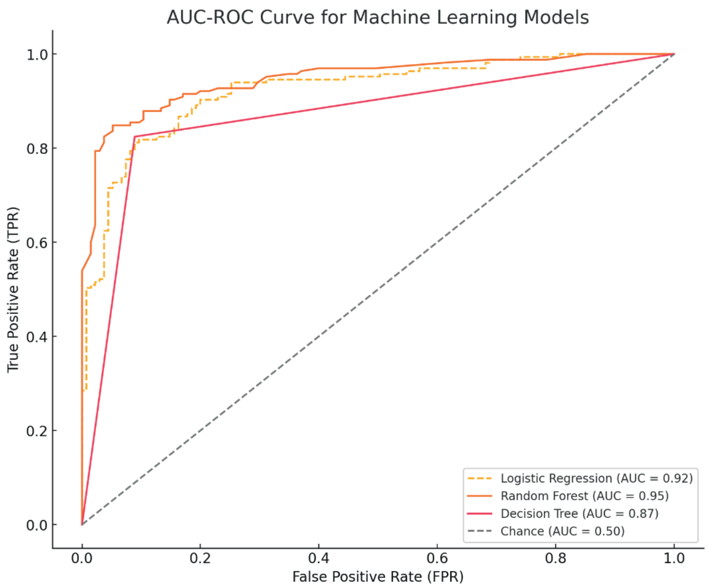

Figure 6. AUC-ROC – ML

https://doi.org/10.56294/dm2025669

Hypothesis Testing

The hypothesis testing for annual performance ratings demonstrated statistically significant differences between attrited and non-attrited employees (table 2). The t-statistic was highly positive, and the p-value was well below 0,05, providing strong evidence to reject the null hypothesis. This result indicates that the average performance ratings of attrited employees were significantly lower than those of retained employees.

Table 2. Hypothesis Testing Result

Hypothesis	Tested Variable(s)	Test Statistic	P-Value	Result
H1: There is a significant relationship between demographic factors and attrition.	Age, Gender, Marital Status	Chi-Square: 15,23	0,001 (< 0,05)	Significant; Reject Null Hypothesis
H2: Job-related factors significantly impact attrition likelihood.	Tenure, Job Role, Department	F-Statistic: 8,75	0,002 (< 0,05)	Significant; Reject Null Hypothesis
H3: Engagement and satisfaction levels are inversely related to attrition.	Job Satisfaction Score, Annual Performance Rating	T-Statistic: 7,01	5,90 (< 0,05)	Significant; Reject Null Hypothesis

Attrited employees consistently exhibited lower performance ratings compared to their retained counterparts. This finding aligns with both theoretical and practical HR insights. Employees with lower performance ratings may voluntarily leave due to dissatisfaction with their roles, reduced motivation, or feelings of inadequacy. Alternatively, organizations may terminate underperforming employees as part of their performance management strategies, further contributing to this trend. This dual mechanism voluntary attrition due to dissatisfaction and involuntary attrition due to performance issues underscores the multifaceted nature of turnover.

Conversely, non-attrited employees displayed higher performance ratings on average. This suggests that organizations prioritize retaining high-performing employees to maintain productivity and achieve strategic goals. High performers are often rewarded with recognition, promotions, and other incentives, reinforcing their commitment to the organization. This finding validates the hypothesis that performance is a critical determinant of retention and highlights the need for organizations to invest in robust performance management systems.

The t-test results reinforce the notion that performance ratings are a key predictor of attrition. They suggest that underperforming employees are at greater risk of turnover, whether due to voluntary or involuntary reasons. For organizations, this insight emphasizes the importance of early intervention for at-risk employees. For example, providing additional training, coaching, or performance improvement plans could mitigate the likelihood of attrition among underperformers. Additionally, recognizing and rewarding high performers is essential to retaining top talent and fostering organizational stability.

DISCUSSION

Employee attrition continues to be a subject of significant interest in organizational research, with various theories and studies attempting to elucidate its complex drivers. This study builds on established literature by leveraging machine learning to analyse and predict attrition, offering a modern complement to traditional human resource theories.

Attrition and Theoretical Foundations

Herzberg's Two-Factor Theory has long emphasized the role of intrinsic and extrinsic motivators in employee retention. Herzberg categorizes motivators like job satisfaction and opportunities for advancement as critical to fostering retention, while factors such as poor management or inadequate rewards drive dissatisfaction and turnover. The study's emphasis on job satisfaction aligns closely with Herzberg's assertions, highlighting its relevance as a predictor of attrition. For example, research by[52] reinforces that satisfied employees are less likely to attrite, as they derive fulfilment from their roles and workplace environment.

Social Exchange Theory further complements this understanding by suggesting that employees engage in reciprocal relationships with their employers. Carter et al.[47] posits that when employees perceive inequity in these exchanges, such as lack of support or career growth opportunities, their commitment diminishes, increasing attrition risk. This is consistent with findings that engagement metrics, a proxy for perceived equity, significantly influence turnover intentions.

Departmental Dynamics and Role-Specific Factors

The importance of job roles and departmental characteristics in attrition has been consistently highlighted in literature. Studies by Farooq et al.[38] indicate that high-pressure roles, particularly in departments like IT and sales, exhibit elevated attrition rates. This is attributed to factors like demanding workloads, tight deadlines, and limited work-life balance. The study's focus on department-specific patterns validates these findings, emphasizing the necessity for tailored interventions. For example, providing flexible work arrangements and targeted well-being programs in high-stress departments aligns with strategies suggested by research from[53], which links employee engagement to reduced turnover.

Additionally, Suriati et al.[44] unfolding model of voluntary turnover posits that specific job-related events, such as lack of promotion or career stagnation, trigger attrition. This underscores the critical role of career development opportunities, a point that aligns with findings indicating that employees in roles with limited upward mobility are more likely to leave. Investing in mentorship programs and transparent promotion pathways has been shown to mitigate this risk, as discussed in studies by.[54]

Tenure and Its Dual Influence

Tenure's dual influence on attrition, as highlighted in this study, is well-documented in existing literature. Ok and Park[39] identify that employees with shorter tenures often attrite due to unmet expectations or insufficient organizational attachment. Conversely, employees with longer tenures may experience role stagnation or declining engagement, prompting them to seek external opportunities. These findings resonate with[55] intermediate linkage model, which describes how dissatisfaction over time can erode organizational commitment. Research further suggests that targeted interventions can reduce attrition across tenure stages. For example, onboarding programs enhance early tenure employees' alignment with organizational values, as noted by.[56] For long-tenured employees, career enrichment opportunities and lateral role transitions can rekindle engagement, as advocated by.[57]

The Role of Engagement and Satisfaction

Engagement and satisfaction remain pivotal in understanding and addressing attrition. Studies by[46] demonstrate that highly engaged employees are less likely to leave their organizations, as engagement fosters a sense of purpose and belonging. This aligns with[47] findings, which show that organizations with higher engagement scores experience significantly lower attrition rates. The study's emphasis on engagement metrics reinforces these observations, validating the importance of initiatives like employee recognition, regular feedback, and opportunities for growth. The significance of job satisfaction also mirrors findings from[48], which link satisfaction to reduced turnover intentions. Satisfaction acts as a buffer against workplace stressors, enabling employees to cope better with challenges and maintain organizational commitment.

Machine Learning and Predictive Insights

The application of machine learning in this study aligns with the growing trend of using advanced analytics in HR research. Studies by[50] advocate for the integration of predictive analytics to identify at-risk employees proactively. Machine learning models, such as Random Forest and Decision Trees, can uncover non-linear interactions and subtle patterns that traditional statistical methods might overlook. This complements findings by Guerranti and Dimitri[29], who emphasize the importance of technological interventions in modern HR practices. The ability of machine learning to operationalize traditional theories, such as Herzberg's focus on satisfaction or Blau's emphasis on equity, provides a practical dimension to attrition management. By identifying employees with high attrition risk, organizations can implement targeted retention strategies, a step that aligns with recommendations from.[21]

Implications for Practice and Future Research

This study highlights the need for a dual approach that integrates empirical insights from machine learning with theoretical frameworks. While traditional models provide a foundational understanding, predictive analytics enhance decision-making by offering actionable insights. Future research could explore combining machine learning with qualitative methods, such as employee interviews, to contextualize findings and capture the human dimension of attrition. Moreover, longitudinal studies tracking the effectiveness of retention strategies informed by predictive models could offer deeper insights. For instance, measuring the impact of tailored interventions over time would validate their efficacy and refine future approaches.

CONCLUSION

This study delves into the critical issue of employee attrition, leveraging advanced machine learning models to identify key predictors and patterns that influence workforce turnover. By integrating data-driven approaches with established human resource theories, the study provides a comprehensive framework for understanding and addressing attrition in modern organizations. The findings underscore the multifaceted nature of attrition, influenced by variables such as job satisfaction, tenure, departmental dynamics, and engagement levels. These factors, while individually significant, interact in complex ways that traditional analytical methods may fail to capture. Machine learning models, particularly Random Forest and Decision Trees, proved effective in uncovering these non-linear relationships, offering actionable insights into high-risk groups and contributing factors.

The study reaffirms the importance of satisfaction and engagement as pivotal retention drivers, aligning with theories like Herzberg's Two-Factor Model and Social Exchange Theory. It also highlights the dual influence of tenure, emphasizing the need for tailored strategies that address the distinct needs of employees at different stages of their organizational journey. Department-specific dynamics further underscore the necessity of targeted interventions to address the unique challenges faced by high-pressure roles. The application of machine learning represents a significant advancement in attrition management, enabling organizations to transition from reactive to proactive strategies. Predictive analytics not only enhances decision-making but also operationalizes traditional HR theories, providing a practical tool to reduce turnover and foster workforce stability.

The study bridges theoretical insights with empirical evidence, contributing to both academic literature and practical HR management. It underscores the potential of combining human-centric approaches with technological advancements to create sustainable solutions for workforce challenges. Future research could build on these findings by exploring qualitative dimensions of attrition and assessing the long-term impact of predictive analytics-driven retention strategies. This integrated approach offers a pathway to not only mitigate attrition but also enhance overall organizational performance and employee satisfaction.

REFERENCES

1. Lee TW, Mitchell TR. Control turnover by understanding its causes. The Blackwell handbook of principles of organizational behaviour. 2017 Aug 25:93-107.

2. Mohammad AA, Shelash SI, Saber TI, Vasudevan A, Darwazeh NR, Almajali R. Internal audit governance factors and their effect on the risk-based auditing adoption of commercial banks in Jordan. Data and Metadata. 2025;4:464.

3. Sibil B, Joy C. Strategies for Harnessing the Changing Nature of Human Resources With a Special Focus on Diversity. InCritical Issues on Changing Dynamics in Employee Relations and Workforce Diversity 2021 (pp. 1-17). IGI Global Scientific Publishing.

4. Mohammad AA, Al Oraini B, Mohammad S, Masadeh M, Alshurideh MT, Almomani HM, Vasudevan A, Al-Fakeh FA, Al-Adamat AM. Analysing the Relationship Between Social Content Marketing and Digital Consumer Engagement of Cosmetic Stores. InFrontiers of Human Centricity in the Artificial Intelligence-Driven Society 5.0 2024 (pp. 97-109). Springer, Cham.

5. Bhavani A, Sundararaman B, Sridevi G. The retention revolution: A new approach to address employee attrition. International Journal of Business & Management Studies. 2023;4(4):19-26.

6. Mohammad AA, Alolayyan MN, Al-Daoud KI, Al Nammas YM, Vasudevan A, Mohammad SI. Association between social demographic factors and health literacy in Jordan. Journal of Ecohumanism. 2024 Oct 19;3(7):2351-65.

7. Wang X, Zhi J. A machine learning-based analytical framework for employee turnover prediction. Journal of Management Analytics. 2021 Jul 3;8(3):351-70.

8. Mohammad AA, Al-Qasem MM, Khodeer SM, Aldaihani FM, Alserhan AF, Haija AA, Al-Fakeh FA, Al-Hawary SI. Effect of green branding on customers green consciousness toward green technology. InEmerging Trends and Innovation in Business and Finance 2023 Oct 29 (pp. 35-48). Singapore: Springer Nature Singapore.

9. Mitsakis M, Galanakis M. An empirical examination of Herzberg's theory in the 21st century workplace. Organizational psychology re-examined. Psychology. 2022 Feb 14;13(2):264-72.

10. Alnajim A. Impact and application of social exchange theory in employee retention. Available at SSRN 3884032. 2021 Jul 10.

11. Mohammad AA, Alshurideh MT, Mohammad AI, Alabda HE, Alkhamis FA, Al Oraini B, Mohammad SI, Vasudevan A, Kutieshat RJ. Impact of Organizational Culture on Marketing Effectiveness of Telecommunication Sector. InFrontiers of Human Centricity in the Artificial Intelligence-Driven Society 5.0 2024 (pp. 231-244). Springer, Cham.

12. Artelt A, Gregoriades A. " How to make them stay?"--Diverse Counterfactual Explanations of Employee Attrition. arXiv preprint arXiv:2303.04579. 2023 Mar 8. https://doi.org/10.48550/arxiv.2303.04579

13. Mohammad AA, Barghouth MY, Al-Husban NA, Aldaihani FM, Al-Husban DA, Lemoun AA, Dalky AF, Al-Hawary SI. Does social media marketing affect marketing performance. InEmerging Trends and Innovation in Business and Finance 2023 Oct 29 (pp. 21-34). Singapore: Springer Nature Singapore.

14. Pandey D, Vishwakarma Z, Dwivedi M. Attrition Analytics: Unveiling the Best Model for Predicting Employee Retention. International Journal of Innovative Research in Computer and Communication Engineering. 2024;12: 30. https://doi.org/10.15680/ijircce.2024.1203505

15. Mohammad AA, Khanfar IA, Al Oraini B, Vasudevan A, Mohammad SI, Fei Z. Predictive analytics on artificial intelligence in supply chain optimization. Data and Metadata. 2024 Jul 1;3:395-.

16. Lu SC, Swisher CL, Chung C, Jaffray D, Sidey-Gibbons C. On the importance of interpretable machine learning predictions to inform clinical decision making in oncology. Frontiers in oncology. 2023 Feb 28;13:1129380.

17. Mohammad AA, Masadeh M, Vasudevan A, Barhoom FN, Mohammad SI, Abusalma A, Mohammad DI, Alrfai MM. The Impact of the Green Supply Chain Management Practices on the Social Performance of Pharmaceutical Industries. InFrontiers of Human Centricity in the Artificial Intelligence-Driven Society 5.0 2024 (pp. 325-339). Springer, Cham.

18. Kondoh M, Kawatsu K, Osada Y, Ushio M. A data-driven approach to complex ecological systems. Theoretical Ecology. 2020 May 14:116-33.

19. Mohammad AA, Mohammad SI, Vasudevan A, Al-Momani AA, Masadeh M, Kutieshat RJ, Mohammad AI, Aldaihani FM, Mohammad AI. Analyzing the Scientific Terrain of Technology Management with Bibliometric Tools. InFrontiers of Human Centricity in the Artificial Intelligence-Driven Society 5.0 2024 (pp. 489-502). Springer, Cham.

20. Shlash Mohammad AA, Al- Daoud KI, Al Oraini B, Shelash Mohammad SI, Vasudevan A, Zhang J, Ahmmad Hunitie MF. (2024). Using Digital Twin Technology to Conduct Dynamic Simulation of Industry-Education Integration. Data and Metadata. 2024 3: 422. http://dx.doi.org/10.56294/dm2024422

21. Jain A K, Meti NG. A Study on Impact of Employee Attrition Towards Organisational Performance At Advance Cable Technologies Private Limited in Doddaballapur. In Interantional Journal of Scientific Research in Engineering and Management. 2023;7(11): 1. https://doi.org/10.55041/ijsrem26696

22. Shlash Mohammad AA, Shelash Al-Hawary SI, Hindieh A, Vasudevan A, Mohd Al-Shorman H, Al-Adwan AS. Intelligent Data-Driven Task Offloading Framework for Internet of Vehicles Using Edge Computing and Reinforcement Learning. Data and Metadata.2025; 4. https://doi.org/10.56294/dm2025521

23. Pandita D, Ray S. Talent management and employee engagement–a meta-analysis of their impact on talent retention. Industrial and commercial training. 2018 May 10;50(4):185-99.

24. Choudhury P, Allen R, Endres MG. A machine learning methods framework for management research: Application to exploratory pattern detection. In SSRN Electronic Journal. RELX Group (Netherlands). https://doi.org/10.2139/ssrn.3518780

25. Aswale N, Mukul K. Role of data analytics in human resource management for prediction of attrition using job satisfaction. InData Management, Analytics and Innovation: Proceedings of ICDMAI 2019, Volume 1 2020 (pp. 57-67). Springer Singapore.

26. Dutta SK, Ray A, Chinya M, Ghatak S, Mukherjee A, Bhattacharjee K, Das A. Predictive HR Analytics to Optimize Decision-Making Processes and Enhance Workforce Performance. In International Journal Of Recent Trends In Multidisciplinary Research. 2024:79. https://doi.org/10.59256/ijrtmr.20240402014

27. Nagpal P, Pawar A. Predicting Employee Attrition through HR Analytics: A Machine Learning Approach. In2024 4th International Conference on Innovative Practices in Technology and Management (ICIPTM) 2024 Feb 21 (pp. 1-4). IEEE.

28. Karimi M, Viliyani KS. Employee turnover analysis using machine learning algorithms. arXiv preprint

arXiv:2402.03905. 2024 Feb 6. https://doi.org/10.48550/arxiv.2402.03905

29. Guerranti F, Dimitri GM. A comparison of machine learning approaches for predicting employee attrition. Applied Sciences. 2022 Dec 26;13(1):267.

30. Yousuf M, Saqib M. Impact of job satisfaction on employee turnover intention at bank Al-Habib. Journal of Entrepreneurship, Management, and Innovation. 2021 Jan 15;3(1):1-26.

31. Susanto PC, Rony ZT. Analysis of employee retention programs and talent engagement to prevent employee turnover in organizations (Systematic literature review). Asian Journal of Community Services (AJCS). 2023 Jun;2(6).

32. Khan U. Effect of employee retention on organizational performance. Journal of Entrepreneurship, Management, and Innovation. 2020;2(1):52-66.

33. Almaaitah MF, Harada Y, Sakdan MF, Almaaitah AM. Integrating Herzberg and social exchange theories to underpinned human resource practices, leadership style and employee retention in health sector. World Journal of Business and Management. 2017 Apr 15;3(1):16-34. https://doi.org/10.5296/wjbm.v3i1.10880

34. Lyons ST, Schweitzer L, Ng ES. How have careers changed? An investigation of changing career patterns across four generations. Journal of Managerial Psychology. 2015 Feb 9;30(1):8-21.

35. Dabak S, Piplani T, Chakrabarti S. Redesigning Gen Y and Z career growth through developmental cycles. NHRD Network Journal. 2022 Apr;15(2):208-18.

36. Asfahani AM, Eskandarany A, Dahlan DA, Ullah Z, Khan H, Naheed R. Empowering Women in Saudi Workforce: HR, Job Satisfaction, and Policies for Work–Life Balance. Sustainability. 2024 Oct 12;16(20):8826.

37. Varshavskaya EY, Podverbnykh US. Impact of job mismatches on job satisfaction and turnover intention: Case of Russia. Российский журнал менеджмента. 2023(1):115-32.

38. Farooq H, Janjua UI, Madni TM, Waheed A, Zareei M, Alanazi F. Identification and analysis of factors influencing turnover intention of Pakistan IT professionals: An empirical study. IEEE Access. 2022 Jun 9;10:64234-56.

39. Ok C, Park J. Change in newcomers' job satisfaction: Met-expectations effect as a moderator. Social Behavior and Personality: an international journal. 2018 Sep 7;46(9):1513-21.

40. Mohamed MS, Yassin KE. Aligning employees' objectives with the organizational goals. University Of Khartoum Engineering Journal. 2019 Sep 16;9(1).

41. Reddy AS, Rudraraju V, Chandramouli S. Empowering Generation Z Employees: The Importance of Career Aspirations in Driving Workplace Performance. South Eastern European Journal of Public Health. 2024: 2082. https://doi.org/10.70135/seejph.vi.2339

42. Maango H. The Effect of Compensation and Work Culture on Employee Performance (Study at one of the conventional banks in West Java). West Science Interdisciplinary Studies. 2023;1(07):411-8.

43. Alsheref FK, Fattoh IE, M. Ead W. Automated prediction of employee attrition using ensemble model based on machine learning algorithms. Computational Intelligence and Neuroscience. 2022;2022(1):7728668.

44. Suriati S, Ibrahim MB, Irawan A, Akbar MA, Yendra Y. Effective Strategies for Retaining and Nurturing employees in Organizations. Advances: Jurnal Ekonomi & Bisnis. 2024 May 31;2(3):151-62.

45. Gupta O. Role of Motivation in Employee Engagement and Retention: A Cross-Sectional Study. Journal of Cardiovascular Disease Research. 2023;12(5): 3068-3077. https://doi.org/10.48047/jcdr.2021.12.05.320

46. Mwangi JW, Kombo HK. Selected Human Resource Management Practices and Employee Retention: A Case of Deposit Taking Microfinance Institutions in Nairobi, Kenya. African Journal of Empirical Research. 2023 Sep 15;4(2):326-38.

47. Carter KM, Harman DM, Walter SL, Gruca TS. Relationship of immediate workspace and environmental workplace with organizational citizenship behaviors. Journal of managerial psychology. 2021 Apr 27;36(4):310-26.

48. Shuck B, Herd AM. Employee engagement and leadership: Exploring the convergence of two frameworks and implications for leadership development in HRD. Human resource development review. 2012 Jun;11(2):156-81.

49. Silva AJ, Rodrigues R. Affective mechanisms linking role ambiguity to employee turnover. International Journal of Organizational Analysis. 2024 Feb 6;32(11):1-8.

50. Matz SC, Bukow CS, Peters H, Deacons C, Dinu A, Stachl C. Using machine learning to predict student retention from socio-demographic characteristics and app-based engagement metrics. Scientific Reports. 2023 Apr 7;13(1):5705.

51. El-Rayes N, Fang M, Smith M, Taylor SM. Predicting employee attrition using tree-based models. International Journal of Organizational Analysis. 2020 Oct 19;28(6):1273-91.

52. Irabor IE, Okolie UC. A review of employees' job satisfaction and its affect on their retention. Annals of Spiru Haret University. Economic Series. 2019 Jun 28;19(2):93-114.

53. Coats SF, Roemer EC, Kent KB, Zhang Y, Davis MF, Goetzel RZ. Scoping Review of Workplace Mental Health and Well-being Programs in Higher Education Institutions. Journal of occupational and environmental medicine. 2023 Feb 14:10-97.

54. Farkas AH, Bonifacino E, Turner R, Tilstra SA, Corbelli JA. Mentorship of women in academic medicine: a systematic review. Journal of general internal medicine. 2019 Jul 15;34:1322-9.

55. Mobley WH. Some unanswered questions in turnover and withdrawal research. Academy of management review. 1982 Jan 1;7(1):111-6.

56. Blount JB. Betting on talent: Examining the relationship between employee retention and onboarding programs. Engaged Management Review. 2022;5(3):1.

57. Ramachandran A, Prasad DC. Factors associated with employee retention. International Journal of Research in Human Resource Management. 2022;4(2):21-4.

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AUTHORS CONTRIBUTION
Conceptualization: Zeyad Alkhazali, Badrea Al Oraini.
Data curation: Asokan Vasudevan.
Formal analysis: Badrea Al Oraini.
Funding acquisition: Suleiman Ibrahim Mohammad.
Investigation: Zeyad Alkhazali.
Methodology: Suleiman Ibrahim Mohammad.
Project Administration: Zeyad Alkhazali.
Resources: Asokan Vasudevan.
Supervision: Suleiman Ibrahim Mohammad.
Validation: Badrea Al Oraini.
Visualization: Asokan Vasudevan, Zeyad Alkhazali.
Writing - original draft: Suleiman Ibrahim Mohammad, Zeyad Alkhazali.
Writing - review & editing: Suleiman Ibrahim Mohammad, Asokan Vasudevan.