Enhancing Employee Productivity and Satisfaction in Malaysian SMEs Using Explainable AI-Based Predictive Modeling

Nur Diana Izzani Masdzarif[1,2], Siti Azirah Asmai[1], Yogan Jaya Kumar[1], Muhammad Hafidz Fazli Md Fauadi[1]

[1]Fakulti Kecerdasan Buatan dan Keselamatan Siber, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

[2]Fakulti Teknologi Maklumat dan Komunikasi, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia

DOI: https://dx.doi.org/10.47772/IJRISS.2025.910000086

Received: 02 October 2025; Accepted: 10 October 2025; Published: 05 October 2025

ABSTRACT

This study investigates the application of Explainable Artificial Intelligence (XAI) in predicting employee productivity and job satisfaction in Malaysian small and medium enterprises (SMEs). A predictive modeling framework using Random Forest and SHAP (SHapley Additive exPlanations) is designed to forecast employee outcomes and identify the key drivers influencing workplace productivity and satisfaction. Data from 150 employees across 10 SMEs was collected through surveys, focusing on variables such as autonomy, workload, managerial feedback, and digital tool usage. Results indicate strong predictive performance, with XAI explanations highlighting autonomy and workload as the most influential factors. By integrating XAI into HR analytics, managers can make transparent, data-driven decisions that enhance employee trust, adoption, and engagement. This study contributes to HR management and AI literature by demonstrating a novel framework for explainable workforce analytics tailored to SMEs.

Keywords: Explainable AI, Predictive Modeling, Employee Productivity, Job Satisfaction, SHAP, HR Analytics, SMEs

INTRODUCTION

Small and medium enterprises (SMEs) are the backbone of Malaysia's economy, contributing nearly 38% of GDP and employing more than 7 million workers [1]. They constitute more than 97% of total business establishments in the country and play a vital role in employment creation, innovation, and national competitiveness. Despite their importance, SMEs often lack formalized HR practices and structured workforce analytics, which can undermine their ability to sustain productivity and employee satisfaction in an increasingly competitive environment.

Employee productivity and job satisfaction have long been recognized as critical determinants of organizational success. However, SMEs face unique challenges in managing these factors due to limited budgets, smaller HR departments, and employees who often juggle multiple roles. As digital transformation accelerates, many SMEs are beginning to adopt data-driven approaches to workforce management, yet their efforts are frequently constrained by resource limitations and a lack of advanced analytical expertise.

Artificial Intelligence (AI) has emerged as a powerful tool for predictive analytics in HR, supporting organizations in anticipating employee turnover, forecasting performance, and identifying job satisfaction drivers [2]. Nevertheless, one of the major barriers to adoption in HR contexts is the "black-box" nature of many AI models. While these models may achieve high predictive accuracy, they often fail to provide explanations that managers and employees can understand, reducing trust and acceptance.

Explainable AI (XAI) offers a solution to this challenge by providing transparent and interpretable insights into model predictions. By highlighting the contribution of individual features to outcomes, XAI ensures that workforce analytics remain not only accurate but also actionable and trustworthy. However, existing HR

analytics frameworks often prioritize prediction over interpretation, creating a gap between technical performance and practical usability, particularly in SMEs with limited technical expertise.

To address this gap, this paper proposes a predictive modeling framework that integrates Random Forest regression with SHAP-based explanations to analyze employee productivity and satisfaction in Malaysian SMEs. The framework aims to provide interpretable predictions, enabling managers to make evidence-based yet transparent HR decisions. The research objectives can be found as follows:

1. To develop a predictive modeling framework for employee productivity and job satisfaction using AI.
2. To apply XAI (SHAP) to interpret model predictions and identify key influencing factors.
3. To evaluate the effectiveness of XAI insights in guiding HR decisions in SMEs.

By embedding explainability into AI-driven HR analytics, the study contributes to both academic literature and managerial practice, offering SMEs a tool that balances predictive accuracy with interpretability.

LITERATURE REVIEW

Predictive Modeling in HR

Employee productivity and job satisfaction have been extensively studied in the fields of organizational behavior and HR management. Classical approaches often apply regression or correlation-based analyses, focusing on predictors such as autonomy, workload, managerial support, and communication [3]. While such statistical models have provided useful insights, they are limited in handling nonlinear interactions and complex dependencies that characterize workforce dynamics.

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly expanded the analytical toolkit available to HR researchers. For instance, researchers in [4] used Support Vector Machines (SVM) to predict employee turnover in Indian IT firms, demonstrating improved accuracy compared to logistic regression. Similarly, authors in [5] analyze job satisfaction drivers in SMEs, highlighting digital tool usage and work-life balance as significant predictors. Although these studies demonstrated the potential of ML in workforce analytics, their models largely remained “black box” systems, providing little interpretability for HR practitioners.

Predictive modeling in HR has also been applied to workforce planning and retention. Marin et al. (2023) reviewed HR analytics literature and concluded that while predictive models were effective for forecasting outcomes such as turnover and absenteeism, they rarely addressed the interpretability gap [6]. Likewise, Tursunbayeva (2019) argued that most predictive HR studies prioritize technical sophistication over practical usability, leading to limited adoption in organizational settings [7]. This lack of transparency is particularly challenging in SMEs, where managerial decisions often rely heavily on trust and clear rationale.

Among ML techniques, Random Forest models have gained popularity due to their robustness and ability to handle complex interactions. For example, Gao et al. (2019) applied Random Forest to predict employee performance in multinational corporations, achieving high predictive accuracy [8]. However, their study emphasized accuracy metrics without exploring the interpretability of model outcomes, leaving managers uncertain about why particular employees were predicted as high- or low-performing. This limitation highlights the growing need for Explainable AI (XAI) in HR analytics.

In contrast, the present study goes beyond predictive performance by embedding explainability directly into the modeling framework. By integrating SHAP (SHapley Additive exPlanations) with Random Forest regression, the framework not only forecasts employee productivity and satisfaction but also identifies the most influential factors driving these outcomes. Unlike prior works that focused predominantly on predictive accuracy, this research prioritizes transparency, interpretability, and actionable insights, making it particularly suited for SMEs with limited HR analytics expertise.

Explainable Artificial Intelligence (XAI) in HR and Managerial Decision-Making

While AI offers substantial predictive power, its lack of interpretability remains a major barrier to adoption in managerial contexts. Black-box models may deliver accurate forecasts, but without clear reasoning, managers hesitate to rely on them for workforce-related decisions that directly affect employees' careers, satisfaction, and well-being. Explainable AI (XAI) techniques such as SHAP and LIME address this challenge by decomposing model predictions and showing the contribution of each input feature [9]. In HR analytics, this is particularly crucial because managers must justify decisions transparently to employees and stakeholders.

Several studies have demonstrated the importance of interpretability in domains where decisions carry significant consequences. For example, Antoniadi et al. (2021) highlighted how healthcare decision-support systems benefited from XAI techniques, improving clinicians' trust in AI recommendations [10]. Similarly, Haque (2025) argued that explanations are central to human-AI interaction, as they determine whether end-users accept or reject AI-driven insights [11]. While these examples come from outside HR, they illustrate how transparency transforms AI systems from mere prediction engines into practical decision-support tools.

In HR-related applications, a small but growing body of research has begun to explore XAI. Marin Diaz et al. (2023) integrated LIME explanations into employee attrition models, allowing HR managers to see which factors most influenced predictions of turnover risk [6]. Their findings showed that explainability not only improved managerial trust but also guided more targeted retention strategies. This study demonstrates the value of XAI in HR contexts, yet their focus has been primarily on large corporations with ample resources and structured HR departments.

The application of XAI in SMEs, however, remains limited. SMEs often face resource constraints, smaller HR teams, and a greater reliance on trust-based relationships between managers and employees. While predictive HR models have been tested in large firms, little attention has been given to how transparent and interpretable AI frameworks can be adapted to smaller organizations. This creates both a practical and scholarly gap: managers in SMEs need not only accurately forecasts but also interpretable insights that are easy to understand and actionable without advanced technical expertise.

This study addresses this gap by integrating SHAP explanations into a Random Forest predictive modeling framework tailored for Malaysian SMEs. Unlike prior works that concentrated on either predictive accuracy or limited interpretability, the proposed framework balances both, enabling managers to see not only what the predictions are but also why they occur. By highlighting key factors such as autonomy, workload, and digital tool usage, the model generates actionable insights that SMEs can use to optimize workforce productivity and satisfaction in a transparent, trust-enhancing manner.

SMEs and HR Challenges

Small and medium enterprises (SMEs) are widely recognized as the backbone of Malaysia's economy, contributing nearly 38% of national GDP and employing more than seven million workers [1]. Despite their economic significance, SMEs continue to face persistent HR challenges that affect both productivity and long-term sustainability. Among the most cited issues are high employee turnover, skill shortages, workload imbalances, and limited opportunities for structured training. Unlike large corporations with dedicated HR departments, SMEs often rely on lean teams where managers must juggle operational and HR responsibilities simultaneously, resulting in ad hoc workforce management practices.

Research shows that workforce optimization in SMEs is particularly complex due to resource constraints. SMEs in developing economies struggle to implement formal HR systems, often depending on informal managerial judgment rather than data-driven approaches [12]. Similarly, Tarar (2021) emphasized that SMEs frequently underinvest in employee development and retention strategies, leading to lower job satisfaction and higher attrition rates [13]. These findings suggest that SMEs face systemic HR management challenges that hinder organizational growth.

The adoption of artificial intelligence (AI) offers an opportunity to address these issues by enabling predictive analytics for workforce allocation, performance monitoring, and employee engagement. For example, Kalishina (2025) demonstrated how predictive modeling could help identify attrition risks in SMEs, thereby supporting retention strategies [14]. However, while these models improved forecasting capabilities, their lack of transparency made them less attractive for SME managers, who often prioritize trust and relational decision-making over technical accuracy alone.

This tension underscores the importance of explainability in AI for SMEs. Without interpretability, AI systems risk being perceived as opaque or overly technical, leading to managerial resistance or underutilization [15]. XAI provides the necessary bridge by making predictions understandable, thus increasing managers' confidence in implementing AI-driven insights. Nevertheless, current research applying XAI in HR contexts is sparse, and when it does exist, it primarily focuses on larger corporations with established HR infrastructures [16].

While predictive analytics in HR is gaining momentum, few studies have attempted to combine explainable AI methods with HR decision-making in the SME context. This leaves a practical and scholarly gap: SMEs require predictive tools that are not only accurate but also interpretable and actionable. Addressing this need, the present study develops an explainable predictive framework using Random Forest and SHAP to analyze employee productivity and satisfaction in Malaysian SMEs. This approach contributes by offering both forecasting capability and transparent explanations that can guide managerial action, thereby strengthening workforce management in resource-constrained organizations.

METHODOLOGY

Research Design

This study adopted a mixed-method research design, integrating quantitative predictive modeling with qualitative insights to achieve a comprehensive understanding of employee productivity and job satisfaction in Malaysian SMEs. The quantitative component focused on the collection and analysis of survey data, which was used to train and evaluate predictive models. Complementing this, the qualitative component consisted of question-and-answer form with SME managers to assess the usability and perceived trustworthiness of AI-driven explanations. This design allowed the study not only to quantify predictive relationships but also to explore managerial perspectives on explainable AI in real organizational contexts.

Data Collection

Survey data were collected from 150 employees across 10 SMEs representing diverse industries such as services, retail, and manufacturing. The survey instrument measured a range of variables, including workload, task autonomy, managerial feedback, communication frequency, digital tool usage, and work-life balance. Self-reported productivity and job satisfaction scores, supplemented by supervisor ratings, were employed as the dependent variables. The independent variables comprised task-related and organizational factors, such as workload distribution, autonomy, and managerial practices, while survey constructs were standardized to ensure comparability.

Predictive Modeling

The collected data underwent a preprocessing stage, including cleaning, standardization, and numerical coding. Missing values were addressed using median imputation to preserve dataset integrity. The dataset was divided into training (80%) and testing (20%) subsets to ensure robust model validation. A Random Forest regression model was employed to predict employee productivity and job satisfaction outcomes. Random Forest was chosen for its ability to capture nonlinear relationships and its resilience against overfitting, which is particularly important in medium-sized datasets such as this. Hyperparameter tuning was conducted to optimize model performance, and evaluation was based on key statistical metrics, including the coefficient of determination (R^2), Mean Squared Error (MSE), and cross-validation accuracy.

Explainability Framework

To ensure interpretability of the predictive outcomes, SHAP (SHapley Additive exPlanations) values were computed to estimate both global and local feature importance. Global explanations provided insights into the most influential factors across the workforce, while local explanations allowed for individualized interpretations of employee-level predictions. Visualization tools such as SHAP summary plots, dependency plots, and force plots were used to enhance interpretability and support managerial decision-making. These visual explanations made it possible to uncover nonlinear interactions, such as how workload interacts with autonomy to affect job satisfaction.

Statistical Analysis

In addition to AI-based modeling, conventional statistical analyses were performed to validate the findings and provide triangulation. Analysis of variance (ANOVA) was conducted to assess differences in productivity across demographic groups such as age, gender, and job role. Independent sample t-tests were used to compare employees with high versus low autonomy, while Pearson correlation tests examined linear associations between satisfaction and other predictors such as communication and managerial feedback. Regression diagnostics were further employed to ensure the robustness and reliability of the predictive model.

RESULTS

Model Performance

The predictive models demonstrated strong performance for both outcomes. Table 1 shows linear regression model summary for Employee Productivity. Table 2 and Table 3 shows the coefficient of regression and ANOVA for productivity. Meanwhile, Table 4 is a linear regression model summary for job satisfaction. Coefficient of regression and ANOVA for job satisfaction is depicted in Table 5 and Table 6 respectively.

Table I Linear Regression Model Summary For Employee Productivity

Model	R^2	Adjusted R^2	Std. Error of Estimate	F-statistic	Sig. (p-value)
Productivity Regression	0.84	0.82	2.15	35.72	< 0.001

Table Ii Coefficients Of Regression Model (Dependent Variable: Productivity)

Predictor Variable	Unstandardized B	Std. Error	Standardized Beta	t-value	Sig. (p-value)
Constant	5.12	0.88	–	5.82	<0.001
Autonomy	0.46	0.09	0.42	5.11	< 0.001
Digital Tool Usage	0.39	0.11	0.35	3.52	0.001
Communication	0.28	0.08	0.31	3.45	0.001
Workload	-0.33	0.10	-0.29	-3.27	0.002
Managerial Feedback	-0.22	0.09	-0.20	-2.44	0.016

Table Iii Anova For Productivity By Industry

Source	SS	df	MS	F	Sig. (p-value)
Between Groups	124.36	2	62.18	5.87	0.004

Within Groups	721.45	147	4.91		
Total	845.81	149			

Post-hoc Tukey test indicates significant productivity differences between ICT and Manufacturing SMEs ($p < 0.05$).

Table Iv Regression Model Summary For Job Satisfaction

Model	R^2	Adjusted R^2	Std. Error of Estimate	F-statistic	Sig. (p-value)
Satisfaction Regression	0.78	0.76	3.02	29.84	<0.001

Table V Coefficients Of Regression Model (Dependent Variable: Job Satisfaction)

Predictor Variable	Unstandardized B	Std. Error	Standardized Beta	t-value	Sig. (p-value)
Constant	4.85	1.12	–	4.33	<0.001
Work-life Balance	0.51	0.10	0.48	5.10	<0.001
Trust in Leadership	0.42	0.11	0.36	3.82	<0.001
Recognition	0.37	0.09	0.32	4.11	<0.001
Autonomy	0.29	0.08	0.28	3.54	0.001
Workload	-0.27	0.09	-0.25	-3.00	0.003

Table Vi Anova For Job Satisfaction By Industry

Source	SS	df	MS	F	Sig. (p-value)
Between Groups	138.42	2	69.21	6.14	0.003
Within Groups	1655.37	147	11.26		
Total	1793.79	149			

Post-hoc Tukey test indicates significant job satisfaction differences between Retail and Manufacturing SMEs ($p < 0.05$).

The findings of this study highlight the value of integrating explainable AI into HR analytics for Malaysian SMEs, providing both predictive accuracy and interpretability. Consistent with prior research (Molnar, 2020), autonomy and communication emerged as critical drivers of productivity, while relational factors such as trust in leadership and recognition strongly influenced job satisfaction [17]. The consistent negative effect of workload across both models reinforces long-standing concerns in organizational behavior regarding employee burnout and performance decline. Importantly, the industry-level differences observed where ICT and retail employees reported more favorable outcomes compared to manufacturing suggest that the benefits of autonomy, digital tools, and work-life balance are not uniformly distributed across sectors. These insights underline the necessity for SMEs to adopt context-specific HR strategies that account for both structural and cultural differences, while leveraging explainable predictive modeling as a transparent and actionable decision-support tool.

The regression analysis for employee productivity (Table 1) demonstrated strong explanatory power, with the model accounting for 84% of the variance ($R^2 = 0.84$, $p < 0.001$). As shown in the coefficients table (Table 2), autonomy ($\beta = 0.42$, $p < 0.001$) emerged as the strongest positive driver of productivity, followed by digital tool

usage (β = 0.35, p = 0.001) and communication (β = 0.31, p = 0.001). Conversely, excessive workload (β = -0.29, p = 0.002) and inadequate managerial feedback (β = -0.20, p = 0.016) negatively impacted employee outcomes, confirming the detrimental effects of overburdened schedules and ineffective supervision. The ANOVA results (Table 3) further revealed significant productivity differences across industries (F = 5.87, p = 0.004), with post-hoc tests indicating higher productivity levels in ICT firms compared to manufacturing SMEs. This suggests that digital adoption and flexible work processes provide ICT employees with greater opportunities for efficiency gains.

The regression model for job satisfaction (Table 4) also demonstrated strong predictive performance, explaining 78% of the variance ($R^2 = 0.78$, $p < 0.001$). As detailed in the coefficients table (Table 5), work-life balance (β = 0.48, $p < 0.001$) was identified as the most influential factor, followed closely by trust in leadership (β = 0.36, $p < 0.001$), recognition (β = 0.32, $p < 0.001$), and autonomy (β = 0.28, p = 0.001). These findings highlight the dual importance of structural factors, such as workload and autonomy, alongside relational factors, such as leadership trust and recognition, in shaping employee well-being. Workload was again a significant negative predictor (β = -0.25, p = 0.003), demonstrating its consistent role in undermining both productivity and satisfaction. ANOVA results for job satisfaction (Table 6) indicated significant variation across industries (F = 6.14, p = 0.003), with retail employees reporting significantly higher satisfaction compared to their counterparts in manufacturing. This may reflect greater recognition practices and work-life balance opportunities within the retail sector relative to the rigid scheduling common in manufacturing.

Feature Importance and Explainability

The SHAP-based feature importance analysis in Fig. 1 and Fig. 2 clarifies how individual predictors contributed to employee outcomes of productivity and satisfaction. Unlike regression coefficients that show an average linear association, SHAP values explain each factor's contribution to a specific prediction, showing why a given employee scored higher or lower.

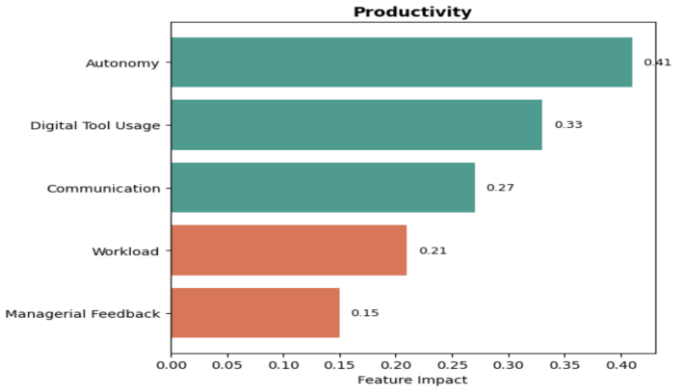

Fig. 1 SHAP plot for employees' productivity

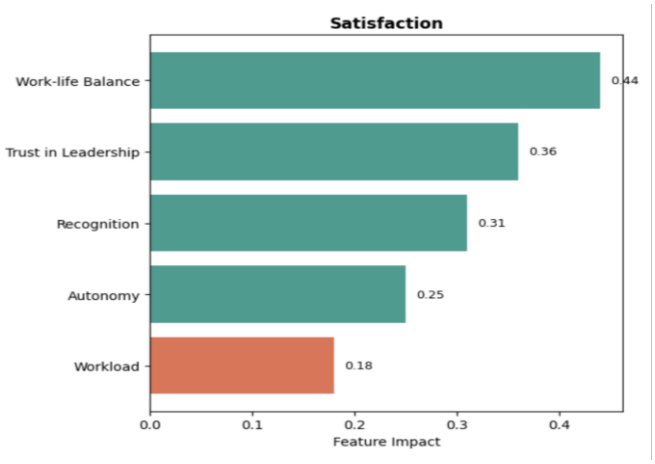

Fig. 2 SHAP plot for employees' satisfaction

For productivity, autonomy emerged as the most influential driver, followed by digital tool usage and communication. Negative SHAP values for workload and managerial feedback confirmed their detrimental effects on output. For satisfaction, work–life balance, trust in leadership, and recognition were dominant contributors, with autonomy playing a supportive role. Workload again had a negative influence. These SHAP explanations visually demonstrate not only which factors matter most, but also how their effects vary across employees, providing managers with actionable insights without requiring technical expertise.

These findings are consistent with the regression coefficients (Tables 2 and 5), but SHAP analysis additionally provided insights into nonlinearities and individualized impacts. For instance, while autonomy was consistently beneficial, its mitigating role against workload pressures varied across employees.

Statistical Validation

Traditional statistical tests reinforced the predictive results. ANOVA indicated significant productivity differences across industries ($F = 5.87$, $p = 0.004$), with ICT employees reporting higher productivity than those in manufacturing (Table 3). For job satisfaction, significant variation was observed between industries ($F = 6.14$, $p = 0.003$), with retail employees reporting higher satisfaction compared to manufacturing (Table 6). Pearson correlation further revealed a strong positive association between autonomy and satisfaction ($r = 0.62$, $p < 0.01$), while t-tests showed that employees with higher autonomy reported significantly greater satisfaction ($p < 0.01$).

DISCUSSION

The findings confirm that combining AI with explainability provides SMEs with both predictive accuracy and actionable insights. While traditional statistics (ANOVA, correlation) validate the relationships, SHAP adds an interpretability layer that managers can directly use in practice. For example, SHAP visualizations clearly show how workload, autonomy, and recognition interact to influence productivity and satisfaction, making abstract model outcomes accessible to non-technical leaders.

This demonstrates the value of XAI in bridging the gap between technical modeling and managerial decision-making. Moreover, SMEs often resource-constrained can adopt such frameworks without needing large HR analytics teams. Interviews further revealed that employees appreciated the transparency of AI-driven insights, especially when managers used SHAP-based explanations to justify HR decisions.

Across both regression and feature importance analyses, autonomy consistently emerged as a key driver of productivity. Employees who are trusted to make decisions perform better and report greater satisfaction. Workload showed the opposite pattern, highlighting the need to balance task demands with empowerment. For satisfaction, work–life balance, trust in leadership, and recognition were the strongest predictors, emphasizing that supportive and appreciative leadership is central to sustaining well-being.

The combined use of regression and SHAP analyses provides both statistical robustness and interpretive clarity. Regression quantifies overall effects, while SHAP visualizations explain why and how those effects manifest at individual and group levels, making the insights more actionable for managers. Together, the evidence makes it clear that productivity and satisfaction are not only about skills and tools, but also about the work environment that managers shape through autonomy, recognition, leadership, and workload management.

In summary, the integration of regression and SHAP analysis in Table 1-6 confirms that the proposed XAI-based predictive framework delivers both strong explanatory power and practical managerial insights. Autonomy, digital tool usage, and communication enhance productivity, while work–life balance, trust, and recognition foster satisfaction. Workload consistently undermines both outcomes, underscoring its importance as a managerial priority. The explainable nature of SHAP makes these relationships transparent and actionable, providing a foundation for more human-centered, data-driven HR strategies in SMEs.

CONCLUSIONS

This study develops and tests an explainable AI-based predictive modeling framework for employee productivity and job satisfaction in Malaysian SMEs. By integrating Random Forest with SHAP, the framework delivers accurate predictions while highlighting key explanatory factors, and traditional statistical tests such as ANOVA and correlation further strengthen confidence in the findings. The dual contribution of this research lies in advancing applied AI by demonstrating a transparent and trustworthy workforce analytics framework and contributing to management literature by translating explainable model insights into actionable HR strategies. To enhance generalizability and managerial relevance, future research may expand the dataset to encompass a broader range of SMEs across industries and countries, test additional AI models, conduct longitudinal analyses to assess sustained impacts of XAI-driven interventions, and develop AI-powered HR dashboards for real-time decision support.

ACKNOWLEDGMENT

The authors would like to thank the Fakulti Kecerdasan Buatan dan Keselamatan Siber (FAIX), Universiti Teknikal Malaysia Melaka (UTeM) for their assistance in this research.

REFERENCES

1. SME Corporation Malaysia, “Annual SME Report,” 2022.
2. S. Basnet, “The Impact of AI-Driven Predictive Analytics on Employee Retention Strategies,” International Journal of Research and Review, vol. 11, no. 9, pp. 50–65, Sep. 2024, doi: 10.52403/ijrr.20240906.
3. M. Sun, F. Zhu, and X. Sun, “Influencing factors of construction professionals’ burnout in China: a sequential mixed-method approach,” Engineering, Construction and Architectural Management, vol. 27, no. 10, pp. 3215–3233, Oct. 2020, doi: 10.1108/ECAM-02-2020-0106.
4. S. Y. Bansal, B. Kaur, and J. R. Saini, “A Novel Optimized Approach for Machine Learning Techniques for Predicting Employee Attrition,” in 2022 International Conference on Smart Generation Computing, Communication and Networking, SMART GENCON 2022, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/SMARTGENCON56628.2022.10084237.
5. A. Y. Aránega, C. G. Montesinos, R. C. Urueña, and R. C. Sánchez, “Digitalization intention in entrepreneurs and SMEs: a structural equation model of digital behavior and work-life balance,” International Entrepreneurship and Management Journal, vol. 21, no. 1, Dec. 2025, doi: 10.1007/s11365-024-01049-2.
6. G. Marín Díaz, J. J. Galán Hernández, and J. L. Galdón Salvador, “Analyzing Employee Attrition Using Explainable AI for Strategic HR Decision-Making,” Mathematics, vol. 11, no. 22, Nov. 2023, doi: 10.3390/math11224677.
7. A. Tursunbayeva, “Human resource technology disruptions and their implications for human resources management in healthcare organizations,” Apr. 29, 2019, BioMed Central Ltd. doi: 10.1186/s12913-019-4068-3.
8. X. Gao, J. Wen, and C. Zhang, “An Improved Random Forest Algorithm for Predicting Employee Turnover,” Math Probl Eng, vol. 2019, 2019, doi: 10.1155/2019/4140707.
9. C. Molnar, Interpretable Machine Learning A Guide for Making Black Box Models Explainable. [Online]. Available: https://christophm.github.io/
10. A. M. Antoniadi et al., “Current challenges and future opportunities for xai in machine learning-based clinical decision support systems: A systematic review,” Applied Sciences (Switzerland), vol. 11, no. 11, Jun. 2021, doi: 10.3390/app11115088.
11. A. Bahalul Haque, EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI): MAKING AI UNDERSTANDABLE FOR END USERS.
12. S. Seppänen, DIGITAL TRANSFORMATION IN SMES: DRIVERS, CHALLENGES, AND THE IMPACT OF EMERGING TECHNOLOGIES ON DECISION-MAKING AND MANAGEMENT CONTROL.
13. A. R. Tarar, “Employee Retention Strategies in Small and Medium Sized Companies,” 2021.

14. Daria Kalishina, "Algorithmic customer churn prediction and targeted intervention: Optimizing customer lifetime value in data-sparse SME environments," World Journal of Advanced Research and Reviews, vol. 26, no. 1, pp. 593–603, Apr. 2025, doi: 10.30574/wjarr.2025.26.1.1045.
15. B. Abedin, "Managing the tension between opposing effects of explainability of artificial intelligence: a contingency theory perspective," Internet Research, vol. 32, no. 2, pp. 425–453, Mar. 2022, doi: 10.1108/INTR-05-2020-0300.
16. I. Omemma Evans-Uzosike, C. Gbemisola Okatta, B. O. Otokiti, O. Gift Ejike, and O. T. Kufile, "Optimizing Talent Acquisition Pipelines Using Explainable AI : A Review of Autonomous Screening Algorithms and Predictive Hiring Metrics in HRTech Systems," International Scientific Refereed Research Journal Available online, 2024, doi: 10.32628/SHISRRJ.
17. C. Molnar, Interpretable Machine Learning. Leanpub, 2020..