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Predicting Employee Engagement Through Extreme Gradient Boosting (XGBoost): An Explainable AI Approach

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A B S T R A C T

Objective: This study aimed to predict employee engagement using Extreme Gradient Boosting (XGBoost) and Explainable Artificial Intelligence (XAI) techniques while identifying the relative importance of psychological, organizational, leadership, and demographic factors influencing employee engagement among employees in South African organizations.

Methods and Materials: This quantitative cross-sectional study was conducted among 1,248 employees working in diverse South African organizations across multiple industries. Data were collected using standardized instruments measuring employee engagement, psychological empowerment, perceived organizational support, job satisfaction, psychological safety, and transformational leadership, alongside demographic and organizational variables. Following data preprocessing, feature engineering, and missing value treatment, the dataset was divided into training and testing subsets using an 80:20 ratio. Extreme Gradient Boosting (XGBoost) served as the primary predictive model and was compared with Multiple Linear Regression, Decision Tree Regression, Support Vector Regression, and Random Forest models. Model performance was evaluated using coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Explainable Artificial Intelligence was implemented using SHapley Additive exPlanations (SHAP) to determine feature importance and interpret model predictions.

Findings: The results demonstrated that XGBoost outperformed all competing models, achieving the highest predictive accuracy (R^2 = 0.902) and the lowest prediction errors (RMSE = 0.276, MAE = 0.198, and MAPE = 4.88%). Random Forest exhibited the second-highest predictive performance, while Multiple Linear Regression produced the weakest results. SHAP analysis revealed that psychological empowerment was the most influential predictor of employee engagement, followed by job satisfaction, perceived organizational support, transformational leadership, and psychological safety. Additional contributors

included performance ratings, training participation, organizational tenure, and workload balance. The explainability analysis further indicated that higher levels of these organizational and psychological resources consistently generated positive effects on engagement predictions, whereas demographic characteristics exhibited comparatively limited predictive influence.

Conclusion: The findings demonstrate that employee engagement can be predicted with high accuracy using XGBoost and explainable artificial intelligence techniques. Psychological empowerment, job satisfaction, organizational support, transformational leadership, and psychological safety emerged as the most critical drivers of engagement. The integration of predictive analytics and explainable AI provides organizations with a powerful evidence-based framework for understanding, forecasting, and enhancing employee engagement while supporting strategic human resource decision-making.

Keywords: *Employee Engagement; Extreme Gradient Boosting; XGBoost; Explainable Artificial Intelligence; SHAP; Human Resource Analytics*

1 Introduction

Employee engagement has emerged as one of the most influential constructs in contemporary organizational research due to its strong association with employee productivity, organizational performance, innovation, retention, and long-term sustainability. In increasingly competitive and uncertain business environments, organizations are challenged not only to attract talented employees but also to maintain their commitment, enthusiasm, and discretionary effort over time. Employee engagement represents a positive and fulfilling work-related psychological state characterized by vigor, dedication, and absorption, reflecting the extent to which employees invest their cognitive, emotional, and behavioral energies in their work roles. Research has consistently demonstrated that highly engaged employees exhibit greater motivation, stronger organizational commitment, enhanced job performance, and lower turnover intentions. Conversely, disengagement contributes to absenteeism, reduced productivity, organizational inefficiency, and talent loss. The strategic importance of engagement has therefore positioned it as a central concern for human resource management, organizational behavior, and leadership research. Recent literature has highlighted the role of engagement as a critical mechanism through which organizations achieve sustainable competitive advantage and organizational effectiveness in dynamic business environments (Orabi et al., 2023; Prajapati, 2022; Rashmi & Dsouza, 2023; Yadav et al., 2022).

The growing importance of employee engagement is closely connected to the global challenge of employee retention. Organizations across sectors are experiencing unprecedented difficulties in retaining skilled employees, particularly in knowledge-intensive industries, healthcare, hospitality, technology, and public service sectors. Employee turnover imposes substantial financial and operational costs associated with recruitment, onboarding, training, productivity loss, and organizational knowledge depletion. Consequently, researchers have increasingly examined engagement as a key antecedent of employee retention and organizational loyalty. Evidence suggests that engaged employees are less likely to seek alternative employment opportunities because engagement strengthens psychological attachment to the organization and enhances perceptions of meaningful work. Studies conducted in healthcare settings, service industries, and multinational corporations have demonstrated that engagement mediates the effects of organizational resources, leadership quality, and workplace conditions on retention outcomes. Furthermore, engagement has been found to reduce turnover intentions by fostering stronger person-organization fit, organizational commitment, and emotional attachment to the workplace (Akinwande et al., 2025; Alhajaj & Ahmad, 2023; Bernardo et al., 2023; Darko et al., 2024; Masood, 2024; Obeng & Atan, 2025; Taufan & Rachmawati, 2023; Urme, 2023).

A substantial body of research has investigated the antecedents of employee engagement, identifying numerous individual, organizational, and leadership-related factors that contribute to its development. Job satisfaction has consistently emerged as one of the strongest predictors of engagement, with satisfied employees demonstrating greater enthusiasm and commitment toward organizational objectives. Similarly, organizational support, workplace wellbeing, psychological safety, meaningful work, and talent development initiatives have been linked to higher engagement levels. Human resource management practices

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such as career development opportunities, performance recognition, training programs, flexible work arrangements, and employee empowerment strategies have also been shown to enhance engagement by fulfilling employees' psychological and professional needs. Research further indicates that organizational cultures emphasizing learning, support, and collaboration foster stronger engagement among employees. The growing emphasis on employee wellbeing programs, mental health support initiatives, and work-life integration strategies reflects organizational recognition that engagement is influenced by a complex interplay of workplace experiences rather than solely financial incentives (Ghani et al., 2022; Iqbal et al., 2023; Kendrick et al., 2023; Lim, 2022; Novrianto et al., 2024; Orujaliyev, 2024; Santoso, 2024; Susanto & Rony, 2023).

Leadership has likewise been identified as a fundamental determinant of employee engagement. Transformational leaders inspire employees through vision, support, intellectual stimulation, and individualized consideration, creating environments that encourage psychological investment in work activities. Employees who perceive supportive and empowering leadership are more likely to experience trust, motivation, and organizational identification, all of which contribute to engagement. Contemporary studies suggest that both transformational and transactional leadership styles influence employee outcomes through engagement-related mechanisms. Moreover, perceived supervisory support serves as a critical contextual factor that enhances employees' perceptions of organizational care and fairness. In modern workplaces characterized by increasing flexibility and remote work arrangements, effective leadership becomes even more important for maintaining employee engagement. Research examining workplace flexibility, supervisory support, and organizational communication consistently demonstrates that employees remain more engaged when leaders actively facilitate autonomy, recognition, and professional growth opportunities. Such findings underscore the importance of leadership behaviors as strategic drivers of engagement and retention outcomes (Ali et al., 2024; Islam et al., 2025; Otoo, 2024; Poluru, 2024).

Despite significant advances in engagement research, methodological limitations remain evident within the literature. Most existing studies rely on traditional statistical approaches such as correlation analysis, multiple regression, structural equation modeling, and mediation analysis. Although these methods have generated valuable theoretical insights, they are often constrained in their ability to model nonlinear relationships, complex interactions, and high-dimensional datasets. Employee engagement is inherently multidimensional and influenced by numerous interconnected variables operating simultaneously at individual, team, and organizational levels. Traditional linear models may therefore fail to capture the complexity of engagement dynamics in contemporary workplaces. Recent developments in human resource analytics and organizational data science have introduced new opportunities for leveraging machine learning techniques to improve predictive accuracy and uncover hidden patterns within organizational datasets. Human resource analytics has increasingly shifted from descriptive and diagnostic approaches toward predictive and prescriptive models capable of supporting evidence-based decision-making. The integration of advanced analytics into workforce management enables organizations to proactively identify engagement risks, predict employee behaviors, and optimize human capital strategies (Gelencsér et al., 2023; Kaaria, 2024; Salmero, 2024; Spencer & Kalyvaki, 2023).

Among contemporary machine learning techniques, Extreme Gradient Boosting (XGBoost) has gained substantial attention because of its superior predictive performance, computational efficiency, and ability to handle large and complex datasets. XGBoost is an ensemble learning algorithm based on gradient-boosted decision trees that excels in modeling nonlinear relationships, feature interactions, and heterogeneous data structures. Compared with traditional statistical methods, XGBoost frequently achieves higher predictive accuracy while maintaining robustness against overfitting. Consequently, the algorithm has been successfully applied in finance, healthcare, marketing, risk management, and organizational analytics. However, a common criticism of advanced machine learning models concerns their limited interpretability. Human resource professionals and organizational decision-makers often require clear explanations regarding why a model produces particular predictions. The emergence of Explainable Artificial Intelligence (XAI) methods addresses this challenge by providing transparent insights into model behavior. Techniques such as SHapley Additive exPlanations (SHAP) allow researchers to quantify the contribution of individual variables to model predictions, thereby transforming complex machine learning outputs into actionable organizational knowledge. Explainable AI therefore represents an important advancement for bridging the gap between predictive accuracy and managerial interpretability in organizational research (Chagadama et al.,

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2022; Kaaria, 2024; Poluru, 2024; Salmero, 2024; Yadav et al., 2022).

The application of explainable machine learning to employee engagement prediction remains relatively underdeveloped despite the increasing availability of workforce data and the growing strategic importance of engagement management. Existing studies primarily focus on identifying correlates of engagement rather than constructing predictive models capable of forecasting engagement outcomes at the individual level. Moreover, limited research has simultaneously examined psychological, organizational, leadership, and demographic variables within an explainable machine learning framework. As organizations continue to invest in digital transformation and human resource analytics, there is a pressing need for predictive models that not only achieve high accuracy but also provide meaningful explanations regarding the drivers of employee engagement. Such models can assist managers in prioritizing interventions, allocating resources effectively, and developing evidence-based engagement strategies. By combining XGBoost with SHAP-based explainability techniques, researchers can generate both accurate predictions and interpretable insights into the mechanisms underlying employee engagement. This integration represents a promising direction for advancing organizational analytics and enhancing strategic human resource management practices in increasingly complex work environments (Islam et al., 2025; Kendrick et al., 2023; Lim, 2022; Orujaliyev, 2024; Otoo, 2024; Prajapati, 2022).

Therefore, the aim of the present study was to predict employee engagement using Extreme Gradient Boosting (XGBoost) and Explainable Artificial Intelligence techniques while identifying the relative importance of psychological, organizational, leadership, and demographic predictors influencing employee engagement among employees in South African organizations.

2 Methods and Materials

This study employed a quantitative, cross-sectional predictive analytics design aimed at developing and validating a machine learning model capable of predicting employee engagement levels using organizational, psychological, and demographic indicators. The research was conducted across multiple medium-sized and large organizations operating in the finance, telecommunications, manufacturing, healthcare, retail, and information technology sectors in South Africa. A total of 1,248 full-time employees participated in the study. Participants were selected through stratified random sampling to ensure adequate representation across industries, organizational levels, age groups, and gender categories. Employees who had completed at least one year of continuous service within their organizations were considered eligible for inclusion, as this criterion ensured sufficient exposure to organizational practices and work environments that could influence engagement levels.

The final sample consisted of employees ranging in age from 21 to 64 years, with an average age of 38.7 years. Approximately 52.1% of participants were male and 47.9% were female. The sample included executive managers, middle managers, supervisors, technical specialists, administrative personnel, and operational staff. Data collection was conducted over a six-month period. Participation was voluntary, and all respondents provided informed consent before completing the survey instruments. Ethical principles regarding confidentiality, anonymity, and data protection were strictly observed throughout the research process. The study was designed not only to identify the most influential determinants of employee engagement but also to evaluate the predictive performance of advanced machine learning algorithms and enhance model interpretability through explainable artificial intelligence techniques.

Employee engagement was measured using the Utrecht Work Engagement Scale (UWES-17), developed by Schaufeli, Salanova, González-Romá, and Bakker. The instrument consists of 17 items distributed across three dimensions including vigor, dedication, and absorption. Respondents rated each item using a seven-point Likert scale ranging from 0 (never) to 6 (always/every day). Higher scores indicated stronger levels of work engagement. Previous international studies have consistently reported strong psychometric properties for the UWES, including satisfactory construct validity, convergent validity, and internal consistency reliability. Reliability coefficients reported in prior research generally exceed 0.85 for the overall scale and its subdimensions.

Psychological empowerment was assessed using Spreitzer's Psychological Empowerment Scale. This instrument contains 12 items measuring four dimensions: meaning, competence, self-determination, and impact. Responses were recorded on a five-point Likert scale ranging from strongly disagree to strongly agree. The scale has demonstrated strong factorial validity and reliability across diverse organizational settings and has been widely

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used in employee behavior and organizational psychology research.

Perceived organizational support was measured using the Survey of Perceived Organizational Support developed by Eisenberger and colleagues. The shortened version consisting of eight items was employed in the present study. Participants responded on a seven-point Likert scale ranging from strongly disagree to strongly agree. The instrument evaluates employees' perceptions regarding the extent to which the organization values their contributions and cares about their well-being. Previous studies have confirmed excellent reliability and validity across different occupational contexts.

Job satisfaction was assessed using the Job Satisfaction Survey developed by Spector. The instrument includes 36 items covering multiple aspects of work, including supervision, communication, promotion opportunities, operating procedures, rewards, coworkers, and working conditions. Responses were measured using a six-point Likert scale. The scale has been extensively validated and has demonstrated strong psychometric properties in both developed and developing economies.

Psychological safety was measured using Edmondson's Psychological Safety Scale, which consists of seven items designed to evaluate employees' perceptions of interpersonal risk-taking and openness within work teams. Responses were recorded using a five-point Likert scale. Previous empirical investigations have reported acceptable validity and reliability coefficients for this measure across various organizational environments.

Leadership quality was assessed using selected dimensions of the Multifactor Leadership Questionnaire (MLQ), developed by Bass and Avolio. The instrument evaluates transformational leadership behaviors including inspirational motivation, intellectual stimulation, idealized influence, and individualized consideration. Participants rated leadership behaviors using a five-point Likert scale. Extensive evidence supports the validity and reliability of the MLQ in organizational research.

In addition to psychometric instruments, demographic and organizational variables were collected, including age, gender, educational attainment, organizational tenure, department, managerial level, workload, remote work frequency, training participation, performance ratings, absenteeism records, and promotion history. These variables were included as predictive features to enhance model performance and facilitate comprehensive employee engagement forecasting.

All instruments employed in the study had previously demonstrated satisfactory levels of content validity, construct validity, convergent validity, and reliability in organizational research. Prior to analysis, internal consistency reliability was re-evaluated using Cronbach's alpha coefficients, all of which exceeded the recommended threshold of 0.70.

Data analysis was conducted using Python programming language and several machine learning libraries including Scikit-learn, XGBoost, SHAP, NumPy, Pandas, and Matplotlib. Preliminary analyses included missing value detection, outlier assessment, descriptive statistics, feature scaling, and multicollinearity diagnostics. Missing observations accounting for less than 5% of the dataset were handled using multiple imputation techniques. Continuous variables were standardized to improve model stability and computational efficiency.

The primary predictive model employed in the study was Extreme Gradient Boosting (XGBoost), a highly efficient ensemble machine learning algorithm based on gradient-boosted decision trees. XGBoost was selected because of its superior ability to model nonlinear relationships, handle high-dimensional datasets, manage feature interactions, and achieve high predictive accuracy while minimizing overfitting. Employee engagement scores served as the target variable, while psychological, organizational, leadership, and demographic factors constituted the predictor variables.

The dataset was randomly divided into training and testing subsets using an 80:20 ratio. Five-fold cross-validation was implemented during model development to ensure robustness and generalizability. Hyperparameter optimization was performed using randomized grid search procedures. Key hyperparameters including learning rate, maximum tree depth, subsample ratio, gamma parameter, minimum child weight, and number of estimators were systematically tuned to identify the optimal model configuration.

Model performance was evaluated using multiple predictive metrics, including coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These indicators provided a comprehensive assessment of predictive accuracy and model effectiveness. To compare predictive capabilities, supplementary models including Random Forest, Support Vector Regression, Decision Tree Regression, and Multiple Linear Regression were also

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developed and evaluated using identical training and testing procedures.

To enhance interpretability and address the "black-box" nature of machine learning algorithms, Explainable Artificial Intelligence (XAI) techniques were incorporated into the analytical framework. Specifically, SHapley Additive exPlanations (SHAP) were utilized to quantify the contribution of each predictor variable to engagement predictions. SHAP summary plots, dependence plots, feature importance rankings, and local explanation analyses were generated to identify the most influential factors affecting employee engagement. These explainability procedures enabled both global and individual-level interpretation of model outputs and provided practical insights for organizational decision-makers seeking to improve workforce engagement.

The final model was selected based on its predictive accuracy, generalization capability, and interpretability. The integration of XGBoost and SHAP analysis provided a comprehensive framework for accurately forecasting employee engagement while simultaneously identifying the organizational and psychological factors most strongly associated with engagement outcomes among South African employees.

3 Findings and Results

A total of 1,248 employees from South African organizations participated in the study. Of the respondents, 650 (52.1%) were male and 598 (47.9%) were female. The average age of participants was 38.7 years (SD = 9.42), with ages ranging from 21 to 64 years. Regarding educational attainment, 18.8% held a high school diploma, 24.6% possessed a diploma or technical qualification, 39.7% held a bachelor's degree, 13.2% had a master's degree, and 3.7% possessed doctoral qualifications. Participants represented a wide range of organizational sectors, including finance (18.5%), information technology (16.8%), healthcare (14.2%), manufacturing (19.4%), telecommunications (12.9%), retail (11.7%), and other service industries (6.5%). The average organizational tenure was 8.4 years (SD = 6.11). Approximately 17.5% occupied senior management positions, 26.8% were middle managers or supervisors, and 55.7% were non-managerial employees. These demographic characteristics indicate that the sample was diverse and representative of multiple organizational contexts, providing a robust basis for machine learning-based employee engagement prediction.

Table 1

Descriptive Statistics of Study Variables

Variable	Mean	SD	Minimum	Maximum
Employee Engagement	4.89	0.93	1.82	6.00
Psychological Empowerment	4.12	0.71	1.96	5.00
Perceived Organizational Support	4.25	0.82	1.55	5.00
Job Satisfaction	4.01	0.76	1.78	5.78
Psychological Safety	3.96	0.73	1.42	5.00
Transformational Leadership	4.08	0.79	1.51	5.00
Workload Balance	3.74	0.88	1.20	5.00
Training Participation	3.85	0.91	1.00	5.00
Performance Rating	4.11	0.69	1.95	5.00

Table 1 presents descriptive statistics for all variables included in the predictive model. Employee engagement demonstrated a relatively high average score (M = 4.89, SD = 0.93), indicating generally favorable engagement levels among employees. Psychological empowerment, perceived organizational support, transformational leadership, and performance ratings also exhibited relatively high mean values, suggesting positive organizational conditions within participating companies. The standard deviations indicate acceptable variability across respondents, enabling meaningful predictive modeling. None of the variables exhibited severe floor or ceiling effects, and the observed ranges confirmed substantial heterogeneity among participants. Such variability is particularly important for machine learning applications because it enhances the model's ability to learn complex relationships and discriminate among different engagement levels.

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Table 2

Comparative Predictive Performance of Machine Learning Models

Model	R^2	RMSE	MAE	MAPE (%)
Multiple Linear Regression	0.612	0.547	0.431	11.84
Decision Tree Regression	0.691	0.482	0.382	10.13
Support Vector Regression	0.754	0.429	0.331	8.67
Random Forest	0.841	0.351	0.267	6.54
XGBoost	0.902	0.276	0.198	4.88

The comparative model evaluation revealed substantial differences in predictive performance across algorithms. XGBoost demonstrated the strongest predictive capability, explaining 90.2% of the variance in employee engagement scores. Furthermore, XGBoost achieved the lowest prediction errors across all evaluation metrics, including RMSE (0.276), MAE (0.198), and MAPE (4.88%). Random Forest produced the second-best performance, whereas traditional linear regression exhibited the weakest predictive accuracy. These findings suggest that employee engagement is influenced by highly nonlinear relationships and complex interactions among organizational variables. The superior performance of XGBoost highlights the value of advanced ensemble learning methods in organizational analytics and supports the suitability of explainable artificial intelligence approaches for workforce prediction tasks.

Table 3

Top Ten Feature Importance Rankings Based on SHAP Values

Rank	Predictor Variable	Mean Absolute SHAP Value
1	Psychological Empowerment	0.381
2	Job Satisfaction	0.337
3	Perceived Organizational Support	0.309
4	Transformational Leadership	0.271
5	Psychological Safety	0.247
6	Performance Rating	0.214
7	Training Participation	0.183
8	Organizational Tenure	0.162
9	Workload Balance	0.147
10	Age	0.118

Results of the SHAP analysis identified psychological empowerment as the most influential predictor of employee engagement. Employees who reported greater autonomy, competence, impact, and meaningfulness consistently demonstrated higher predicted engagement scores. Job satisfaction emerged as the second most influential factor, followed closely by perceived organizational support. Leadership-related variables also played a substantial role, with transformational leadership and psychological safety ranking among the five most important predictors. Interestingly, demographic characteristics such as age and tenure exhibited lower predictive contributions compared to psychological and organizational variables. These findings suggest that employee engagement is primarily driven by employees' subjective workplace experiences rather than demographic characteristics, emphasizing the strategic importance of organizational climate, leadership practices, and empowerment initiatives.

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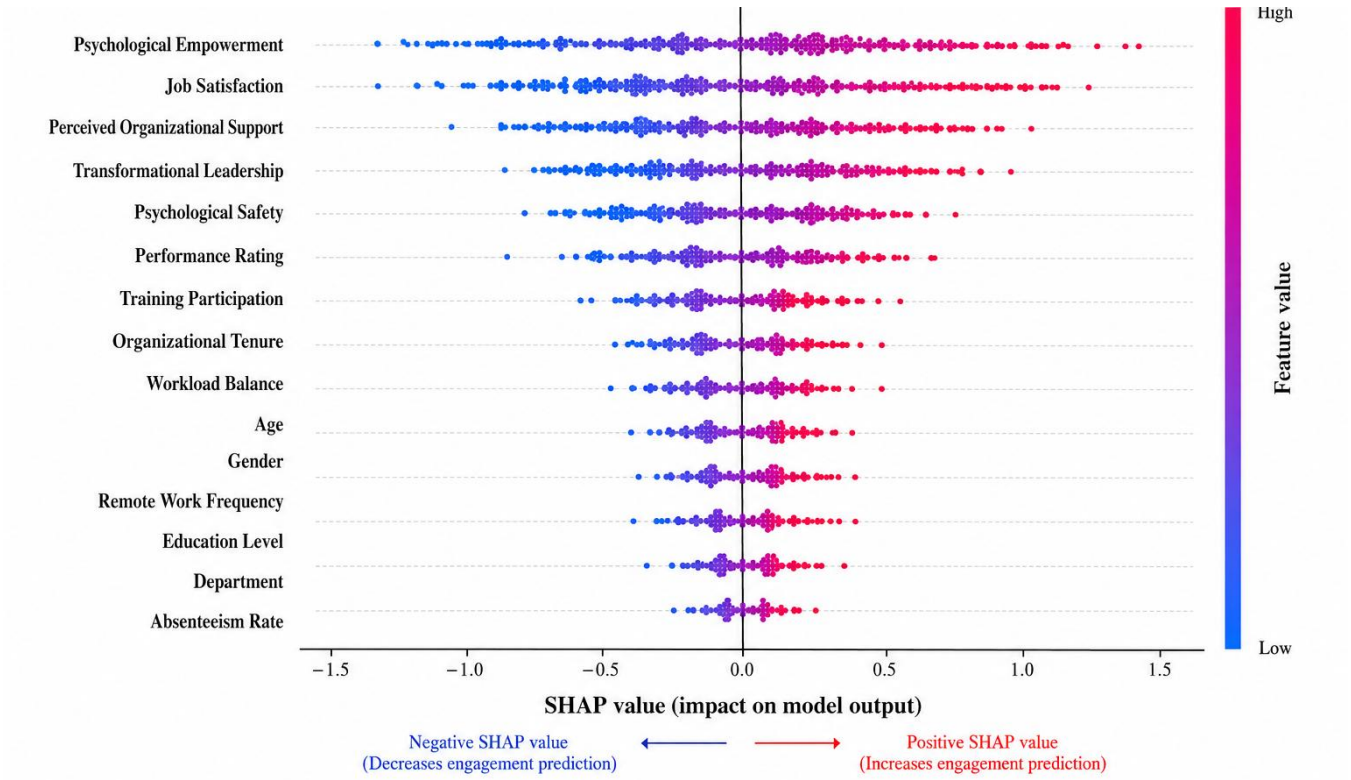
Figure 1

SHAP Summary Plot Illustrating Global Feature Contributions to Employee Engagement Predictions



The SHAP summary plot demonstrated clear patterns regarding how individual variables influenced engagement predictions across the dataset. Higher levels of psychological empowerment, job satisfaction, perceived organizational support, transformational leadership, and psychological safety were consistently associated with positive SHAP values, indicating increased employee engagement predictions. Conversely, lower values of these variables contributed negatively to predicted engagement outcomes. The dispersion of SHAP values further revealed considerable interaction effects among organizational factors, supporting the nonlinear modeling capabilities of XGBoost. The figure also demonstrated that empowerment and job satisfaction generated the largest prediction shifts, confirming their dominant influence within the model. The overall distribution pattern suggested that improvements in these factors could produce substantial gains in employee engagement across diverse organizational settings.

Table 4

SHAP-Based Directional Effects of Key Predictors

Predictor	Low Values Effect	High Values Effect
Psychological Empowerment	Decreases Engagement	Increases Engagement
Job Satisfaction	Decreases Engagement	Increases Engagement
Organizational Support	Decreases Engagement	Increases Engagement
Transformational Leadership	Decreases Engagement	Increases Engagement
Psychological Safety	Decreases Engagement	Increases Engagement
Performance Rating	Slight Decrease	Moderate Increase
Training Participation	Slight Decrease	Moderate Increase

The directional analysis derived from SHAP values provided additional insight into how predictor levels influenced engagement outcomes. High psychological empowerment produced the strongest positive effect on predicted engagement, followed by job satisfaction and organizational support. Employees who perceived greater support from their organizations and experienced higher-quality leadership consistently demonstrated elevated

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engagement scores. Psychological safety also emerged as an important driver, indicating that environments characterized by trust, openness, and interpersonal respect contribute substantially to employee engagement. Although performance ratings and training participation had smaller effects relative to psychological variables, their contributions remained meaningful. Collectively, these findings demonstrate that employee engagement is shaped by a multifaceted network of organizational and psychological influences, with empowerment, satisfaction, support, leadership quality, and psychological safety representing the most powerful determinants. The explainable AI framework successfully identified not only the predictive accuracy of the model but also the specific organizational factors that should be prioritized to maximize workforce engagement and organizational effectiveness.

4 Discussion

The findings of the present study demonstrate that employee engagement can be predicted with a high degree of accuracy using advanced machine learning techniques, particularly Extreme Gradient Boosting (XGBoost). Among the evaluated predictive models, XGBoost substantially outperformed traditional statistical and machine learning approaches, achieving an R^2 value of 0.902 and the lowest prediction errors across all evaluation metrics. Furthermore, the Explainable Artificial Intelligence analysis revealed that psychological empowerment, job satisfaction, perceived organizational support, transformational leadership, and psychological safety were the most influential predictors of employee engagement. These findings provide important theoretical and practical insights regarding both the determinants of employee engagement and the utility of explainable machine learning methods within organizational research. The results suggest that employee engagement is influenced by a complex network of interacting psychological and organizational factors that cannot be fully captured through conventional linear modeling approaches. Consequently, the study contributes to the growing literature advocating the integration of predictive analytics and human resource management to support evidence-based organizational decision-making.

One of the most important findings was the superior predictive performance of XGBoost compared with Multiple Linear Regression, Decision Tree Regression, Support Vector Regression, and Random Forest models. This result suggests that employee engagement is characterized by nonlinear relationships and complex interactions among predictor variables. Traditional statistical models typically assume linearity and independence among variables, whereas XGBoost can identify intricate patterns that may remain undetected using conventional approaches. This finding aligns with recent developments in human resource analytics, which emphasize the increasing importance of predictive modeling and advanced analytics for understanding employee behavior and workforce dynamics (Kaaria, 2024). The findings also support broader organizational research suggesting that employee attitudes and behaviors emerge from multifaceted interactions among individual, social, and organizational factors rather than isolated influences (Gelencsér et al., 2023; Iqbal et al., 2023). The strong predictive capability observed in the present study indicates that explainable machine learning models can serve as valuable tools for organizations seeking to proactively identify engagement risks and implement targeted interventions before disengagement translates into performance decline or employee turnover.

The SHAP analysis identified psychological empowerment as the strongest predictor of employee engagement. Employees who perceived higher levels of autonomy, competence, impact, and meaningfulness exhibited substantially higher engagement scores. This finding is consistent with engagement theory, which posits that employees become more psychologically invested in their work when they experience a sense of control and personal significance in their roles. Empowerment enables employees to perceive their work as meaningful and enhances intrinsic motivation, thereby strengthening engagement. The finding aligns with previous research emphasizing the importance of employee development, learning opportunities, self-efficacy, and growth-oriented workplace cultures in fostering positive employee outcomes (Alhajaj & Ahmad, 2023; Novrianto et al., 2024). Furthermore, studies examining talent management and retention have highlighted that employees are more likely to remain engaged when organizations create environments that support professional growth and individual contribution (Susanto & Rony, 2023; Urme, 2023). The current findings therefore reinforce the view that empowerment represents a foundational psychological mechanism through which organizations can enhance workforce engagement and commitment.

Job satisfaction emerged as the second most influential predictor of engagement. Employees reporting higher satisfaction levels consistently demonstrated stronger

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engagement outcomes. This finding is unsurprising given the substantial theoretical and empirical overlap between satisfaction and engagement. Job satisfaction reflects employees' evaluations of their work experiences, whereas engagement captures their active psychological investment in work activities. Positive work experiences often create emotional and cognitive conditions that facilitate higher engagement. The result strongly supports previous studies demonstrating positive associations among satisfaction, engagement, organizational commitment, and retention intentions (Lim, 2022; Orabi et al., 2023). Similarly, research examining workplace wellbeing and organizational effectiveness has concluded that employees who experience positive work conditions and satisfaction are more likely to contribute discretionary effort and demonstrate stronger organizational loyalty (Santoso, 2024; Yadav et al., 2022). Therefore, improving job satisfaction remains a critical pathway through which organizations can strengthen employee engagement and overall organizational performance.

Perceived organizational support also demonstrated substantial predictive importance. Employees who believed that their organizations valued their contributions and cared about their wellbeing exhibited significantly higher engagement levels. This finding is consistent with social exchange theory, which suggests that employees reciprocate supportive organizational treatment through greater commitment, effort, and engagement. When employees perceive that organizational leaders genuinely support their wellbeing and professional success, they are more likely to develop positive attitudes toward their work and organization. The result supports prior evidence indicating that organizational support functions as a key antecedent of engagement, retention, and organizational citizenship behaviors (Islam et al., 2025; Otoo, 2024). Furthermore, studies investigating retention and turnover have shown that supportive organizational environments reduce employees' intentions to leave while simultaneously strengthening emotional attachment to the organization (Masood, 2024; Obeng & Atan, 2025). The present findings therefore emphasize the strategic value of cultivating supportive organizational climates as a means of sustaining employee engagement.

Transformational leadership was identified as another major determinant of engagement. Employees who perceived higher levels of inspirational motivation, intellectual stimulation, individualized consideration, and idealized influence from their leaders demonstrated higher predicted engagement scores. This result is consistent with leadership theories emphasizing the motivational influence of transformational leadership behaviors. Transformational leaders create compelling visions, encourage innovation, recognize employee contributions, and foster trust-based relationships, all of which enhance employee engagement. The findings closely align with previous research showing that engagement mediates the relationship between leadership styles and positive organizational outcomes, including retention and performance (Ali et al., 2024). Similarly, research examining supervisory support and workplace flexibility has found that supportive leadership contributes significantly to employees' motivation, commitment, and engagement levels (Poluru, 2024). These findings suggest that leadership development initiatives focused on transformational competencies may represent an effective strategy for increasing employee engagement across diverse organizational settings.

Psychological safety also emerged as a highly influential predictor. Employees who perceived their work environments as safe, respectful, and supportive of interpersonal risk-taking demonstrated stronger engagement levels. Psychological safety enables employees to express ideas, ask questions, admit mistakes, and contribute creatively without fear of negative consequences. Such conditions facilitate collaboration, learning, innovation, and meaningful participation in organizational processes. This finding aligns with studies emphasizing the importance of employee wellbeing, mental health support, and supportive workplace cultures in promoting positive employee outcomes (Kendrick et al., 2023; Santoso, 2024). Moreover, workplace environments characterized by trust and openness have been associated with stronger organizational commitment, engagement, and retention outcomes across multiple sectors (Gelencsér et al., 2023; Spencer & Kalyvaki, 2023). The current results therefore highlight psychological safety as an essential component of sustainable employee engagement strategies.

The SHAP analysis further indicated that training participation, workload balance, organizational tenure, and performance ratings contributed meaningfully to engagement predictions, although their effects were smaller than those of the core psychological and organizational variables. These findings suggest that engagement is influenced by a combination of developmental opportunities, work design characteristics, and accumulated organizational experiences. Employees who receive regular training opportunities may perceive greater investment from

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their organizations and stronger opportunities for growth, thereby increasing engagement. This interpretation aligns with literature emphasizing continuous learning cultures and employee development as drivers of workforce motivation and engagement (Novrianto et al., 2024; Urme, 2023). Likewise, balanced workloads contribute to healthier work experiences and reduce the risk of burnout, which is consistent with research linking work-life integration and wellbeing to engagement outcomes (Santoso, 2024; Yadav et al., 2022). The influence of tenure may reflect the gradual development of organizational identification and embeddedness over time, supporting findings that stronger workplace connections contribute to retention and engagement (Akinwande et al., 2025; Islam et al., 2025).

Another noteworthy finding concerns the relatively lower predictive importance of demographic variables such as age and gender. Although these variables contributed modestly to engagement predictions, their influence was substantially weaker than that of psychological, leadership, and organizational factors. This result suggests that employee engagement is primarily shaped by workplace experiences rather than demographic characteristics. Such findings support contemporary organizational perspectives emphasizing the importance of contextual and environmental influences over fixed personal attributes in explaining employee attitudes and behaviors (Prajapati, 2022; Rashmi & Dsouza, 2023). This observation further reinforces the practical implication that organizations can actively influence engagement through strategic interventions targeting organizational culture, leadership quality, support systems, and employee development regardless of workforce demographic composition.

Several limitations should be acknowledged when interpreting the findings of this study. First, the cross-sectional research design restricts the ability to establish causal relationships among the investigated variables. Although the machine learning models demonstrated strong predictive capabilities, predictive accuracy should not be interpreted as evidence of causation. Second, the study relied primarily on self-reported survey data, which may be subject to common method bias, social desirability effects, and individual response tendencies. Third, data were collected exclusively from organizations operating in South Africa, which may limit the generalizability of the findings to other cultural, economic, or organizational contexts. Fourth, although a wide range of predictors was included, other potentially relevant variables such as organizational justice, employee personality traits, emotional intelligence, and team-level dynamics were not incorporated into the predictive models. Finally, while XGBoost and SHAP provided substantial interpretability advantages, the model still represents a simplified representation of the highly complex processes underlying employee engagement.

Future studies should employ longitudinal research designs to examine how engagement predictors evolve over time and to establish stronger causal inferences. Researchers may also investigate the predictive value of additional psychological, behavioral, and organizational variables, including resilience, emotional intelligence, organizational justice, trust, innovation climate, and digital transformation readiness. Comparative studies across different countries and industries would provide valuable insights regarding the generalizability of explainable machine learning models in employee engagement research. Future investigations may further explore hybrid artificial intelligence frameworks that combine machine learning algorithms with deep learning architectures to enhance predictive performance. Additionally, experimental and intervention-based studies could examine how organizational changes targeting empowerment, leadership development, or psychological safety influence engagement predictions generated by explainable AI systems.

Organizations should prioritize employee empowerment initiatives by increasing autonomy, participation in decision-making, skill development opportunities, and meaningful work experiences. Human resource professionals should implement systematic engagement monitoring systems supported by predictive analytics to identify employees at risk of disengagement and proactively address emerging concerns. Leadership development programs should emphasize transformational leadership competencies, including coaching, communication, recognition, and employee support behaviors. Organizations should also invest in creating psychologically safe work environments where employees feel comfortable expressing ideas, sharing concerns, and participating actively in organizational processes. Furthermore, employee wellbeing programs, continuous learning initiatives, flexible work arrangements, and organizational support mechanisms should be integrated into broader engagement strategies. The adoption of explainable artificial intelligence tools can assist managers in understanding the key drivers of engagement within their organizations and enable more targeted, data-driven decision-making to improve workforce performance, retention, and organizational sustainability.

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5 Conclusion

A particularly important contribution of the present study lies in the comparison of forecasting approaches. The Autoencoder Neural Network outperformed Random Forest, XGBoost, Support Vector Regression, and Multiple Linear Regression across all evaluation metrics. This finding highlights the value of deep learning techniques for modeling organizational resilience, a phenomenon characterized by complexity, interdependence, and nonlinear relationships. Traditional statistical models typically assume linearity and may therefore overlook latent structures embedded within organizational data. In contrast, autoencoders are specifically designed to extract hidden representations and uncover complex relationships among variables. The superior predictive performance observed in this study supports the broader movement toward artificial intelligence-driven organizational analytics and data-informed resilience management. Contemporary research increasingly recognizes that resilience is influenced by multiple interacting organizational factors that may not be adequately captured through conventional analytical methods (Chen et al., 2023; Vihma & Hukkinen, 2024). The ability of the Autoencoder Neural Network to identify latent resilience patterns suggests that advanced machine learning approaches may offer substantial advantages for strategic forecasting, risk management, and organizational decision-making. The findings therefore contribute not only to resilience theory but also to the growing literature on the application of artificial intelligence in organizational research.

This study has several limitations that should be acknowledged. First, the cross-sectional design limits the ability to examine causal relationships among crisis management indicators and organizational resilience over time. Second, data were collected through self-report measures, which may be subject to common method bias and respondent subjectivity. Third, although the sample included organizations from multiple sectors in Chile, the findings may not be fully generalizable to organizations operating in different national, cultural, or institutional contexts. Fourth, the study focused on a selected set of crisis management indicators and did not include all possible determinants of resilience, such as organizational culture, innovation capability, psychological safety, or external stakeholder relationships. Finally, although the Autoencoder Neural Network demonstrated strong predictive performance, the interpretation of deep learning models remains more challenging than that of traditional statistical approaches.

Future research should employ longitudinal designs to investigate how organizational resilience evolves across different phases of crisis development and recovery. Additional studies could incorporate objective organizational performance indicators alongside perceptual measures of resilience to enhance measurement accuracy. Comparative studies across countries and industries would further improve understanding of contextual influences on resilience development. Researchers may also examine hybrid machine learning architectures that combine deep learning with explainable artificial intelligence techniques to improve both predictive accuracy and interpretability. Furthermore, future investigations should explore additional resilience antecedents, including organizational culture, digital transformation, innovation ecosystems, employee well-being, and stakeholder collaboration mechanisms.

From a practical perspective, the findings suggest that organizations should prioritize investments in crisis leadership development, organizational learning systems, preparedness planning, communication infrastructure, and business continuity capabilities. Leaders should establish systematic crisis preparedness programs that incorporate scenario planning, simulation exercises, and continuous organizational learning mechanisms. Organizations should also strengthen communication channels to facilitate rapid information sharing during disruptions and develop flexible resource management systems that support adaptive responses. The successful application of Autoencoder Neural Networks in this study further suggests that organizations can benefit from adopting advanced analytics and artificial intelligence tools to monitor resilience indicators, forecast vulnerabilities, and support proactive decision-making. By integrating crisis management capabilities with data-driven forecasting systems, organizations can enhance their ability to anticipate disruptions, improve adaptive capacity, and sustain performance in increasingly uncertain environments.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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