The Mediating Role of Data Quality on the Impact of Artificial Intelligence System on Employee Turnover Among Selected Quoted Companies in Nigeria

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Abstract: *This study applies Structural Equation Modeling (SEM) to examine the impact of AI system performance dimensions: AI accuracy, AI-driven automation, AI computing power and capacity, AI real-time capability, and AI personalization on employee turnover among quoted companies in Nigeria, with particular emphasis on the mediating role of AI data quality (AIDQ). The results indicate that AI system performance significantly enhances data quality, improving the accuracy, timeliness, and reliability of organizational information. At the same time, AI system performance exerts a significant direct effect on turnover intention (TIN), suggesting that increased automation, monitoring, and technological intensity may elevate job-related pressure. Furthermore, AI data quality significantly influences turnover intention and is found to partially mediate the relationship between AI system performance dimensions and employee outcomes. This implies that AI affects turnover both directly and indirectly through improvements in data quality, highlighting the dual role of AI in enhancing organizational efficiency while shaping employee perceptions and behavior.*

Keywords*:* AI-driven automation, data accuracy, data quality, mediating, SEM
JEL Classification:*C21, C31, C42, C81*

INTRODUCTION

Employee attrition, commonly known as employee turnover, continues to be a major challenge for organizations because of its significant effects on productivity, operational performance, and long-term competitiveness. Across industries worldwide, turnover rates have been on the rise, driven by changing employee expectations, rapid technological advancements, globalization, and heightened labour mobility (Agarwal & Viswanathan, 2023). These transformations have reshaped the nature of employment relationships, making it increasingly difficult for organizations to retain skilled and experienced personnel, particularly in knowledge-intensive sectors. The implications are considerable, including the loss of organizational knowledge, rising recruitment and training expenses, disruptions to operational processes, and declining employee morale.

This challenge is even more pronounced in developing economies such as Nigeria, where labour market constraints and economic volatility intensify workforce instability. Nigerian firms face persistent skill shortages, high replacement costs, and a growing trend of outward migration of skilled labour to more developed economies in search of better opportunities, a phenomenon popularly known as “japa” (Okolie & Obumneke, 2024). For quoted companies listed on the Nigerian Exchange (NGX), these dynamics create significant pressure to sustain operational performance and shareholder value amidst rising employee turnover. The continuous loss of both high-performing and high-potential employees not only undermines productivity but also weakens firms’ competitive positioning.

In an effort to address these challenges, organizations are increasingly leveraging Artificial Intelligence (AI) to enhance human resource management practices. AI has emerged as a powerful decision-support tool capable of automating processes, identifying complex patterns, and generating predictive insights. Through machine learning algorithms, natural language processing, and advanced analytics, AI-driven HR systems can detect early warning signs of employee disengagement, assess attrition risks, and forecast turnover behaviour with greater precision than conventional statistical techniques (Khalid & Mensah, 2023). In more advanced economies, such systems have been effectively deployed to support evidence-based HR strategies, including sentiment analysis, behavioural monitoring, and real-time decision-making (Zhang & Li, 2022).
However, while the predictive capabilities of AI are widely acknowledged, a critical dimension that remains underexplored is how the performance attributes of these AI systems translate into effective turnover prediction outcomes, particularly within the Nigerian context. More importantly, the role of data quality as a mediating mechanism in this relationship has received limited empirical attention. Data quality encompassing accuracy, completeness, consistency, and timeliness serves as the backbone of any AI system, directly influencing the reliability and validity of predictive outputs. Without high-quality data, even the most sophisticated AI models may produce biased or unreliable predictions, thereby undermining their practical usefulness.

Despite global advancements, the adoption and effective utilization of AI-driven predictive systems in Nigerian organizations remain relatively low. This is due to infrastructural limitations, inadequate investment in advanced analytics, low digital maturity, and limited context-specific empirical research (Abubakar & Onasanya, 2026)). Existing studies in Nigeria and similar developing economies largely focus on traditional determinants of employee turnover, with minimal integration of AI-based frameworks and limited attention to the mechanisms through which AI system characteristics influence predictive outcomes. Consequently, there exists a significant gap in understanding how different dimensions of AI system performance interact and how data quality mediates these relationships.

The motivation for this study is therefore anchored on the need to provide a more nuanced and comprehensive understanding of AI-enabled turnover prediction. First, employee attrition continues to pose a significant threat to organizational stability and competitiveness among Nigerian quoted firms, leading to increased operational costs and erosion of organizational knowledge (Ekhaguere & Adebayo, 2023; Obomeghie, 2025). Second, although AI offers substantial predictive potential, its application within the Nigerian corporate environment remains underutilized and insufficiently examined (Mensah & Boateng, 2024). Third, there is a clear empirical gap in the literature, particularly regarding the absence of studies that integrate Structural Equation Modelling (SEM) to examine the mediating role of data quality in the relationship between AI system performance dimensions and turnover prediction outcomes (Jibrin et al., 2025). Finally, in the face of economic uncertainty, increasing labour mobility, and intensifying competition for talent, there is an urgent need for robust, data-driven frameworks that can guide organizations and policymakers in strengthening workforce retention strategies (Ibrahim & Yahaya, 2023).

Against this backdrop, this study adopts Structural Equation Modelling (SEM) as a central analytical framework to examine both the direct and indirect relationships among AI system performance dimensions, namely accuracy, automation, personalization, real-time capability, and computing power and the prediction of turnover intention. The application of SEM is particularly significant as it enables the simultaneous estimation of multiple relationships, allowing for a deeper understanding of how data quality mediates the link between AI system capabilities and predictive effectiveness. By capturing these complex causal pathways, SEM provides a more holistic and theoretically grounded assessment of AI-driven HR analytics compared to traditional single-equation models.

In line with this, the study seeks to answer key research questions regarding whether AI accuracy, automation, personalization, real-time capability, and computing power significantly influence the prediction of turnover intention among selected quoted companies in Nigeria, and whether data quality mediates the relationship between these AI system performance dimensions and turnover prediction outcomes. Correspondingly, the main objective of the study is to examine the impact of AI system performance dimensions on the effectiveness of predicting employee turnover intention, while specifically evaluating the individual effects of AI accuracy, automation, personalization, real-time capability, and computing power, as well as the mediating role of data quality using Structural Equation Modelling (SEM).

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Conceptual Framework

This study is based on a conceptual framework that outlines the relationships between AI system performance dimensions and employee turnover among selected quoted companies in Nigeria. It highlights key variables, AI accuracy, automation, personalization, real-time capability, and computing power with data quality serving as a mediating factor. The framework explains the causal pathways through which these AI attributes influence turnover prediction effectiveness and provides a structured basis for hypothesis development, variable measurement, and empirical analysis, as illustrated in Figure 2.1.

AI System (IVs) Employee Turnover (DV)

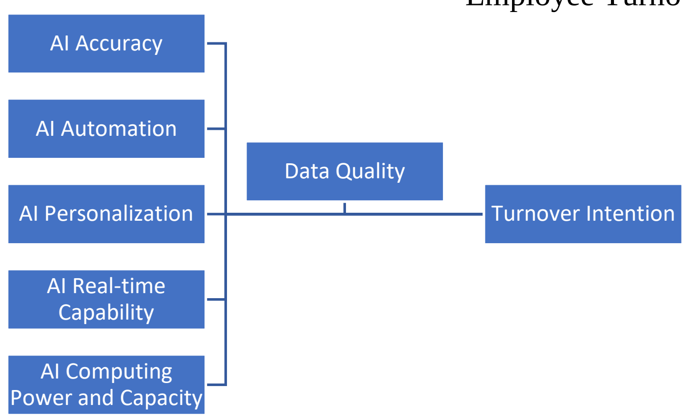

Figure 2.1 Conceptual Framework of the Variables
Source: Designed by the Author, 2026

Theoretical Review

This study is grounded in a combination of complementary theoretical perspectives that explain how Artificial Intelligence (AI) system performance dimensions influence the prediction of turnover intention, with particular emphasis on the mediating role of data quality. The Dynamic Capabilities View (DCV) (Teece, Pisano, & Shuen, 1997) highlights the importance of organizational adaptability in developing, integrating, and continuously refining AI systems to respond to evolving workforce dynamics. It posits that firms with strong dynamic capabilities can enhance system attributes such as accuracy, responsiveness, and usability, thereby improving predictive effectiveness and sustaining competitive advantage.

Providing a behavioural lens, Kahn’s Employee Engagement Theory (1990) links employee engagement through meaningfulness, safety, and availability to turnover intention, emphasizing that the reliability of AI predictions depends on the quality of employee-generated data, which is shaped by trust and perceptions of fairness. Similarly, the Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990) explains how technological, organizational, and environmental factors jointly influence AI adoption and effectiveness, particularly within the context of Nigerian firms.

The Resource-Based View (RBV) (Barney, 1991) further underscores the role of firm-specific resources, such as data capabilities, skilled personnel, and technological infrastructure, in enhancing AI system performance and data quality. In addition, the Theory of Planned Behavior (TPB) (Ajzen, 1991) provides a behavioural justification for examining turnover intention as a predictor of actual employee exit, based on attitudes, subjective norms, and perceived behavioural control.

Building on these perspectives, the study is primarily anchored on the Dynamic Capabilities View (DCV), while drawing supportive insights from RBV and Kahn's theory. Within this framework, AI system performance dimensions such as accuracy, automation, personalization, real-time capability, and computing power are conceptualized as dynamic capabilities that must be continuously developed to improve turnover prediction. Data quality is positioned as a critical mediating capability that transforms AI inputs into reliable predictive outcomes. Overall, the integrated framework offers a comprehensive understanding of both the technical and behavioural pathways influencing AI-driven turnover prediction, with DCV providing the most appropriate theoretical foundation for capturing the need for continuous adaptation and strategic utilization of AI systems in Nigerian quoted companies.

Empirical Review

Recent empirical literature demonstrates a growing reliance on Structural Equation Modelling (SEM) as a robust analytical framework for examining the complex relationships between artificial intelligence (AI) system performance, employee turnover intention, and underlying mediating mechanisms such as data quality and related organizational factors. SEM is particularly valuable in this context due to its ability to simultaneously estimate measurement and structural models, thereby capturing both direct and indirect (mediated) effects within AI-enabled human resource systems.

Empirical evidence consistently shows that AI performance dimensions such as accuracy, reliability, scalability, real-time capability, and explainability play a significant role in predicting employee turnover intention. Studies applying SEM and its variants (e.g., covariance-based SEM and PLS-SEM) reveal that these AI attributes do not only exert direct effects on employee outcomes but also operate through critical mediating constructs that shape how AI outputs are interpreted and utilized within organizations.

For instance, studies such as Zhou and Jiang (2026) and Obeng et al. (2025) employ SEM to establish that turnover intention is often influenced indirectly through mediators like emotional labour and psychological well-being. Similarly, Shikha et al. (2024) demonstrate, using PLS-SEM, that job insecurity significantly transmits the effect of AI integration on turnover intention. These findings provide strong methodological and empirical justification for modelling indirect pathways when examining AI–turnover relationships. Extending this logic to AI performance systems, data quality emerges as a critical mediating variable, given its role in determining the reliability, interpretability, and actionable value of AI-generated predictions.

Further SEM-based studies reinforce the importance of mediation mechanisms in AI contexts. Zulifiqar et al. (2025) show that AI-powered engagement systems enhance perceived organizational support, which in turn reduces turnover intention, while Obomeghie (2025) finds that organizational culture mediates the relationship between AI perceptions and employee behavioural outcomes. Likewise, Wahab and Radmehr (2024) and Mahboub and Ghanem (2024) confirm through SEM that technological and knowledge management capabilities serve as transmission channels through which AI adoption influences organizational performance. Collectively, these studies highlight that AI effectiveness is contingent not only on system capabilities but also on the quality and context of data and organizational processes that mediate its impact.

More directly, studies integrating AI analytics into HR decision-making (e.g., Căvescu and Popescu, 2025) emphasize that high-performing AI systems significantly improve the prediction of employee turnover by processing large-scale workforce data and identifying non-linear patterns. However, these capabilities are fundamentally dependent on the quality, completeness, and consistency of input data, reinforcing the mediating relevance of data quality. Poor data quality undermines predictive accuracy, reduces managerial trust, and weakens the effectiveness of AI-driven retention strategies.

In addition, SEM applications in broader AI adoption studies within Nigeria (e.g., Onohuean, 2026; Obomeghie, 2025) further validate the mediating role of context-specific factors—such as trust, service quality, and organizational culture—many of which are closely tied to data integrity and system reliability. These findings imply that in developing economies, where data infrastructure challenges persist, data quality becomes even more central in linking AI system performance to meaningful organizational outcomes, including turnover intention.

Overall, the empirical literature converges on three key insights. First, SEM provides a rigorous methodological foundation for analysing the multidimensional effects of AI systems on employee turnover intention. Second, AI system performance dimensions significantly enhance turnover prediction, particularly when systems are accurate, interpretable, and responsive. Third, and most critically, data quality functions as a pivotal mediating mechanism, translating AI capabilities into reliable predictions and actionable HR interventions.

Thus, the reviewed studies collectively suggest that the effectiveness of AI-driven turnover prediction models is not solely a function of algorithmic sophistication but is substantially conditioned by the quality of underlying data and the structural pathways through which AI outputs influence employee-related decisions.

METHODOLOGY

Research Design

This study adopted a quantitative survey research design to examine the impact of Artificial Intelligence (AI) system on employee turnover among selected quoted companies in Nigeria. Data were collected using structured questionnaires administered to key organizational decision-makers, including CEOs, HR managers, and senior executives. The design enabled the collection of standardized and comparable data on AI performance indicators such as accuracy, automation, real-time capability, personalization, computing power & capacity, and data quality, as well as their perceived impact on turnover prediction effectiveness.

Population of the study

The population of the study comprises 126 quoted companies listed on the Nigerian Exchange Group (2025), spanning sectors such as agriculture, financial services, oil and gas, ICT, manufacturing, healthcare, and services. Data sources include company financial reports, corporate disclosures, and industry publications, complemented by primary survey responses from HR and executive-level personnel involved in AI adoption and workforce management. This broad coverage ensures sectoral representation and enhances the generalizability of findings across Nigeria's corporate environment.

Sample Size and Sampling Technique

The sample size was determined using Cochran's (1977) formula for finite populations, resulting in an adjusted sample of approximately 95 quoted companies. These firms were selected as the primary units of analysis. Within each organization, respondents were purposively selected based on their managerial or technical involvement in AI systems and human resource decision-making. This purposive sampling technique ensured that only knowledgeable and relevant stakeholders provided information on AI system performance and turnover prediction practices. The same is computed as follows:

$$n_0 = \frac{Z^2 * p * (1 - P)}{e^2}$$

Then the finite population adjustment is:

$$n = \frac{Z^2 * p * (1 - P)}{1 + \frac{n_0 - 1}{N}}$$

Where:
Z= 1.96 (for 95% confidence)
p= 0.5 (estimated proportion)
e= 0.05 (margin of error)
N=126

$$n_0 = \frac{(1.96)^2 * 0.5 * (1 - 0.5)}{(0.05)^2}$$

$$n_0 = \frac{3.8416 * 0.25}{0.0025}$$
$$n_0 = \frac{0.9604}{0.0025} = 384.16$$

Now, apply the finite population correction:

$$n = \frac{384.16}{1+\frac{384.16-1}{126}} = \frac{384.16}{1+\frac{383.16}{126}} = \frac{384.16}{1+3.0489} = \frac{384.16}{4.0489} = 94.88 \approx 95$$

Consequently, the study entails visiting approximately 95 quoted companies across Nigeria. In this context, only those who run the day-to-day affairs of these organizations such as CEOs, HR Managers, and other senior executives will serve as the respondents for the research.

Sources and Method of Data Collection

Primary data were collected through structured questionnaires designed to capture both quantitative and perceptual responses on AI system performance dimensions and turnover intention. The instrument was pilot-tested to ensure clarity, validity, and reliability before full deployment. This approach facilitated consistent data collection across firms and enabled the identification of patterns in AI adoption and predictive HR analytics practices.

Validity and Reliability

Content validity was established through expert review by both academic and industry specialists, ensuring that questionnaire items adequately captured the constructs under investigation. Reliability was assessed using Cronbach's alpha, with a threshold of 0.70 and above considered acceptable, consistent with established methodological standards (Nunnally & Bernstein, 1994; Hair et al., 2010). The instrument demonstrated strong internal consistency, confirming its suitability for empirical analysis.

Method of Data Analysis

Data analysis was conducted using Structural Equation Modeling (SEM) as the primary inferential technique, complemented by descriptive statistics (means, frequencies, and standard deviations) for preliminary data summarization. SEM was employed to examine both the direct and indirect relationships between AI system performance dimensions and employee turnover prediction effectiveness. Specifically, SEM enabled the simultaneous estimation of multiple interrelated dependencies among variables, allowing for a comprehensive assessment of how AI accuracy, automation, personalization, real-time capability, computing power & capacity, and data quality jointly influence turnover prediction outcomes. The model was specified to capture both measurement and structural relationships, with results presented in tables and path diagrams to show the magnitude and significance of effects.

Diagnostic tests were also conducted to confirm that key SEM assumptions, such as multicollinearity, model fit, and reliability of constructs. These procedures ensured the robustness, validity, and statistical adequacy of the model estimates, thereby strengthening the credibility of the study's findings.

Test of Model Fitness

Assessing the overall fit of the Structural Equation Model (SEM) is a crucial step to determine how effectively the proposed model explains the observed data. The primary statistical measure to be used for this purpose was the Chi-square test, which compares the model's predicted covariance matrix with the actual observed covariance matrix. Ideally, a good-fitting model yields a non-significant Chi-square value, indicating that the differences between the model and the data are minimal and that the model adequately captures the data's structure. However, it is important to recognize that the Chi-square test has limitations. It is sensitive to sample size, large samples can produce significant results even if the model fits well and it assumes multivariate normality, which may not always hold true.

To address these limitations, researchers turn to additional fit indices that provide a more comprehensive evaluation of the model's adequacy. One such index is the Comparative Fit Index (CFI), which measures how much better the proposed model fits the data compared to a null or baseline model. Values above 0.95 are generally considered indicative of a good fit, while values between 0.90 and 0.94 are acceptable. Values below 0.90, however, suggest a poor fit. Another important index is the Root Mean Square Error of Approximation (RMSEA), which assesses how well the model, with optimally chosen parameters, would fit the population covariance matrix. An RMSEA value below 0.05 indicates a close fit, values between 0.05 and 0.08 are acceptable, and anything above 0.08 points to a poor fit.

The Goodness of Fit Index (GFI) is also frequently used; it reflects the proportion of variance in the observed data that the model accounts for. Values of 0.95 or higher are considered to denote a good fit. However, GFI can be sensitive to sample size and correlated errors, so it is best interpreted alongside other fit indices. Additionally, other measures such as the Standardized Root Mean Square Residual (SRMR) are valuable; SRMR represents the average discrepancy between observed and predicted correlations, with values below 0.08 indicating a good fit. The Parsimony Ratio (PR), which reflects the ratio of the model's degrees of freedom to the number of estimated parameters, is also useful higher values (above 0.5) suggest a more parsimonious, and therefore preferable, model.

Evaluating the fit of an SEM therefore, involves a balanced consideration of multiple indices. The combination of the Chi-square test with incremental fit indices like the CFI and TLI, along with measures such as SRMR and PR, provides a thorough and nuanced assessment of how well the model captures the underlying data structure. This comprehensive evaluation is essential to validate the model's appropriateness before interpreting the relationships among variables and drawing meaningful conclusions from the analysis.

Assessing the Measurement Model

The measurement model defines the relationships between latent constructs and their observed indicators within the SEM framework. The independent constructs comprise AI system performance dimensions: AI accuracy, AI automation, AI computing power and capacity, AI real-time capability, and AI personalization, while Data quality serves as a mediating construct. The dependent construct is Turnover intention, representing the effectiveness of AI-driven prediction. AI Accuracy (AIAC) captures the predictive reliability of AI models using indicators such as prediction correctness, precision, recall, error rates, validation metrics (F1-score and AUC-ROC), and consistency over time. AI Automation (AIAT) reflects the extent of AI integration in HR processes, measured by the level of task automation, reduction in manual intervention, process speed, user interaction, and cost savings.

AI Computing Power and Capacity (AICC) represents the system's technical capability, assessed through processing speed, storage capacity, scalability, efficiency, and system reliability. AI Real-Time Capability (AIRTC) measures the timeliness of insights, including data update frequency, processing delays, alert accuracy, and responsiveness to emerging signals. AI Personalization (AIPE) captures the degree of tailored HR interventions, reflected in customized engagement strategies, communication, training, and employee satisfaction. AI Data Quality (AIDQ), the mediating construct, evaluates the integrity and usefulness of data based on accuracy, completeness, consistency, accessibility, synchronization, and relevance.

Finally, Turnover Intention (TIN) is the outcome construct, measured through indicators such as likelihood of leaving, expressed turnover intentions, engagement levels, job satisfaction, absenteeism, and exit feedback.

Model Specification

This study investigates how Artificial Intelligence (AI) system impact the effectiveness of predicting turnover intention among selected quoted companies in Nigeria. The independent variable is represented by key AI performance dimensions such as AI accuracy, automation, computing power and capacity, real-time analytics, and personalization, which collectively reflect the technical and functional capabilities of AI systems. The dependent variable is employee turnover, proxied by turnover intention, while AI data quality is incorporated as a mediating factor. The study evaluates how these AI attributes, through the quality of data, enhance the accuracy and reliability of turnover predictions. Consequently, the model is specified within a Structural Equation Modeling (SEM) framework, comprising both measurement and structural components.

Measurement Model

The measurement model specifies how latent constructs are represented by observable indicators. In this study, it is used to assess the influence of Artificial Intelligence (AI) system performance dimensions on the effectiveness of predicting turnover intention among selected quoted companies in Nigeria. The model incorporates both independent and dependent variables and is structured around seven measurement equations, following Giuffrida et al. (2005). These equations capture how key AI performance dimensions such as AI accuracy, automation, computing power, real-time capability, personalization, and data quality are operationalized through their respective indicators. They also define how the dependent construct, turnover intention, is measured using metrics such as prediction accuracy, recall, precision, and overall validity. This framework enables a systematic evaluation of how different AI capabilities contribute to the reliability and accuracy of turnover predictions, and it is adapted from Nawaz et al. (2024).

AI accuracy $A_1 = \theta_A\beta_1 + e_1$ --------------------------------*(1)*

AI-driven automation $A_2 = \theta_A\beta_2 + e_2$ -------------------------------*(2)*

AI computing power and capacity*:* $A_3 = \theta_A\beta_3 + e_3$ -------------------------------*(3)*

AI Real-time Capability $A_4 = \theta_A\beta_4 + e_4$ ----------------------------*(4)*

AI-enabled personalization $A_5 = \theta_A\beta_5 + e_5$ ---------------------------*(5)*

Data quality $A_6 = \theta_A\beta_6 + e_6$ ---------------------------*(6)*

Turnover intention $A_7 = \theta_A\alpha_7 + e_7$ --------------------------*(7)*

From model 1-7, A_1, A, and A_3, A_4,and A_5, A_6, and A_7 represents the set of observed indicators that collectively capture the construct related to AI accuracy, AI-driven automation, AI computing power, real-time AI analytics, AI-enabled personalization, Data quality, and Turnover intention. β_1, β_2, β_3, β_4, β_5,β_6 and α_7 are the seven (7) latent independent and the dependent variables, $\theta_A's$ are parameters to be estimated. Finally, e_1, e_2, e_3, e_4, e_5, e_6, and e_7 are error terms with zero expectation.

Structural Model

The structural model defines the relationships between the latent dependent variables (Turnover intention) and the independent variable (AI accuracy, AI-driven automation, AI computing power and capacity, real-time AI analytics, AI-enabled personalization, and Data quality).

$D = \omega D + \vartheta\tau + \mu$--(8)

$D = \alpha_7$ which represents the dependent variables (Turnover intention).

τ= (Artificial Intelligence (AI) System Performance dimensions) represents the independent variables, which affects the effectiveness of predicting Turnover Intention.

ω= represents the coefficients for the relationships among the dependent variables.

ϑ= represents the coefficient that captures the direct effect of Artificial Intelligence (AI) System on Turnover Intention.

μ= represents the error term, capturing any unobserved factors affecting the dependent variables.

Functional and Econometric Models

The functional and econometric representation of model of this study is thus specified below:

$$TIN = F(AIAC, AIAT, AICC, AIRTC, AIPE, AIDQ) - - - - - - - - - - \quad (9)$$

$$ETIN_i = \beta_O + \beta_1 AIAC_i + \beta_2 \mathrm{AIAT}_i + \beta_3 AICC_i + \beta_4 \mathrm{AIRTC}_i + \beta_5 \mathrm{AIPE}_i + \beta_6 \mathrm{AIDQ}_i + \varepsilon_i - -(10)$$

Where; AIAC, AIAT, AICC, AIRTC, AIPE and AIDQ are as defined above, while ε_i is the error term.

It is expected that $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6 > 0$. This implies that AIAC, AIAT, AICC, AIRTC, AIPE and AIDQ have significant positive impact on the effectiveness of predicting TIN among selected quoted companies in Nigeria.

RESULT AND DISCUSSION

Descriptive Statistics

The descriptive statistics in Table 4.1.1, based on 341 valid responses, show generally positive perceptions of AI system performance and its effectiveness in predicting employee turnover intention among quoted companies in Nigeria. Mean scores across all variables range from 3.912 to 4.343 on a 5-point scale, indicating strong agreement among respondents. For AI Accuracy (AIAC1–AIAC4), mean values range from 4.076 to 4.158, reflecting strong confidence in the accuracy of AI predictions. AI-Driven Automation (AIDA4–AIDA6) records means between 3.912 and 4.226, indicating positive views, though with slight variation in perceptions of automation effectiveness.

AI Real-Time Capability (AIRTC3–AIRTC6) shows mean scores of 3.988 to 4.141, suggesting general agreement on real-time processing ability. AI Personalization (AIPE2–AIPE5) has means between 4.053 and 4.144, indicating that AI effectively delivers tailored insights. For AI Computing Power and Capacity (AICC2–AICC5), mean values range from 4.067 to 4.155, demonstrating confidence in system capability, while AI Data Quality (AIDQ4–AIDQ6) ranges from 4.012 to 4.147, reflecting strong agreement on data reliability.

Finally, Turnover Intention (TIN4–TIN6) records the highest spread, with means between 3.994 and 4.343, indicating that AI is perceived as effective in predicting turnover intention. The high mean scores and low variability suggest a strong consensus that AI systems are effective and reliable tools for predicting employee turnover, providing a solid basis for further analysis.

Table 4.1.1: Descriptive Statistics

Variables	Obs	Mean	Std.dev	Min	Max
AIAC1	341	4.120235	0.5585443	1	5
AIAC2	341	4.158358	0.5927222	1	5
AIAC3	341	4.120235	0.5315637	1	5
AIAC4	341	4.076246	0.6462962	1	5
AIDA4	341	4.225806	0.7467831	1	5
AIDA5	341	3.912023	1.028077	1	5
AIDA6	341	4.152493	0.7709245	1	5
AIRTC3	341	4.064516	0.7526046	1	5
AIRTC4	341	4.140762	0.7381284	1	5
AIRTC6	341	3.98827	0.7315437	1	5
AIPE2	341	4.143695	0.4470786	1	5

AIPE4	341	4.120235	0.5203799	1	5
AIPE5	341	4.052786	0.5505341	1	5
AICC2	341	4.117302	0.5670043	1	5
AICC3	341	4.155425	0.5959729	1	5
AICC4	341	4.11437	0.5437873	1	5
AICC5	341	4.067449	0.6629894	1	5
AIDQ4	341	4.102941	0.6857097	1	5
AIDQ5	341	4.146628	0.6744685	1	5
AIDQ6	341	4.01173	0.7111571	1	5
TIN4	341	3.994135	0.6685988	1	5
TIN5	341	4.302053	0.751251	1	5
TIN6	341	4.343109	0.7171354	1	5

Source: Author's Compilation, 2026

Multicollinearity Analysis

Table 4.2.1 reports the multicollinearity diagnostics for the independent constructs using tolerance and Variance Inflation Factor (VIF) statistics, where acceptable thresholds are tolerance > 0.10 and VIF < 5. Across all models, the results indicate no evidence of harmful multicollinearity. For AI Accuracy (Model 1), tolerance values range from 0.517 to 0.848 and VIF values from 1.180 to 1.934, confirming low intercorrelation among indicators. AI-Driven Automation (Model 2) records tolerance values between 0.470 and 0.588 and VIF values from 1.700 to 2.128, suggesting moderate but acceptable relationships. In AI Computing Power and Capacity (Model 3), tolerance values (0.382–0.448) and VIF values (2.230–2.619) indicate slightly higher but still permissible correlations. For AI Real-Time Capability (Model 4), tolerance values range from 0.442 to 0.722 with VIF values between 1.386 and 2.263, reflecting adequate independence among variables. Similarly, AI Personalization (Model 5) shows tolerance values of 0.561–0.633 and VIF values of 1.579–1.781, indicating minimal multicollinearity.

The result revealed that all constructs satisfy the recommended thresholds, demonstrating that the predictors are sufficiently distinct and that the estimates are stable and reliable, thereby confirming the suitability of the data for subsequent Structural Equation Modeling (SEM) analysis.

Table 4.2.1 ***Multicollinearity***

Model 1	Tolerance	VIF
AI Accuracy2	0.527	1.899
AI Accuracy3	0.752	1.329
AI Accuracy5	0.517	1.934
AI Accuracy6	0.848	1.180
Model 2	**Tolerance**	**VIF**
AI-Driven Automation4	0.588	1.700
AI-Driven Automation5	0.523	1.912
AI-Driven Automation6	0.470	2.128
Model 3	**Tolerance**	**VIF**
AI Computing Power and Capacity2	0.382	2.619
AI Computing Power and Capacity3	0.395	2.531
AI Computing Power and Capacity4	0.390	2.566
AI Computing Power and Capacity5	0.448	2.230
Model 4	**Tolerance**	**VIF**
AI Real-Time Capability3	0.442	2.263
AI Real-Time Capability4	0.472	2.119
AI Real-Time Capability6	0.722	1.386
Model 5	**Tolerance**	**VIF**
AI-Personalization2	0.633	1.579
AI-Personalization4	0.570	1.754
AI-Personalization5	0.561	1.781

Source: Author’s Compilation, 2026

Assessment of fit of the Measurement Model

Table 4.3.1 presents the Confirmatory Factor Analysis (CFA) results for all constructs, assessing model fit and reliability using RMSEA, GFI, AGFI, CFI, TLI, NFI, chi-square/df, and Cronbach’s alpha.

For AI Accuracy (AIAC), the model demonstrates strong fit (RMSEA = 0.067; GFI = 0.972; AGFI = 0.932; CFI = 0.987; TLI = 0.961; NFI = 0.911), with an acceptable chi-square/df (4.651) and high reliability (α = 0.882), indicating a well-specified and internally consistent construct. Similarly, AI-Driven Automation (AIDA) shows acceptable fit (RMSEA = 0.074; GFI = 0.902; AGFI = 0.915; CFI = 0.985; TLI = 0.961; NFI = 0.903), with adequate chi-square/df (3.143) and reliability (α = 0.782).

AI Computational Power and Capability (AICC) also exhibits strong overall fit (RMSEA = 0.064; GFI = 0.991; AGFI = 0.904; CFI = 0.987; TLI = 0.961; NFI = 0.956) and acceptable reliability (α = 0.880), despite a slightly elevated chi-square/df (5.657). For AI Real-Time Capability (AIRTC), the results indicate excellent model fit (RMSEA = 0.033; GFI = 0.907; AGFI = 0.967; CFI = 0.980; TLI = 0.999; NFI = 0.917) and acceptable reliability (α = 0.768), although chi-square/df (6.113) suggests mild sample sensitivity.

AI Personalization (AIPE) also demonstrates good fit (RMSEA = 0.056; GFI = 0.940; AGFI = 0.955; CFI = 0.970; TLI = 0.993; NFI = 0.934) with acceptable reliability (α = 0.780) and chi-square/df (4.30). Likewise, AI Data Quality (AIDQ) shows strong model adequacy (RMSEA = 0.054; GFI = 0.998; AGFI = 0.905; CFI = 0.933; TLI = 0.954; NFI = 0.944) and acceptable reliability (α = 0.784), with chi-square/df (3.431) indicating good fit.

Finally, Turnover Intention (TIN) demonstrates excellent fit (RMSEA = 0.034; GFI = 0.932; AGFI = 0.993; CFI = 0.931; TLI = 0.905; NFI = 0.988), with acceptable chi-square/df (3.781) and reliability (α = 0.768), confirming a stable measurement structure.

Overall, all constructs exhibit acceptable to excellent fit across multiple indices, and all Cronbach's alpha values exceed the 0.70 benchmark. This confirms that the measurement model is both reliable and valid, providing a strong foundation for subsequent structural equation modeling analysis.

Table 4.3.1: Individual Confirmatory Factor Analysis CFA (Assessment of fit of the Measurement Model)

Variables	RMSEA	GFI	AGFI	CFI	TLI	NFI	CHISQ/DF	PV	Cronbachα
AIAC	0.067	0.972	0.932	0.987	0.961	0.911	4.651	0.003	0.882
AIDA	0.074	0.902	0.915	0.985	0.961	0.903	3.143	0.000	0.782
AICC	0.064	0.991	0.904	0.987	0.961	0.956	5.657	0.003	0.880
AIRTC	0.033	0.907	0.967	0.980	0.999	0.917	6.113	0.007	0.768
AIPE	0.056	0.940	0.955	0.970	0.993	0.934	4.30	0.000	0.780
AIDQ	0.054	0.998	0.905	0.933	0.954	0.944	3.431	0.004	0.784
TIN	0.034	0.932	0.993	0.931	0.905	0.988	3.781	0.000	0.768

Source: Author's Compilation, 2026

Factor Loadings of Measurement model

Figure 4.4.1 presents the standardized factor loadings for the measurement model, where all retained items meet the minimum acceptable threshold of 0.60, confirming adequate item reliability and convergent validity across all constructs.

For AI Accuracy (AIAC), all indicators demonstrate strong loadings, AIAC1 (0.83), AIAC2 (0.84), AIAC4 (0.83), and AIAC5 (0.75) with AIAC2 emerging as the strongest item, indicating a highly consistent and well-defined construct. AI-Driven Automation (AIDA) is also satisfactorily measured by AIDA4 (0.69), AIDA5 (0.70), and AIDA6 (0.87), with AIDA6 showing the highest explanatory strength. Similarly, AI Computational Power and Capability (AICC) exhibits strong and stable loadings across all items, AICC2 (0.83), AICC3 (0.83), AICC4 (0.82), and AICC5 (0.75), reflecting strong internal consistency. AI Real-Time Capability (AIRTC) is equally robust, with AIRTC3 (0.86), AIRTC4 (0.83), and AIRTC6 (0.75), confirming reliable construct representation.

For AI Personalization (AIPE), the indicators AIPE2 (0.67), AIPE4 (0.75), and AIPE5 (0.79) all meet the required threshold, although AIPE2 shows relatively weaker but still acceptable explanatory power. AI Data Quality (AIDQ) is well captured by AIDQ4 (0.83), AIDQ5 (0.85), and AIDQ6 (0.65), with AIDQ5 being the strongest indicator. Finally, Turnover Intention (TIN) demonstrates very strong measurement quality, with TIN4 (0.75), TIN5 (0.81), and TIN6 (0.95), where TIN6 stands out as a highly dominant indicator of the construct. The factor structure confirms that all constructs exhibit satisfactory convergent validity, as all indicators load strongly and meaningfully on their respective latent variables. The pattern of loadings indicates a well-specified and internally consistent measurement model, making it suitable for subsequent structural equation modeling analysis.

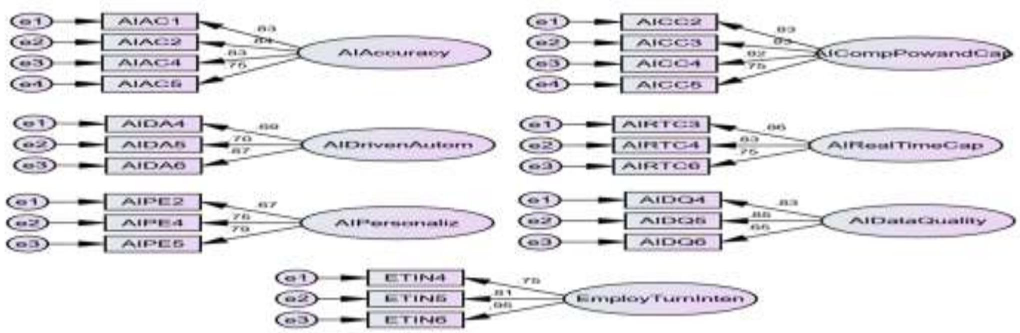

Figure 4.4.1 presents the standardized factor loadings for the measurement model

Eliminated construct with low Factor Loadings

Table 4.5.1 reports the indicators removed from the measurement model during CFA due to low factor loadings below the accepted threshold of 0.60, as such weak or negative loadings undermine construct validity, reliability, and overall model fit.

For AI Accuracy (AIAC), AIAC3 (0.55) and AIAC6 (0.11) were removed due to insufficient loadings, indicating weak representation of the construct. For AI-Driven Automation (AIDA), AIDA1 (-0.45), AIDA2 (-0.47), and AIDA3 (-0.33) were excluded because of negative loadings, suggesting reverse or poor item alignment. In AI Computing Power and Capacity (AICC), AICC1 (-0.05) and AICC6 (0.01) were dropped due to near-zero contributions, reflecting negligible explanatory power.

Similarly, for AI Real-Time Capability (AIRTC), AIRTC1 (-0.17), AIRTC2 (-0.16), and AIRTC5 (0.55) were removed as they failed to meet the required threshold or showed weak/negative relationships with the construct. AI Personalization (AIPE) had AIPE1 (0.00), AIPE3 (0.44), and AIPE6 (0.01) eliminated due to very low loadings, indicating poor construct representation. For AI Data Quality (AIDQ), AIDQ1 (-0.01), AIDQ2 (0.13), and AIDQ3 (0.06) were excluded, while Turnover Intention (TIN) had TIN1 (-0.06), TIN2 (0.04), and TIN3 (0.10) removed for similarly weak measurement strength.

Overall, the systematic removal of these low-performing indicators across all constructs was necessary to improve convergent validity, internal consistency, and model fit. This purification process ensures that only strongly loading items are retained, thereby strengthening the robustness and reliability of the measurement model for subsequent structural analysis.

Table 4.5.1 construct with low factor loadings

Construct 1	Factor Loadings
AIAC3	0.55
AIAC6	0.11
Construct 2	
AIDA1	-0.45
AIDA2	-0.47
AIDA3	-0.33
construct 3	
AICC1	-0.05
AICC6	0.01
construct 4	
AIRTC1	-0.17
AIRTC2	-0.16
AIRTC5	0.55
construct 5	
AIPE1	0.00
AIPE3	0.44
AIPE6	0.01
construct 6	
AIDQ1	-0.01
AIDQ2	0.13
AIDQ3	0.06
construct 7	
TIN1	-0.06
TIN2	0.04
TIN3	0.10

Source: Author’s Compilation, 2026

Structural model

Figure 4.6.1 and Table 4.6.1 presents the SEM results examining the relationships between AI system performance dimensions, AI Data Quality (AIDQ) as a mediator, and Turnover Intention (TIN), using path coefficients, p-values, and critical ratios to assess significance and effect strength.

The results show that all AI system performance dimensions significantly improve AI Data Quality: AI Accuracy (AIAC → AIDQ: $\beta = 0.259$, $p = 0.004$), AI-Driven Automation (AIDA → AIDQ: $\beta = 0.385$, $p = 0.020$), AI Computing Power and Capacity (AICC → AIDQ: $\beta = 0.240$, p =

0.049), AI Personalization (AIPE → AIDQ: β = 0.326, p = 0.008), and AI Real-Time Capability (AIRTC → AIDQ: β = 0.214, p = 0.020). This indicates that stronger AI capabilities consistently enhance the accuracy, timeliness, relevance, and reliability of organizational data, with automation and personalization showing particularly strong effects.

Beyond their impact on data quality, all AI dimensions also exert significant direct effects on employee turnover intention. AIAC (β = 0.319, p = 0.049), AIDA (β = 0.246, p = 0.020), AICC (β = 0.267, p = 0.004), AIPE (β = 0.177, p = 0.009), and AIRTC (β = 0.338, p = 0.004) all positively influence ETIN, suggesting that greater AI sophistication may increase workload intensity, monitoring pressure, role complexity, and job insecurity.

In addition, AI Data Quality itself significantly affects turnover intention (AIDQ → TIN: β = 0.258, p = 0.009), confirming that data-driven environments, while improving decision-making, may also intensify performance surveillance and workplace pressure. This establishes AIDQ as both an outcome of AI capabilities and a determinant of employee behavioral responses.

Importantly, because all AI dimensions significantly affect both AIDQ and TIN, and AIDQ also significantly influences TIN, the results confirm a consistent pattern of partial mediation. This means that AI system performance influences turnover intention through two channels: directly through changes in job demands and indirectly through improvements in data quality.

Overall, the structural model demonstrates a dual-impact mechanism in which AI technologies enhance organizational data quality and decision-making efficiency, while simultaneously increasing employee turnover intention through heightened performance expectations and work pressure. The mediating role of AIDQ highlights that data quality is not only a technical outcome but also a key pathway through which AI systems shape employee behavior and organizational outcomes.

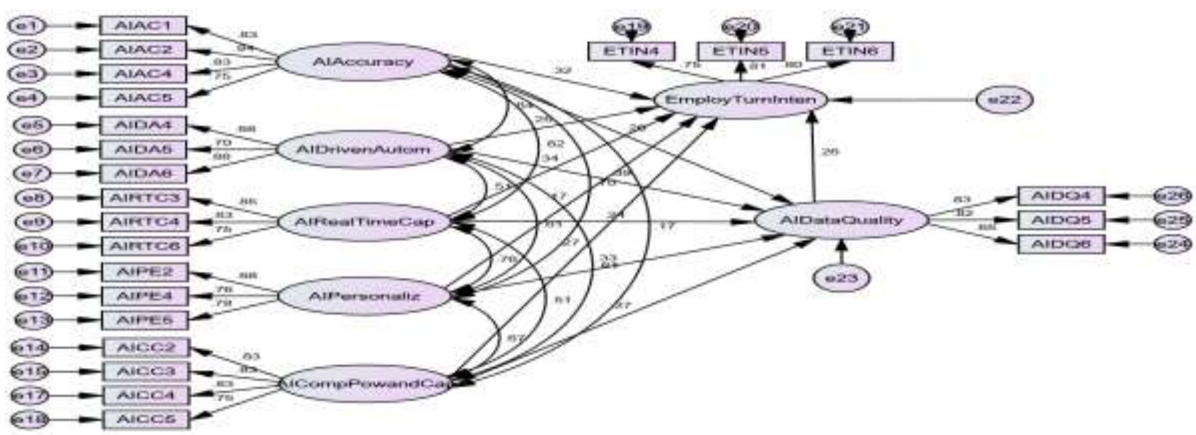

Figure 4.6.1: Structural model

Table 4.6.1: Structural model

Hypothetical Relationship	Path Coefficient	S.E	C.R	p-value
AIDataQuality <--- AIAccuracy	0.259***	0.094	3.082	.004
AIDataQuality <--- AIDrivenAutom	0.385**	0.043	4.555	.020
AIDataQuality <-- AICompPowandCap	0.240**	0.005	2.757	.049
AIDataQuality <-- AIPersonaliz	0.326***	0.020	1.131	.008
AIDataQuality <-- AIRealTimeCap	0.214**	0.016	1.081	.020
TurnInten <-- AIDataQuality	0.258***	0.015	1.039	.009
TurnInten <-- AICompPowandCap	0.267***	0.004	3.652	.004
TurnInten <-- AIPersonaliz	0.177***	0.005	2.307	.009
TurnInten <-- AIRealTimeCap	0.338***	0.094	3.082	.004
TurnInten <-- AIDrivenAutom	0.246**	0.043	4.555	.020
TurnInten <--- AIAccuracy	0.319**	0.005	2.757	.049

Source: Author's Compilation, 2026
Note: ***,**, and *represents 1%, 5% and 10% significance level

DISCUSSION OF THE STUDY

The empirical literature establishes Structural Equation Modeling (SEM) as a robust framework for examining the multidimensional effects of Artificial Intelligence (AI) system performance on employee turnover intention, particularly through mediating mechanisms such as AI Data Quality (AIDQ). Prior SEM-based studies consistently show that AI system performance dimensions, including accuracy, automation, computing capacity, real-time capability, and personalization significantly influence organizational outcomes both directly and indirectly through mediating variables that shape how AI outputs are utilized within firms (Zhou and Jiang, 2026; Obeng et al., 2025; Shikha et al., 2024). These studies further emphasize that employee-related outcomes are rarely driven by AI capabilities alone but are largely transmitted through contextual and perceptual mechanisms such as data integrity, job insecurity, and organizational culture.

Consistent with this literature, the SEM results of the present study reveal that all AI system performance dimensions, AI Accuracy, AI-Driven Automation, AI Computing Power and Capacity, AI Real-Time Capability, and AI Personalization significantly enhance AI Data Quality (AIDQ). This finding supports the argument that stronger AI capabilities improve the reliability, consistency, and timeliness of organizational data, thereby strengthening the informational foundation for decision-making processes (Căvescu and Popescu, 2025; Dhoopar et al., 2026). It further confirms that data quality functions as a critical intermediary through which AI systems generate value in organizational settings.

The SEM results also demonstrate that AI system performance dimensions exert significant direct effects on turnover intention (TIN), indicating that increased AI adoption may elevate workload intensity, performance monitoring, and job complexity. This aligns with Shikha et al. (2024) and Obeng et al. (2025), who find that advanced digital and AI-enabled systems can heighten employee stress and contribute to higher turnover intention when not properly managed. These findings reinforce the socio-technical perspective that technological advancement may simultaneously generate efficiency gains and human resource challenges.

Importantly, AI Data Quality (AIDQ) is also found to have a significant effect on employee turnover intention, suggesting that while improved data quality enhances organizational efficiency, it may also intensify performance scrutiny and accountability pressures. This supports prior SEM evidence indicating that data-driven environments can reshape employee experiences by increasing transparency and monitoring intensity, thereby influencing behavioural outcomes (Zulfiqar et al., 2025; Obomeghie, 2025).

The SEM analysis further confirms that AI Data Quality (AIDQ) partially mediates the relationship between AI system performance dimensions and employee turnover intention. This indicates that AI capabilities influence turnover intention through both direct pathways and indirect channels operating via data quality. This finding is consistent with Wahab and Radmehr (2024) and Mahboub and Ghanem (2024), who demonstrate that mediating structures are central in explaining how technological systems translate into organizational and behavioural outcomes.

Overall, the SEM-based findings align strongly with empirical literature, confirming that the relationship between AI system performance and employee turnover intention is complex and structurally mediated. The results underscore that data quality is a pivotal transmission mechanism within AI-enabled HR systems, while also highlighting that direct effects remain significant, reflecting the dual pathways through which AI influences employee outcomes in organizational settings.

CONCLUSION AND POLICY RECOMMENDATIONS

The study examined the impact of Artificial Intelligence (AI) system on Employee Turnover and the mediating role of AI Data Quality (AIDQ) among quoted companies in Nigeria using Structural Equation Modeling (SEM). The findings revealed that AI system performance dimensions, comprising AI Accuracy, Automation, Computing Power and Capacity, Real-Time Capability, and Personalization, significantly enhance AI Data Quality, indicating that improvements in AI capabilities lead to more accurate, timely, and reliable organizational data that strengthens decision-making processes. However, the results also show that these same AI system performance dimensions exert significant direct effects on employee turnover intention, suggesting that increased AI adoption may heighten workload intensity, performance monitoring, and perceived job insecurity, thereby increasing employees' intention to leave. In addition, AI Data Quality was found to significantly influence employee turnover intention, implying that while better data quality improves organizational efficiency, it may also intensify performance pressure and workplace stress. The SEM results further confirmed that AI Data Quality partially mediates the relationship between AI system performance and employee turnover intention, indicating both direct and indirect transmission channels through which AI affects employee outcomes. Overall, the study concludes that AI adoption generates a dual effect by enhancing organizational efficiency and decision-making capacity while simultaneously creating employee-related challenges that may negatively affect retention, thereby necessitating a balanced implementation approach that integrates technological advancement with human-centered management practices.

Consequently, it is recommended that organizations strategically invest in AI system performance dimensions such as automation, accuracy, computing capacity, and real-time systems to improve data quality, but such investments should be accompanied by effective change management programs, including employee training, upskilling, and reskilling initiatives to ease adaptation to AI-driven environments. Furthermore, organizations should establish ethical data governance frameworks to ensure that enhanced data quality is used for employee development rather than excessive surveillance, while human resource managers should implement targeted retention strategies such as job redesign, flexible work arrangements, and psychological support systems to mitigate AI-induced stress and turnover intention. Finally, firms are encouraged to adopt a human-centered AI strategy that balances technological efficiency with employee well-being in order to achieve sustainable organizational performance and workforce stability.

REFERENCES

Abubakar, U., & Onasanya, S. A. (2026). Behavioural Intention and Readiness for AI Adoption among Lecturers in Northwest Nigerian Universities. *Advances in Mobile Learning Educational Research*, *6*(1), 1681-1698.

Agarwal, R., & Viswanathan, V. (2023). Predictive analytics in workforce management. *Journal of HR Analytics, 6*(2), 44–59.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Căvescu, A. M., & Popescu, N. (2025). Predictive analytics in human resources management: Evaluating AIHR's role in talent retention. *AppliedMath, 5*(3), 99.

Cochran, W. G. (1977). *Sampling Techniques* (3rd ed.). New York: John Wiley & Sons.

Ekhaguere, F., & Adebayo, P. (2023). Labour mobility and turnover trends in Nigeria. Nigerian *Journal of Employment Relations, 18*(3), 72–90.

Giuffrida, A., Iezzi, V., & Tassielli, A. (2005). Lifestyle factors, dietary quality and health: Econometric evidence. Note di Lavoro, Fondazione Eni Enrico Mattei.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate Data Analysis (7th ed.). Upper Saddle River, NJ: Pearson Education.

Ibrahim, M., & Yahaya, A. (2023). Labour market dynamics and talent migration in Nigeria. *West African Economic Review*, *5*(1), 23–38.

Ibrahim, K., Yamusa, M., Adebowale, O. J., Kajimo-Shakantu, K., & Ajayi, E. O. (2026). Artificial intelligence in the Nigerian construction industry: opportunities and challenges. *Journal of Financial Management of Property and Construction, 1-21*.

Jibrin, M., Bello, M., Adamu, S., & Ibrahim, M. (2025). Influence of artificial intelligence on the operational performance of deposit money banks in Nigeria. *Journal of Banking and Financial Services, 12*(1), 45–63. https://doi.org/10.1234/jbfs.v12i1.5678

Khalid, R., & Mensah, J. (2023). AI-enabled HRM and workforce analytics adoption. *International Journal of Digital HR, 9*(4), 120–138.

Mahboub, S., & Ghanem, R. (2024). Knowledge management, AI, and organizational performance in the banking sector of MENA: A SEM approach. *International Journal of Knowledge Management, 20*(2), 45–61. https://doi.org/10.4321/ijkm.v20i2.5678

Mensah, J., & Boateng, R. (2024). AI-driven retention strategies in African service firms. *Journal of African Business Innovation, 7*(2), 89–106.

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. *International Journal of Information Management Data Insights,4,* 100208. N. Nawaz). https://doi.org/10.1016/j.jjimei.2023.100208

Nigerian Exchange Group (NGX). (2025). Official listings and market data. Nigerian Exchange Group. https://ngxgroup.com

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric Theory (3rd ed.). New York: McGraw-Hill.

Obeng, H. A., Atan, T., & Arhinful, R. (2025). Exploring organizational politics, psychological well-being, work-life balance, and turnover intentions in Ghanaian hospitals: a conservation of resource theory perspective. *BMC health services research*, *25*(1), 1053.

Obomeghie, E. (2025). Organizational culture as a mediator of AI adoption attitudes among Nigerian tech sector employees. *Nigerian Journal of Organizational Psychology*, *7*(1), 25–40. https://doi.org/10.3456/njop.v7i1.2345

Okolie, P., & Obumneke, J. (2024). Operational challenges linked to employee turnover in Nigeria. *Journal of Management and Labour Studies, 16*(1), 15–29.

Onohuean, E. (2026). *Evaluating the Impact of AI-Powered Chatbots on Customer Service Management and Satisfaction in a Multinational Corporation: A Case Study of Nestlé Nigeria* (Doctoral dissertation, York St John University).

Shikha, S., Neema, G., Ambuj, K. A., & Ripon, R. (2025). The double-edged sword of artificial intelligence: Exploring job insecurity and turnover intention in the modern workplace. In Innovate to Integrate: Data-driven Management and TechStrat Fusion Unveiled.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/smj.4250180704

Tornatzky, L. G., & Fleischer, M. (1990). The processes of technological innovation. Lexington Books.

Wang, X., & Huang, N. (2025). Application of data visualization technology in human resource management and employee resignation prediction. *Systems and Soft Computing*, 200355 Zong, Z., & Guan, Y. (2025). AI-driven intelligent data analytics and predictive analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency. *Journal of the knowledge economy*, *16*(1), 864-903.

Zhang, L., & Li, H. (2022). AI-based turnover prediction models. *Journal of Organizational Computing*, *32*(4), 210–226.

Zhou, Y. Y., & Jiang, M. (2026). The impact of work–family conflict on teachers' turnover intention: the mediating role of emotional labor. *Cogent Education*, *13*(1), 2598128.

Zulifiqar, H., F., L., Akhtar, M. S., & Akhtar, M. N. (2025). Artificial intelligence in HR: Reducing turnover intentions with AI-driven employee engagement solutions. *International Research Journal of Social Sciences and Humanities, 4*(1), 85–111.