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AI ADOPTION AND PSYCHOLOGICAL CONTRACT BREACH IN NIGERIA'S PUBLIC SECTOR: MEDIATING EFFECTS OF JOB DISPLACEMENT ANXIETY AND RESKILLING SUPPORT, AND THE MODERATING ROLE OF TRUST IN MANAGEMENT

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ABSTRACT

This study explores the psychological and relational effects of the adoption of Artificial Intelligence (AI) in the public sector organisations in Nigeria that are undergoing digital transformation. The study is grounded in the framework of several theories, namely Conservation of Resources Theory, Technology Threat Avoidance Theory, Social Exchange Theory, Human Capital Theory, and Psychological Contract Theory. A model was developed and tested the relationship between AI adoption to job displacement anxiety, perceived reskilling support, and psychological contract breach, while also testing the moderating effect of trust in management. The study involved a quantitative cross sectional survey of 300 respondents from selected public sector organizations in Nigeria from December 2025 to February 2026. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used for analysing the data. The results show that the use of AI had a significant impact on job displacement anxiety and on the perceived support for reskilling. Job displacement anxiety had the greatest positive direct effect on psychological contract breach, and as well as the adoption of AI. The perceived reskilling support was less strongly but still significantly, related to psychological contract breach. The negative correlation between the adoption of AI and psychological contract breach was significantly reduced when trust in management was high, suggesting that trust in management was a protective factor in the context of digital transformation. The study provides an integrated theory of how employees react to the use of AI and highlights the importance of transparency in AI governance, leadership building trust in AI, and continuous investment in reskilling workers to support successful public sector digital transformation.

Keywords: Artificial intelligence adoption, psychological contract breach, job displacement anxiety, perceived reskilling support, trust in management.

INTRODUCTION

Artificial intelligence (AI) is transforming organisational processes, decision-making and employment relations, and a growing body of empirical evidence documents its implications for workforce relationships and employee outcomes (Brougham & Haar, 2018; Malik et al., 2022; Braganza et al., 2021). Prior studies show that AI use affects job security, autonomy and organisational relationships by changing the nature of work, reducing reliance on routine tasks, and introducing new forms of algorithmic control (Brougham & Haar, 2018; Malik et al., 2022; Braganza et al., 2021). These changes have been studied extensively in private-sector settings, but far less in public-sector organisations, where bureaucratic rigidity, institutional constraints and legacy systems tend to slow the pace of technology adoption and constrain workforce adaptation. In Nigeria specifically, these structural constraints are compounded by uneven technological readiness and limited reskilling infrastructure, which together make AI adoption as much an institutional and relational transformation as well as a technical one (Nwosu et al., 2024).

A central debate in the literature concerns whether AI functions primarily as a threat to jobs or as a driver of job transformation. On one side of the argument, AI adoption has been associated with fears of job displacement, as employees perceive AI and algorithmic systems as substitutes for human labour (Brougham & Haar, 2020; Ogunlade et al., 2026); this has been corroborated by evidence from Nigeria which links AI use to increased job insecurity, workforce polarisation, and weak organisational readiness for skill transition (Oladokun et al., 2025; Ijeoma, 2025). Importantly, this threat perception appears conditional rather than automatic; it is most pronounced where AI is introduced abruptly, without transparency, or without accompanying investment in workforce capability, and considerably weaker where organisations manage the transition carefully. Consistent with this, another stream of research shows that AI can boost productivity, enrich jobs, and support skill development when combined with proper organisational investment (Jaiswal et al., 2022; Bharti et al., 2026; Vrontis et al., 2022). This divergence of viewpoints reflects a broader theoretical tension between substitution effects, in which AI displaces labour, and complementarity effects, in which AI augments human capability. Whether AI adoption produces negative or positive outcomes, therefore depends substantially on the support structures an organisation puts in place, the skills available to its workforce, and how carefully the change is managed and communicated.

There remains a significant gap in our understanding of the impact of AI use on employee-organisation relations, particularly in the public sector. Most of the previous studies have been conducted separately on job insecurity and performance outcomes, and little research has been conducted on the cognitive and relational meaning of employees' experiences of technological disruption (Ghasemaghaei, 2026; Moin et al., 2025). However, while psychological contract breach is one way in which employees evaluate organisational obligations (Rousseau, 1995; Morrison & Robinson, 1997), the links between job displacement anxiety and perceived reskilling support with psychological contract breach have not been examined. This gap is significant because job displacement anxiety and reskilling support are two different, but complementary evaluations employees make when facing job displacement driven by AI. One perspective is about the threat of job displacement and the other is about the organisation's investment in the employees' ability to change. Both appraisals are likely to influence how employees understand organisational change, as either being consistent with or a violation of the employer's implicit obligations to them. Moreover, the boundary condition of trust in management has not been adequately explored in theory and practice because the role of trust in the perception of uncertainty and organisational change has not been fully examined (Dirks & Ferrin, 2002; Fulmer & Gelfand, 2012). In Nigeria, the relational impacts of AI adoption could be exacerbated by the institutional challenges and skill deficits that exist.

In response to these challenges, the present study is aimed at empirically validating a framework that explores the mechanisms by which the use of AI influences employee outcomes. The mechanisms are interconnected and are mediated by processes related to resources, cognition and relationships. Specifically, the study aims to examine the mediating roles of job displacement anxiety and perceived reskilling support in the relationship between AI adoption and psychological contract breach, and the moderating role of trust in management in that relationship. In this framework, job displacement anxiety and perceived reskilling support serve as the two mediating variables, while trust in management serves as the moderating variable. The study has three important contributions to make especially in the context of public sector organisations in Nigeria. First, it adds to theory development by combining the concepts of job displacement anxiety, perceived reskilling support, and psychological contract breach in a single explanatory model. Second, it builds on prior studies by adding trust in management as a key boundary condition influencing employee perceptions of technological change. Third, it provides a framework to understand the opportunity in employment and the risk to jobs in an AI context in the public sector, demonstrating how institutional structures and capabilities shape the opportunity of employment and the risk to jobs.

LITERATURE REVIEW

Theoretical Foundation

This study combines five complementary theories into a unified causal model of employees' reactions to AI-induced changes in the workplace. Conservation of Resources (COR) theory is the key theoretical framework, suggesting that people strive to conserve valued resources, including job security, skill relevance, and career continuity; and they feel threatened by the loss of these resources (Hobfoll, 1989; Hobfoll et al., 2018). AI use can, thus lead to job displacement anxiety when employees feel that the introduction of AI will lead to a loss of their resources, but it can also be considered a resource gain if it improves productivity and learning opportunities.

In addition to COR, Technology Threat Avoidance Theory (TTA) provides an understanding of how employees cognitively evaluate AI-related threats. Employees assess the threat level and their capacity to deal with the threat using current skills and resources within the organisation (Liang & Xue, 2009). The more employees feel that their coping resources are inadequate in the face of perceived threats, the greater their anxiety level will be; but the less their anxiety will be when they feel that they have access to sufficient reskilling opportunities.

The present study also builds on Social Exchange Theory (SET) and Human Capital Theory to account for perceived reskilling support. According to SET, organizational investment in employee development demonstrates commitment, which fosters a positive attitude and behavior in the employees in return (Blau, 1964; Cropanzano et al., 2017). Human Capital Theory also sees training as a strategic investment to sustain the capability of the workforce in the context of technological change (Lee & Bruvold, 2003). These theories imply that visible and meaningful reskilling programs indicate that the organisation supports reskilling, while poor investment indicates neglect.

These resource, cognitive, and relational processes lead to Psychological Contract Theory (PCT) which addresses how employees perceive the change in their organisation as AI is implemented, or as either a fulfilled or broken contract (Rousseau, 1995; Morrison & Robinson, 1997). The judgments made by employees about whether organisations continue to fulfill implicit obligations around fairness, job security, and career development are largely dependent on the way AI is implemented, rather than because of the technology itself.

Finally, Trust Theory is used as the boundary condition of the model. Uncertainty is decreased and the interpretation of organisational action during technological change is influenced by trust in management (Dirks & Ferrin, 2002; Colquitt et al., 2007; Fulmer & Gelfand, 2012). High trust fosters employees' sense that the use of AI is a valid investment in the organisation, while low trust can make them think that AI implementation is an exploitative investment. These theories form a single causal chain where Resource and Threat Appraisal (RTA) affects Relational Evaluation (SET and Human Capital Theory). This, in turn affects Psychological Contract Interpretation (PCT), which is mediated by trust in management.

Hypothesis Development

AI Adoption and Job Displacement Anxiety

AI is well-documented as having an impact on the nature of work and employment, and employees are likely to perceive a greater risk of job displacement. Conservation of Resources (COR) theory states that psychological strain is caused when people feel that their valued resources are in danger, such as their job security, career continuity, and so on (Hobfoll, 1989; Hobfoll et al., 2018). Automation and algorithmic systems are often perceived to be able to replace human labor, resulting in fears and anxieties about job security and vulnerability (Brougham & Haar, 2018; Brougham & Haar, 2020; Malik et al., 2022). Empirical research further indicates that perceived technological threat is a major factor that has been found to be linked to anxiety, technostress and withdrawal behaviors (Gusti et al., 2026; Haq et al., 2026; Kumar et al., 2024). However, new studies indicate that with digital skills and organizational support, AI can enhance productivity and the job quality for workers (Kellogg et al., 2020; Vrontis et al., 2022; Bharti et al., 2026). This will create a double-edged sword scenario: AI can be perceived as a threat and an opportunity, but as a replacement-oriented and poorly supported tool, the displacement anxiety will likely be strengthened (Lingmont & Alexiou, 2020; Probst et al., 2025; Wu & Wen, 2025). As such, hypothesis H1 is proposed:

H1: AI adoption is positively associated with job displacement anxiety.

AI Adoption and Perceived Reskilling Support

The adoption of AI reshapes the way skills are required, leading to the need for reskilling the workforce and the potential for a sense of neglect within the organization. In terms of Social Exchange Theory, training and development are viewed as a message of organisational commitment and reciprocity (Blau, 1964; Cropanzano et al., 2017), and in the view of Human Capital Theory, organisations need to invest in employee capability to maintain productivity in the face of technological change (Lee & Bruvold, 2003). But real-world data suggests that the rate of AI transformation can outrun the pace of reskilling within organisations, resulting in a lack of training and a lack of confidence in the organisation's support (Jaiswal et al., 2022; Bodea et al., 2024; Depoo et al., 2025). Meanwhile, research indicates that AI can be a catalyst for structured upskilling and learning systems, thereby improving the adaptability of employees when adequate investments are made (Śledziowska et al., 2025; Zhang et al., 2025; Zhou et al., 2024). This is one of the critical boundary conditions; the degree of developmental investment that is visible and meaningful in the context of AI adoption. When organisations focus on efficiency in automation, but neglect to invest in human capital, employees are likely to feel that their needs are not being met (Arranz Lahuerta et al., 2025; Zirar et al., 2023). This hypothesised negative relationship is not inconsistent with the earlier observation that AI can enhance skill development under strong organisational investment; rather, it reflects the dominant empirical pattern in under-resourced or

transition-stage contexts, including much of the Nigerian public sector, where the pace of AI rollout tends to outstrip the pace of reskilling investment. H2, therefore captures the expected pattern under limited developmental investment, while acknowledging that reskilling support could, in principle, rise alongside AI adoption where investment is deliberate and well-resourced.

H2: AI adoption is negatively associated with perceived reskilling support.

Job Displacement Anxiety and Psychological Contract Breach

Job displacement anxiety is likely to raise psychological contract breach, as employees will view job insecurity as a breach of the implicit obligations of the organisation. According to the perspective of Psychological Contract Theory, breach occurs when an employee feels that expected or implied expectations have not been met (Rousseau, 1995; Morrison & Robinson, 1997), and this sense of breach is heightened when there is uncertainty and perceived vulnerability. Empirical studies have shown that job insecurity has negative relational consequences including lower trust (Cheng & Chan, 2008; Song, 2021; Zhao et al., 2023), deviance and withdrawal behaviours. The impact is even greater in the context of AI, as disruption in the job market and in organisational plans raises uncertainty about future employment (Salama et al., 2025; Khairy et al., 2025; Ghasemaghaei, 2026). However, the relationship is not unconditional, as transparent communication and organisational support can mitigate negative interpretations (Braganza et al., 2021; Chinyamurindi, 2021). However, without these mitigating factors, the anxiety of job displacement is likely to exacerbate perceptions of psychological contract violation. Therefore, H3 has been proposed:

H3: Job displacement anxiety is positively associated with psychological contract breach.

Perceived Reskilling Support and Psychological Contract Breach

Perceived reskilling support is expected to attenuate psychological contract breach by signalling that the organisation is fulfilling its implicit developmental obligations during technological transition. Drawing on the tenets of Social Exchange Theory, it becomes clear that employees reciprocate perceived organisational investment in training with positive attitudes, increased trust, and reduced breach perceptions (Blau, 1964; Cropanzano et al., 2017). Empirical evidence confirms that learning opportunities enhance adaptability and strengthen employee resilience in AI-driven environments (Jaiswal et al., 2022; Zhang et al., 2025; El-Hishi, 2026). However, the effectiveness of such support is contingent on its quality and alignment; superficial or misaligned training may fail to reduce insecurity and may reinforce perceptions of organisational neglect (Guest, 2017; Donald et al., 2020). Only substantive and accessible reskilling initiatives can reliably buffer negative psychological outcomes (Zhou et al., 2024; Xiaoxin et al., 2025; Fan et al., 2025). In light of these views, H4 has been proposed:

H4: Perceived reskilling support is negatively associated with psychological contract breach.

AI Adoption and Psychological Contract Breach

With the adoption of AI, the direct increase in psychological contract breach could be due to changes in the perceived balance of obligations between employees and organisations. According to the view of Psychological Contract Theory (Rousseau, 1995; Morrison & Robinson, 1997), breach happens when there is a mismatch between the expectations of fairness, security and reciprocity, and what the organisation does. AI technologies, especially those that involve algorithmic control, can transform the

nature of work, increase surveillance, and diminish autonomy, thus impacting on existing expectations (Kellogg et al., 2020; Braganza et al., 2021). Empirical research indicates that the use of AI is linked to trust issues, a rise in feelings of insecurity, and a decline in employee–organisation relationships (Moin et al., 2025; Ghasemaghaei, 2026). There is also a counter-narrative in the literature that suggests that AI can improve the quality of the job and organizational performance when used transparently and inclusively (Vrontis et al., 2022; Khan et al., 2026). Therefore, depending on how it is implemented, the use of AI can either enhance or undermine the psychological contract. If AI is seen as an imposed, hidden, or replacement of human effort, employees will view it as a violation of organizational responsibilities (Kumar et al., 2024; Khairy et al., 2025). In the Nigerian public sector specifically, bureaucratic layers can limit employees' visibility into how AI-related decisions are made, and formal channels for consultation are often weak; under these conditions, AI adoption is more likely to be experienced as an imposed rather than a negotiated change. This context increases the likelihood that AI adoption registers as a direct signal of reduced organisational commitment, independent of its effect through job displacement anxiety or reskilling support, and is the basis for the hypothesised direct, positive association as expressed in H5.

H5: AI adoption is positively associated with psychological contract breach.

Mediating Role of Job Displacement Anxiety

Job displacement anxiety is hypothesised to mediate the relationship between AI adoption and psychological contract breach because AI first registers as a perceived resource threat (per COR and TTA, as outlined above), and it is this threat appraisal — rather than the AI adoption itself — that is subsequently converted into a relational judgement about the employer. In other words, anxiety is the psychological mechanism that translates AI-related resource threat into relational judgment. This is because empirical studies have shown that AI-driven job insecurity is associated with burnout, technostress, and withdrawal behaviours (Brougham & Haar, 2020; Malik et al., 2022; Gusti et al., 2026; Nguyen & Nguyen, 2025), and it is this anxiety that most directly predicts how employees evaluate the organisation's fulfilment of its obligations. Consistent with TTA's coping-resource logic, the indirect effect via anxiety should be attenuated where contextual coping resources — such as skill availability and organisational support — are high and strengthened when such resources are low (Kim & Kim, 2024; Bharti et al., 2026; Zhang et al., 2025). Job displacement anxiety is, therefore expected to be a crucial mediator between AI adoption and psychological contract breach, particularly where employees perceive AI as a threat to their job security (Khalifa & Shehata, 2025; Wu & Wen, 2025). Therefore, H6 has been proposed:

H6: Job displacement anxiety mediates the relationship between AI adoption and psychological contract breach.

Mediating Role of Perceived Reskilling Support

Perceived reskilling support is hypothesized to be a mediator between AI adoption and psychological contract breach because employees assess technological change based on the developmental resources that are made available to them. Social Exchange Theory posits that the more an organisation invests in training, the more likely that it will foster reciprocal relationships (Blau, 1964; Cropanzano et al., 2017), and Human Capital theory emphasizes the need for ongoing skill development in changing contexts (Lee & Bruvold, 2003). Empirical research indicates that the introduction of AI leads to a rise in the need for digital skills and learning agility, highlighting the importance of reskilling in the context

of employee adaptation (Jaiswal et al., 2022; Bodea et al., 2024; Śledziowska et al., 2025). However, there are also contrasting pathways that are emphasized in the literature, such as when strong reskilling systems increase employee confidence, decrease employee insecurity, and improve organisational perceptions (Zhang et al., 2025; Zhou et al., 2024; Bharti et al., 2026). Thus, reskilling support serves as a relational process that can be seen as either an organisational neglect or investment in the adoption of AI. In cases where support is lacking, the adoption of AI is more likely to result in a breach of the psychological contract (Fan et al., 2025; El-Hishi, 2026). This was why hypothesis H7 was proposed:

H7: Perceived reskilling support mediates the relationship between AI adoption and psychological contract breach.

Moderating Role of Trust in Management

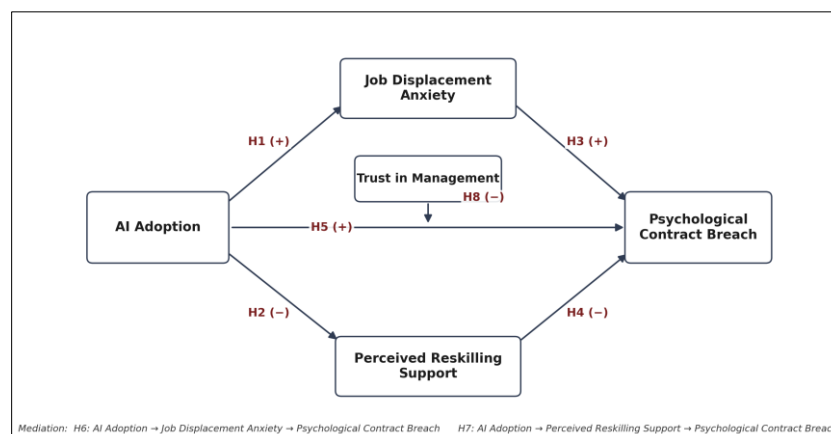
The positive relationship between AI adoption and psychological contract breach is expected to be reduced by trust in management as it influences the interpretation of organisational actions in the presence of uncertainty. According to trust theory, employees are more likely to take risks if they feel that management is competent and trustworthy (Dirks & Ferrin, 2002; Colquitt et al., 2007; Fulmer & Gelfand, 2012). Trust is important in AI environments as employees might not be fully aware of how algorithms make decisions or what the organisation's goals are (Kellogg et al., 2020; Braganza et al., 2021). Empirical studies demonstrate that the adoption of AI can reduce trust when it is not transparent and inclusive, but boost it when it is transparent and inclusive (Ghasemaghahi, 2026; Moin et al., 2025; Vrontis et al., 2022). As such, trust serves as a boundary condition regulating employee responses to AI. In the case of high trust, employees will be less likely to see AI usage as a violation of their duties, while in the case of low trust, negative perceptions will be heightened (Khaliq et al., 2022; Seshasai & Balaji, 2026). Therefore, this study has hypothesized H8:

H8: Trust in management negatively moderates the positive relationship between AI adoption and psychological contract breach, such that the relationship is weaker when trust is higher.

The hypothesised relationships among the study variables are summarised in the research framework presented in Figure 1, which depicts the direct effect of AI adoption on psychological contract breach, the two mediating pathways through job displacement anxiety and perceived reskilling support, and the moderating role of trust in management.

Figure 1

Research Framework of the Study



METHODOLOGY

Research Design

The study used a quantitative cross-sectional survey design to explore the relationships between artificial intelligence (AI) adoption, job displacement anxiety, perceived reskilling support, trust in management, and psychological contract breach among employees in selected public service organisations in Nigeria that are undergoing digital transformation. The quantitative approach was deemed suitable for the study because it aimed to test the theoretically formulated hypotheses and investigate direct, mediating and moderating relationships, using Partial Least Squares Structural Equation Modelling (PLS-SEM). The cross-sectional design allowed the collection of employee perceptual data at one time, a common approach in organisational behaviour and human resource management research where experimental manipulation is not possible. This design was well-suited for the study's purpose of capturing the perceptions of employees regarding the transformation of the workplace with AI in natural settings.

Research Context, Population, and Sampling

The study was carried out in selected public service organisations in Nigeria that had undergone a significant digital transformation process and use of AI-enabled technology. Organisations were included if they meet the following criteria: (a) had a documented digital transformation programme; (b) had introduced digital systems that were AI-enabled or intelligent, for example, automated workflow, a chatbot platform, digital HR analytics, or decision-support tools; and (c) had employees whose job had been directly impacted by these systems. The organisations that participated were the Kwara State Internal Revenue Service (KW-IRS), the National Identity Management Commission (NIMC), the National Information Technology Development Agency (NITDA), and the Federal Ministry of Communications, Innovation and Digital Economy (FMCIDE). Cochran's formula (1997) was used to determine the minimum sample size, with a 95% confidence level, 5% margin of error and 50% population proportion, which yielded a minimum sample size of 384. Therefore, 384 questionnaires were distributed and from these only 300 were usable for analysis (78.1% response rate). A purposive sampling technique was used in conjunction with a convenience sampling technique. Purposive sampling was used to ensure that respondents had experience of AI-enabled work processes, and convenience sampling was used to deal with practical access constraints in the public sector.

Data Collection

The main data were obtained through a structured online survey questionnaire which was administered over a period of three months (December 2025 – February 2026) to the selected public service organisations in Nigeria. The online survey approach was adopted because it proved to be efficient in reaching the respondents who were spread across various institutions, minimized administrative burden and enabled the collection of responses in a timely fashion. The link to the questionnaire was distributed to employees of the selected organisations through institutional contacts, professional networks, email and digital communication channels.

The survey instrument had two major sections. The first section recorded the demographic information of the respondents, such as gender, age, educational qualification and work experience. The second section consisted of items related to the adoption of AI, fear of job loss, perceived reskilling support, psychological contract breach, and trust in management. There was complete voluntary participation

and respondents were informed about the academic purpose of the study before their participation. Confidentiality and anonymity were also assured to minimize social desirability bias and to ensure that the responses were honest, particularly in light of the potential sensitivity of the questions related to job security, trust in the organization and perceptions of technological change. Respondents were required to give informed consent electronically prior to completing the survey.

Measurement of Variables

The study constructs were all measured by multi-item scales that were validated and adapted from prior empirical studies and contextualized for the study of AI-driven public sector transformation. The level of AI adoption was operationalised, drawing on prior conceptualisations of organisational AI and digital-technology adoption (Braganza et al., 2021; Vrontis et al., 2022), as employees' perception of the extent to which AI-enabled or intelligent digital technologies had been adopted within the organisation's operations, processes and decision-making. To distinguish AI adoption from general digitalisation, items directed respondents to concrete AI-enabled functions relevant to Nigerian public-sector operations — including automated or algorithm-assisted case processing and decision support, chatbot- or virtual-assistant-based service channels, predictive analytics used in planning or resource allocation, and AI-enabled digital human-resource systems — rather than to routine digitisation of paper records or generic office software.

Job displacement anxiety was assessed through scales adapted from Brougham and Haar (2018; 2020), which measured employee concerns about job insecurity, redundancy and being replaced by automation technologies. Conceptually, perceived reskilling support was measured by the extent to which employees perceived their organisation supported their capability development, digital training and skill adaptation, as per Jaiswal et al. (2022) and Lee and Bruvold (2003). The psychological contract breach was assessed by items adapted from Morrison and Robinson (1997), which tapped into the employee's perceptions that the organisation had not met the implicit promises connected to security, fairness and developmental support. Established measures of trust in management based on confidence in management integrity, competence and fairness (Dirks & Ferrin, 2002) were used to assess trust in management. Five indicators were used for each of the five constructs, resulting in 25 measurement items (AI1–AI5, JDA1–JDA5, PRS1–PRS5, PCB1–PCB5 and TM1–TM5). Consistency and comparability across constructs were achieved by using a five-point Likert scale from 1 = strongly disagree, to 5 = strongly agree for all items. For transparency, the full set of 25 measurement items, together with their source scales, is reported in Appendix A.

Data Analysis

Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyse the data by using SmartPLS 4 software. PLS-SEM was deemed suitable because of the following reasons: it is feasible for predictive modelling; can deal with complex structural relationships (mediation and moderation); is robust in the presence of non-normal data distribution; is appropriate for behavioural research involving latent constructs. The analysis was conducted in line with the prescribed two stage evaluation process. The measurement model was evaluated by examining the outer loadings, Cronbach's alpha, rho_A, composite reliability, Average Variance Extracted (AVE), and Heterotrait–Monotrait ratio (HTMT). Second, the structural model was evaluated using bootstrapping with **5,000 resamples** to estimate path coefficients, t-values, p-values, mediation effects, and moderation effects. Model explanatory power (R^2), predictive relevance (Q^2), and effect sizes (f^2) were also assessed to determine the robustness and predictive capability of the structural model.

Common Method Bias

In order to reduce common method bias (CMB), procedural and statistical methods were used in the study, which also used self-reported cross sectional survey data. Respondent anonymity and confidentiality were guaranteed, and items on the questionnaires were clearly formulated, and predictor and outcome constructs were conceptually separated to minimize response bias and social desirability effects. Harman's single factor test (1967) statistically yielded five factors; the largest factor accounted for 31.77% of the variance, which was less than 50%, meaning that no single factor dominated the data. Additionally, the full collinearity VIF values ranged from 1.14 to 1.81, which was below the suggested threshold of 3.3 (Hair et al., 2019), further supporting the conclusion that the results of this study were unlikely to be compromised by the presence of full collinearity.

RESULTS

Respondents' Demographic Profile

Table 1 shows the demographic profile of the 300 survey respondents. The sample included slightly more female ($n = 161$, 53.7%) than male respondents ($n = 139$, 46.3%). The largest age group was 26 to 35 years (31.7%), followed by 36 to 45 years (23.7%), together representing 55.4% of respondents in early- to mid-career stages. The largest educational group was bachelor's degree holders (43.7%), followed by postgraduate degree holders (25.0%), for a combined 68.7% of respondents. Regarding work experience, the largest proportion of respondents had 1–5 years of experience ($n = 97$, 32.4%), followed by those with 6–10 years ($n = 87$, 29.0%). Overall, 61.4% of respondents had between one and ten years of work experience, indicating that the sample was predominantly composed of employees with sufficient organisational experience to provide informed perceptions of AI adoption, job displacement anxiety, reskilling support, trust in management, and psychological contract breach.

Table 1

Respondents' Demographic Characteristics

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	139	46.3
	Female	161	53.7
Total		300	100.0
Age Group	18–25 years	52	17.3
	26–35 years	95	31.7
	36–45 years	71	23.7
	46–55 years	56	18.7
	56 years and above	26	8.7
Total		300	100.0
Educational Qualification	OND/NCE	52	17.3
	Bachelor's Degree	131	43.7
	Postgraduate Degree	75	25.0
	Professional Certification	42	14.0
Total		300	100.0
Work Experience	Less than 1 year	20	6.7
	1–5 years	97	32.4
	6–10 years	87	29.0
	11–15 years	57	19.0
	16 years and above	39	12.9
Total		300	100.0

Measurement Model Assessment

Reliability and Convergent Validity

The results of the measurement model are as shown in Table 2. The loadings of the indicators were higher than 0.70 for all the constructs, except for TM1 (0.679), which was allowed, as it had a loading value above the minimum threshold of 0.40 and the reliability level for the construct was good (Hair et al., 2019). The Cronbach's alpha values (range 0.891–0.905) and composite reliability values (range 0.902–0.929) were above the recommended values (Nunnally, 1978), indicating good internal consistency. Trust in Management had a lower rho A (0.665), but the reliability overall was still good. AVE values ranged from 0.650 to 0.725, which was greater than the benchmark of 0.50, and this indicated that the convergent validity was acceptable (Fornell & Larcker, 1981).

Table 2

Measurement Model Assessment: Reliability and Convergent Validity

Construct	Indicator	Outer loading	A	rho_A	CR	AVE	Interpretation
AI Adoption	AI1	0.887	0.905	0.906	0.929	0.725	Excellent reliability and convergent validity
	AI2	0.851					
	AI3	0.850					
	AI4	0.836					
	AI5	0.832					
Job Displacement Anxiety	JDA1	0.867	0.902	0.905	0.928	0.719	Excellent reliability and convergent validity
	JDA2	0.853					
	JDA3	0.849					
	JDA4	0.819					
	JDA5	0.852					
Perceived Reskilling Support	PRS1	0.854	0.900	0.908	0.926	0.715	Excellent reliability and convergent validity
	PRS2	0.878					
	PRS3	0.845					
	PRS4	0.818					
	PRS5	0.831					
Psychological Contract Breach	PCB1	0.877	0.891	0.894	0.920	0.696	Excellent reliability and convergent validity
	PCB2	0.822					
	PCB3	0.847					
	PCB4	0.794					
	PCB5	0.828					
Trust in Management	TM1	0.679	0.894	0.665	0.902	0.650	Acceptable reliability and convergent validity
	TM2	0.847					
	TM3	0.815					
	TM4	0.851					
	TM5	0.828					

Notes. CR = Composite Reliability (rho_C). All outer loadings ≥ 0.70 , except TM1 ($\lambda = 0.679$), retained given satisfactory construct-level reliability. AVE threshold = 0.50; Cronbach's α and CR threshold = 0.70

Discriminant Validity

The Heterotrait–Monotrait (HTMT) criterion was used for assessing discriminant validity (Henseler et al., 2015). The HTMT values for all were below the conservative 0.85 value, as can be seen in Table 3. The highest correlations were found between Job Displacement Anxiety and Psychological Contract Breach (0.626), AI Adoption and Psychological Contract Breach (0.575), and AI Adoption and Job Displacement Anxiety (0.565), which indicated that these variables can be considered to have moderate yet acceptable conceptual overlap. Construct distinctiveness was evidenced by the low HTMT of items across all constructs (0.048-0.347) and the low HTMT of the interaction term as well. The low HTMTs of the items across all constructs (0.048-0.347) and of the interaction term confirmed construct distinctiveness.

Table 3

Discriminant Validity Assessment (HTMT Ratios)

Construct	AI Adoption	JDA	PRS	PCB	TM	TM × AI
AI Adoption	—					
Job Displacement Anxiety	0.565	—				
Perceived Reskilling Support	0.250	0.196	—			
Psychological Contract Breach	0.575	0.626	0.412	—		
Trust in Management	0.080	0.064	0.347	0.048	—	
Trust in Management × AI Adoption	0.022	0.061	0.044	0.196	0.042	—

Notes. HTMT = Heterotrait–Monotrait ratio. Values below 0.85 indicate satisfactory discriminant validity (Henseler et al., 2015). JDA = Job Displacement Anxiety; PRS = Perceived Reskilling Support; PCB = Psychological Contract Breach; TM = Trust in Management. Dashes (—) denote self-referential comparisons.

Structural Model Results

Direct Effects

High AI adoption was associated with higher perceived job displacement anxiety, which was supported ($\beta = 0.513$, $t = 12.266$, $p < 0.001$) and was the largest direct path in the model. The support of AI was also negatively correlated with the perceived reskilling support ($\beta = -0.227$, $t = 4.217$, $p < 0.001$), which aligned with the interpretation of AI adoption by employees being geared toward operational efficiency instead of investment in the workforce. H3 was supported ($\beta = 0.369$, $t = 7.689$, $p < 0.001$); psychological contract breach was positively correlated with job displacement anxiety, meaning that the higher the job displacement anxiety, the more likely the workers would perceive that their psychological contracts had been violated. The perceived reskilling support was supported ($\beta = -0.286$, $t = 6.312$, $p < 0.001$); the more visible the reskilling investment, the less the breach was perceived as an issue, suggesting that a reskilling investment in the form of a visible resource was a relational resource that reduced the perception of breach. AI adoption was supported ($\beta = 0.255$, $t = 4.935$, $p < 0.001$), suggesting that the adoption of AI still had a direct link with psychological contract breach, as well as indirect links through job displacement anxiety and reskilling support.

Table 4

Structural Model Results: Path Coefficients

H	Structural path	β	STDEV	t-value	p-value	Decision
H1	AI Adoption $\rightarrow$ Job Displacement Anxiety	0.513	0.042	12.266	< 0.001	Supported
H2	AI Adoption $\rightarrow$ Perceived Reskilling Support	-0.227	0.054	4.217	< 0.001	Supported
H3	Job Displacement Anxiety $\rightarrow$ Psychological Contract Breach	0.369	0.048	7.689	< 0.001	Supported
H4	Perceived Reskilling Support $\rightarrow$ Psychological Contract Breach	-0.286	0.045	6.312	< 0.001	Supported
H5	AI Adoption $\rightarrow$ Psychological Contract Breach	0.255	0.052	4.935	< 0.001	Supported
H6	AI Adoption $\rightarrow$ JDA $\rightarrow$ Psychological Contract Breach	0.189	0.030	6.372	< 0.001	Supported (Partial Mediation)
H7	AI Adoption $\rightarrow$ PRS $\rightarrow$ Psychological Contract Breach	0.065	0.019	3.441	0.001	Supported (Partial Mediation)
H8	Trust in Management $\times$ AI Adoption $\rightarrow$ PCB	-0.176	0.065	2.691	0.007	Supported (Moderation)

Notes. Bootstrap resamples = 5,000. Two-tailed significance. β = standardised path coefficient; STDEV = standard deviation of bootstrap estimates; JDA = Job Displacement Anxiety; PRS = Perceived Reskilling Support; PCB = Psychological Contract Breach. ***p < 0.001.

Mediation Effects

The relationship between AI adoption and psychological contract breach was partially mediated by job displacement anxiety ($\beta = 0.189$, $t = 6.372$, $p < 0.001$), consistent with H6. Because the direct effect of AI adoption on psychological contract breach remained significant ($\beta = 0.255$, $p < 0.001$) alongside this indirect effect, the results indicated complementary partial mediation rather than full mediation (Zhao et al., 2010). H7 was also supported ($\beta = 0.065$, $t = 3.441$, $p = 0.001$); AI adoption was negatively associated with perceived reskilling support, which was, in turn, negatively associated with breach perceptions, indicating a second partial mediation pathway. Compared with the indirect effect via perceived reskilling support ($\beta = 0.065$), the larger indirect effect via job displacement anxiety ($\beta = 0.189$) indicated that job displacement anxiety was the more dominant of the two mediating mechanisms.

Moderation Effect

H8 was supported ($\beta = -0.176$, $t = 2.691$, $p = 0.007$). The interaction effect was significant and negative, indicating a buffering effect; the more trusting employees were toward management, the weaker the positive association between AI adoption and psychological contract breach. Employees who trusted organisational leaders were less likely to interpret AI-driven change as exploitative, even under technological uncertainty. Trust in management, therefore functioned as a key boundary condition shaping how employees interpreted AI implementation.

Structural Model Quality

Model quality was assessed using R^2 , adjusted R^2 , Q^2 , and Cohen's f^2 (Hair et al., 2019; Cohen, 1988), as reported in Table 5. The model explains 26.3% of variance in Job Displacement Anxiety ($Q^2 = 0.180$; moderate), 5.1% in Perceived Reskilling Support ($Q^2 = 0.030$; weak), and 48.5% in Psychological Contract Breach ($Q^2 = 0.340$; moderate–substantial). Effect size analysis confirmed that AI adoption exerted a large effect on job displacement anxiety ($f^2 = 0.356$), while job displacement anxiety had a medium effect on psychological contract breach ($f^2 = 0.193$). Trust in management demonstrated a negligible direct effect ($f^2 = 0.016$), but a meaningful small moderation effect ($f^2 = 0.060$).

Table 5

Structural Model Quality Assessment

Construct / Predictor	R^2	Adj. R^2	f^2	Q^2	Interpretation
Endogenous Constructs					
Job Displacement Anxiety	0.263	0.260	—	0.180	Moderate explanatory power; medium predictive relevance
Perceived Reskilling Support	0.051	0.048	—	0.030	Weak explanatory power; small predictive relevance
Psychological Contract Breach	0.485	0.476	—	0.340	Moderate–substantial explanatory power; medium–high predictive relevance
Effect Sizes (f^2)					
AI Adoption → Job Displacement Anxiety	—	—	0.356	—	Large effect
AI Adoption → Perceived Reskilling Support	—	—	0.054	—	Small effect
AI Adoption → Psychological Contract Breach	—	—	0.089	—	Small effect
Job Displacement Anxiety → Psychological Contract Breach	—	—	0.193	—	Medium effect
Perceived Reskilling Support → Psychological Contract Breach	—	—	0.134	—	Small–medium effect
Trust in Management → Psychological Contract Breach	—	—	0.016	—	Negligible effect
Trust in Management × AI Adoption → PCB	—	—	0.060	—	Small moderation effect

Notes. R^2 = coefficient of determination; Adj. R^2 = adjusted R^2 ; f^2 = Cohen's effect size (0.02 = small, 0.15 = medium, 0.35 = large; Cohen, 1988); Q^2 = predictive relevance. PCB = Psychological Contract Breach. Dashes (—) indicate non-applicable cells.

DISCUSSION

The results broadly support the integrated theoretical framework, indicating that AI adoption is associated with employees' psychological and relational reactions, both directly and indirectly. Consistent with Conservation of Resources (COR) theory, AI adoption showed a strong positive association with job displacement anxiety, supporting the proposition that AI-driven automation was

appraised as a threat to resources employees value, including job security and career continuity (Hobfoll, 1989; Hobfoll et al., 2018). This is consistent with prior work linking technological disruption to job insecurity, technostress, and withdrawal behaviour (Brougham & Haar, 2020; Malik et al., 2022; Kumar et al., 2024). AI adoption was also negatively associated with perceived reskilling support, suggesting that employees in this sample tended to interpret technological change as oriented toward automating tasks rather than developing the workforce. Viewed through the lens of Social Exchange Theory, this pattern indicates a perceived breakdown in reciprocity: when AI adoption is not accompanied by visible training investment, employees appear to read this as the organisation withdrawing from its side of the exchange relationship rather than reinvesting in it, which in turn weakens the reciprocal commitment employees feel toward the organisation (Blau, 1964; Cropanzano et al., 2017). The direct positive association between AI adoption and psychological contract breach further supports the position of Psychological Contract Theory (Rousseau, 1995; Morrison & Robinson, 1997; Braganza et al., 2021), that is, where AI is introduced in a hidden or replacement-oriented manner, employees appear to interpret this as an infringement of implicit obligations around fairness, security, and developmental reciprocity. This direct association is particularly plausible in the Nigerian public sector context of this study, where limited consultation and communication channels around technological change may lead employees to experience AI adoption as an imposed rather than negotiated process, independent of the anxiety or reskilling pathways.

The mediation findings also help to us to understand the psychological processes between AI adoption and breach perceptions. Job displacement anxiety was positively related to psychological contract breach, which is in line with previous findings that job insecurity negatively affects employee trust and relational stability (Cheng & Chan, 2008; Song, 2021; Zhao et al., 2023). Additionally, job displacement anxiety was the more potent of the two mediators, suggesting that threat appraisal was the more salient pathway that explained negative employee interpretations of AI adoption, compared to perceived reskilling support. The finding is consistent with the postulations of Technology Threat Avoidance (TTA) theory and cognitive appraisal logic that employees' negative reaction to a technological threat is a result of a negative appraisal of coping resources when the perceived threat is greater than the coping resources (Liang & Xue, 2009). The relatively lower impact of perceived reskilling support indicates that developmental support might not be enough to adequately mitigate anxiety stemming from an AI perceived displacement threat. This aligns with prior research finding that meaningful reskilling is linked to greater adaptation and organizational commitment when it is viewed as substantive and not symbolic (Jaiswal et al., 2022; Zhou et al., 2024; Zhang et al., 2025).

Furthermore, the moderation results indicate that trust in management is a key boundary condition for AI-assisted organisational change. The significant negative interaction effect shows that trust buffers the association between AI adoption and psychological contract breach, consistent with the literature and with trust theory (Dirks & Ferrin, 2002; Colquitt et al., 2007; Fulmer & Gelfand, 2012), although the effect size is small ($f^2 = 0.060$; see Table 5) and should be interpreted as a modest, rather than substantial, buffering effect. This indicates that employees' reactions to AI extend beyond the technology itself and depend, in part, on the organisational environment in which it is applied. Taken together, these findings extend theory by integrating resource-loss logic, cognitive threat appraisal, exchange relationships, and psychological contract evaluation into a single explanatory account. Practically, the results suggest that more than simply adopting the technology is needed for successful implementation — proactive approaches to engaging employees, building trust, and investing in workforce training are likely to help sustain the employment relationship and mitigate employee concerns.

THEORETICAL IMPLICATIONS

This study's results align with prior theories about employee responses to technological disruption, as AI adoption is unable to be explained by any single determinative theory. Conservation of Resources (COR) theory suggests that perceived threats to valued resources, such as job security, trigger stress and defense mechanisms (Hobfoll, 1989; Hobfoll et al., 2018), and this is also evident in the strong relationship between the adoption of AI and job displacement anxiety. However, the buffering effect of trust in management undermines the automatic nature and negativity of the resource-threat responses, suggesting that the context of the organisation can shape the interpretation of the cognitive response to technological threats. Similarly, the tenets of Technology Threat Avoidance Theory suggests that threat appraisal depends on the relative level of threat resources and coping resources (Liang & Xue, 2009), and the present research has employed this logic to demonstrate the influence of threat appraisal outcomes by an important psychological boundary condition, that is, trust.

The results also have implications for the theories of Social Exchange Theory and Psychological Contract Theory. Social Exchange Theory suggests that developmental investment will lead to increased reciprocal commitment (Blau, 1964; Cropanzano et al., 2017), but the relatively weak mediation effect of perceived reskilling support indicates that investment alone may not be enough to compensate for the high levels of employment insecurity in AI contexts. This suggests that relational exchange processes may be less important when employees feel threatened with regard to the continuity of their jobs. Further, the concept of breach perceptions is extended to situations where managers' actions are interpreted symbolically to breach the contract, as well as situations where managers' actions explicitly breach the contract. The present study also offers a more comprehensive and contextualized theoretical framework in which the evaluation of the resources, the exchange of relationships, the cognitive threat appraisal, and the trust which will have an impact on employee reactions to the implementation of AI.

PRACTICAL IMPLICATIONS

The findings are relevant to organisations adopting AI technologies, highlighting the need for careful implementation. First, do not see technological adoption as just an operational or efficiency problem – employees see AI from a psychological and relational perspective. To help reduce uncertainty and threat amplification, organisations have to be transparent about the purpose, implications and impact of AI on their workforce. Secondly, reskilling initiatives must be less symbolic and more substantive and role-oriented in terms of development investments that are clearly visible and are made with the aim to enhance the future employability of employees. Third, it was determined that leadership trust was a protective factor; that is, the credibility, fairness and participative communication of the management was found to be key elements in reducing resistance and maintaining employment relations during technological change. HR managers should, therefore, incorporate AI governance into their employee engagement programs, change management efforts, and workforce capability planning to ensure long-term success for AI adoption.

LIMITATIONS AND FUTURE RESEARCH

The study has some limitations that can be looked into in future studies. For example, the cross-sectional nature of the study restricts the capacity for causal inference and fails to capture the potential for shifts in employee perceptions of AI adoption over time, necessitating future research with longitudinal designs to better understand the process of adaptation over time. Self-reported survey data can be subject to common method biases and perceptual subjectivity, so multi-source/mixed-method approaches are needed that incorporate managerial/organisational data. The perceived reskilling support is a relatively weak predictor, meaning other factors like leadership communication, organisational learning culture, transparency in AI governance, and practices for HR capability development need to be investigated. Lastly, the model should be validated in different industries and countries to enhance its generalizability, as there may be industry and country variations in the context of the model.

CONCLUSION

This study offers empirical evidence of the link between the use of AI and the psychological and relational perceptions of employees in public sector organisations in the process of digital transformation. Overall, the findings suggest that the more AI is adopted, the more anxiety employees feel about job displacement, the less they feel their organisation supports their reskilling, and the more they feel their employer has broken their psychological contract — meaning that when employees experience technological change, they see it as more than just an efficiency tool; they take it as a message about job security, fairness, and employer commitment. Moreover, the mediation analysis reveals that the most direct and salient psychological pathway between AI adoption and psychological contract breach is through job displacement anxiety, indicating that job displacement anxiety is the immediate and most salient psychological reaction to technological disruption, whereas reskilling support has a comparatively weaker effect. Moreover, trust in management was found to be a key protective factor, with increased trust linked to reduced perceptions of breach when dealing with AI adoption, highlighting the need for fostering trust and transparency within the organisation during the transition to AI. In general, the findings indicate that the response of employees to the use of AI was not only shaped by the characteristics of the technology itself, but also by how the technology was managed, communicated, and regulated in organisations. Adopting AI in a human-centred way, thus demands a combination of technological innovation, trust-building leadership, substantive reskilling investments, clear communication, and the proactive management of employee uncertainty, especially within complex and resource-limited public sector institutions.

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APPENDIX A: MEASUREMENT ITEMS

All items were measured on a five-point Likert scale ranging from **1 = Strongly disagree** to **5 = Strongly agree**. The measurement scales were adapted from established instruments and contextualised for AI-enabled digital transformation in Nigerian public sector organisations while retaining the conceptual meaning of the original constructs.

AI Adoption (adapted from Braganza et al., 2021; Vrontis et al., 2022)

- AI1. My organisation uses AI-enabled or intelligent digital systems in its day-to-day operations.
- AI2. AI-based tools are used to support decision-making in my department.
- AI3. My job now involves direct interaction with AI-enabled or algorithm-based systems (e.g., automated case processing, chatbots, predictive analytics).
- AI4. My organisation is actively expanding its use of AI-enabled technologies.
- AI5. AI-enabled systems play an important role in how work is carried out in my organisation.

Job Displacement Anxiety (adapted from Brougham & Haar, 2018, 2020)

- JDA1. I am concerned that AI-enabled technologies could eventually replace my job.
- JDA2. I worry that my skills will become less relevant because of AI adoption in my organisation.
- JDA3. I feel anxious about my job security because of the growing use of AI at work.
- JDA4. I am concerned that automation will reduce the number of roles available in my organisation.
- JDA5. Thinking about the future use of AI in my organisation makes me feel uneasy about my career.

Perceived Reskilling Support (adapted from Jaiswal et al., 2022; Lee & Bruvold, 2003)

- PRS1. My organisation provides adequate training to help me adapt to AI-enabled changes at work.
- PRS2. I have access to opportunities to develop new digital skills relevant to AI adoption.
- PRS3. My organisation invests meaningfully in reskilling employees affected by AI adoption.
- PRS4. I feel supported by my organisation in building the skills needed to work alongside AI systems.
- PRS5. My organisation's training programmes are well aligned with the skills that AI adoption requires of me.

Psychological Contract Breach (adapted from Morrison & Robinson, 1997)

- PCB1. I feel that my organisation has not fulfilled the promises it made to me regarding job security.
- PCB2. My organisation has failed to deliver on what I expected in terms of fair treatment during technological change.
- PCB3. I feel that my organisation has not lived up to its obligations to support my career development.
- PCB4. The way AI has been introduced makes me feel that my organisation has broken its commitments to employees.
- PCB5. Overall, I feel that my organisation has not honoured its implicit obligations to me as an employee.

Trust in Management (adapted from Dirks & Ferrin, 2002)

- TM1. I trust that management is competent to manage AI-related changes in my organisation.
- TM2. I believe management is honest and transparent about the reasons for adopting AI.
- TM3. I trust management to act in employees' best interests during technological change.
- TM4. I have confidence that management will treat employees fairly as AI adoption continues.
- TM5. I believe management genuinely cares about the impact of AI adoption on employees.