

Article

Human-Ai Interface: Assessing The Role Of Explainable Ai (Xai) In Mitigating Knowledge Worker Resistance And Fostering Trust During Ai-Driven Business Process Automation

Evelyn Chichi Otuya¹ , Abdullahi Ayegba²

^{1,2}Department of Management of Information Technology,
African University of Science and Technology, Abuja, Nigeria.

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Abstract: The increasing adoption of Artificial Intelligence (AI) in business process automation has transformed organizational operations by improving efficiency, accuracy, and decision-making. However, many knowledge workers remain reluctant to embrace AI systems due to concerns about transparency, fairness, accountability, and the fear of job displacement. Explainable Artificial Intelligence (XAI) has emerged as a promising solution by making AI decisions more understandable and transparent to users. This study examines the role of XAI in reducing knowledge worker resistance and enhancing trust during the implementation of AI-driven business process automation. A mixed-methods research design was adopted, combining quantitative survey data with qualitative insights from knowledge workers across selected organizations in Nigeria. Data were analyzed using descriptive statistics, regression analysis, and thematic analysis to explore the relationships among explainability, trust, resistance to AI adoption, and organizational acceptance. The findings indicate that AI systems with higher levels of explainability significantly improve users' trust and confidence while reducing resistance to AI adoption. The study further reveals that transparency, clear communication, and employee involvement during AI implementation positively influence acceptance and successful integration of AI technologies in organizational processes. The study concludes that Explainable AI is not only a technological enhancement but also a strategic tool for promoting employee trust and supporting effective digital transformation. It recommends that organizations prioritize explainability, invest in AI literacy and training, and develop transparent AI governance frameworks to encourage successful adoption of AI-driven business process automation.

Keywords: Explainable Artificial Intelligence (XAI), Artificial Intelligence, Business Process Automation, Knowledge Workers, Trust, Employee Resistance, Digital Transformation, Human-AI Interface.

1. Introduction

Artificial Intelligence (AI) has become an important technology shaping 21st-century organizations. Its ability to support automation, improve productivity, enhance decision-making, and increase operational efficiency has accelerated the adoption of data-driven and technology-enabled business processes[1]. As global competition intensifies, organizations increasingly deploy AI-driven Business Process Automation (BPA) to improve efficiency, reduce operational costs, minimize errors, and accelerate workflows[2]. Unlike traditional automation that focuses primarily on rule-based and repetitive tasks, AI-driven BPA extends automation capacities to complex, knowledge-intensive activities by leveraging machine learning, natural language processing, predictive analytics, and intelligent agents. When workers are unable to understand how

AI systems reach their decisions, uncertainty and distrust may increase, particularly in sensitive and high-stakes application domains where transparency and trustworthiness are important[3].

Explainable Artificial Intelligence (XAI) has emerged as a promising approach to address this challenge. XAI refers to methodologies and techniques that make AI systems understandable, interpretable, and explainable to human users[4]. It provides insights into how algorithms process data, weigh variables, identify patterns, and produce outcomes. By rendering AI outcomes transparent, XAI enhances cognitive alignment between human expectations and automated logic. In organizational contexts, XAI has the potential to reduce fear, mitigate perceptions of loss of control, and foster trust in automated processes[5]. In developing economies such as Nigeria, the significance of human–AI collaboration is even more pronounced. Nigeria is experiencing an accelerated shift toward digital transformation, with several sectors including banking, telecommunications, public services, and education investing in AI-enabled solutions[6][7]. However, socio-technical adoption challenges persist. Low digital literacy, inadequate AI awareness, infrastructural constraints, and cultural skepticism toward algorithmic systems can hinder successful AI deployment[8]. In such environments, the lack of explainability in AI systems can deepen mistrust and resistance among knowledge workers, ultimately undermining organizational investment in automation.

Thus, understanding the human–AI interface is essential for ensuring that technological transformation aligns with worker expectations, organizational culture, and ethical principles. This study examines the role of Explainable AI (XAI) in mitigating knowledge worker resistance and fostering trust during the deployment of AI-driven Business Process Automation. It builds on interdisciplinary research in AI ethics, behavioural psychology, human–computer interaction, and technology acceptance to explore how transparency and interpretability can enhance the effectiveness of automation initiatives.

The study contributes to global discussions on ethical AI deployment by emphasizing the practical significance of human-centered automation. It also develops insights that are highly relevant to Nigeria’s digital transformation agenda, where balancing technological innovation with human acceptance is crucial for organizational sustainability and socio-economic development.

1.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), proposed by Davis[9], explains technology acceptance through users’ perceptions of usefulness and ease of use. Perceived usefulness refers to the extent to which an individual believes that using a system will enhance job performance, while perceived ease of use concerns the extent to which the system is perceived to be free of effort. These perceptions influence users’ acceptance and intention to use information technologies.

1.1.1. Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA), developed by Fishbein, Ajzen[10], posits that behavioural intention is shaped by an individual’s attitude toward a behaviour and subjective norms. The theory suggests that individuals are more likely to form intentions to perform a behaviour when they hold favourable attitudes toward it and perceive social support for the behaviour. In the context of AI adoption, workers’ attitudes toward AI, including positive or negative perceptions, may therefore influence their willingness to interact with automated systems.

1.1.2. Artificial Intelligence and Business Process Automation

AI-driven BPA utilizes intelligent systems to automate both repetitive and knowledge-intensive tasks. Technologies include machine learning, natural language processing, predictive analytics, and robotic process automation (RPA). McKinsey[11] report that organizations deploy AI to optimize decision-making and reduce error rates across domains such as finance, HR, logistics, and healthcare.

However, scholars have raised concerns that the increasing complexity and opacity of AI systems can create challenges for human oversight, fairness, accountability, and transparency[12]. Complex AI models may operate as “black boxes,” making it difficult for users to understand how particular outputs are generated. Consequently, the adoption of Business Process Automation is not purely a technical process but also requires appropriate human oversight, organizational adaptation, and consideration of social and ethical implications.

1.1.3. Knowledge Workers and AI Adoption

Knowledge workers rely on expertise, judgment, and analytical reasoning[13]. When AI is introduced into their workflow, they may perceive it as:

1. A threat to job security – fear of automation[14].
2. A threat to autonomy – loss of control over professional discretion.
3. An opaque tool – lack of algorithmic transparency.

Resistance arises when workers believe AI undermines their role, authority, or competence. argue that knowledge-intensive roles require trust, clarity, and feedback elements often missing in black-box AI systems.

1.1.4. Resistance to Technology

identifies four primary drivers of resistance:

Routine seeking – preference for stability

Emotional reaction – fear or anxiety towards change

Short-term focus – discomfort with immediate disruption

Cognitive rigidity – difficulty understanding complex technologies

AI exacerbates these factors due to its perceived opacity and sophistication. It is noted that lack of transparency increases psychological resistance because workers feel uncertain about how decisions are made.

1.1.5. Trust in AI Systems

Trust is a core determinant of AI adoption. Afroogh[15], argue that trust in AI involves:

Competence – belief that AI produces correct results

Benevolence – belief that AI has user’s best interests

Integrity – belief that AI operates fairly and ethically

Trust may decline when AI systems produce decisions that users cannot understand or adequately evaluate. Doshi-Velez and Kim emphasized the importance of interpretability in enabling humans to assess properties such as safety, fairness, reliability, and trustworthiness in machine-learning systems.

1.1.6. Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence refers to approaches that enable AI systems to provide understandable explanations of their decisions or outputs to human users. XAI is particularly important in applications where users need to understand, evaluate, and appropriately manage AI-generated decision.

1.2. Benefits of XAI in organizations:

XAI can enhance user trust by making AI decisions more transparent and understandable[16]. It can support transparency, accountability, and responsible evaluation of AI systems. XAI also facilitates the interpretation of complex machine-learning models, enabling users to better understand how AI systems generate their outputs[17][18]. Consequently, XAI can strengthen human understanding and support meaningful human involvement in AI-assisted decision-making.

2. METHODOLOGY

2.1 Research Philosophy

Research philosophy refers to the system of beliefs and assumptions underlying the choice of research methods, research design, and interpretation of findings[19]. This study adopts a pragmatic research philosophy, which emphasizes practical problem-solving and allows researchers to combine quantitative and qualitative approaches. Pragmatism is particularly suitable for investigating socio-technical phenomena such as the human–AI interface because it enables the statistical measurement of constructs such as trust, resistance, and behavioural intention while also providing a deeper understanding of employees' experiences and perceptions[20].

Pragmatism aligns with the objectives of this study in three major ways:

1. **Flexibility in Methods:** It enables the integration of surveys, interviews, and document reviews to obtain comprehensive evidence on knowledge workers' interaction with AI-driven BPA.
2. **Focus on Outcomes:** It emphasizes practical and actionable findings that can assist organizations in effectively implementing AI-driven Business Process Automation.
3. **Acknowledgement of Multiple Realities:** It recognizes that knowledge workers' perceptions and responses to AI may differ according to personal experiences, organizational conditions, and socio-cultural contexts.

2.2 Research Design

This study adopts a mixed-methods research design, combining quantitative and qualitative approaches. Mixed methods enable triangulation, enhance the validity of findings, and provide deeper insight into complex human–AI interactions[21].

2.2.1 Quantitative Component

Purpose: Measure knowledge worker perceptions of trust, resistance, and the effect of XAI features.

Instrument: Structured questionnaire using a Likert-scale (1–5) to capture attitudes toward explainability, trust, perceived usefulness, and behavioural intention.

Justification: Quantitative data allows statistical testing of relationships between XAI, trust, and resistance.

2.2.2 Qualitative Component

Purpose: Explore subjective experiences, opinions, and narratives around AI adoption and resistance.

Instrument: Semi-structured interviews with key personnel (Managers, IT staff, HR professionals) to gain insights into organizational culture, AI integration challenges, and perceptions of XAI.

Justification: Provides context, explanation, and deeper understanding of survey results.

2.2.3 Mixed Methods Integration

Quantitative results provide patterns, trends, and correlations, while qualitative insights explain underlying reasons, perceptions, and contextual factors. The integration strengthens conclusions and practical relevance.

2.3 Population of the Study

The population comprises knowledge workers in organizations implementing AI-driven BPA in Nigeria. Knowledge workers are defined as employees performing cognitive, analytical, and decision-intensive tasks. Sectors considered include:

- Banking and finance
- Human resources and administrative operations
- IT and data analytics
- Healthcare
- Logistics and supply chain management

The estimated target population across these sectors is approximately 1,500 employees in medium- and large-scale organizations. Knowledge workers were chosen due to their direct interaction with AI systems and their centrality in ensuring successful adoption.

2.4 Sampling Technique and Sample Size

2.4.1 Sampling Technique

A purposive sampling approach is adopted to select participants who directly interact with AI-driven systems. This ensures respondents are relevant and knowledgeable about the research constructs. Within the selected organizations, participants include:

- IT managers overseeing AI system deployment
- HR managers involved in AI-supported recruitment and HR automation
- Analysts and operations staff using automated tools

2.4.2 Sample Size

The sample size was determined using Cochran's formula for large populations:

$$n_0 = \frac{Z^2 \cdot P(1-P)}{E^2} \quad \dots 1$$

Where:

n_0 is the sample size,

Z = Z score (1.96 for 95% confidence level, and 2.58 for 99% confidence level),

P = estimated proportion of the population (0.5 if not known),

e = Margin error.

$$n_0 = [(1.96)^2 \times 0.5 \times 0.5] / (0.05)^2 = 384$$

Accounting for non-response and incomplete data, a sample of 400 knowledge workers is targeted. For qualitative interviews, 20–25 participants are selected until thematic saturation is achieved.

2.5 Data Collection Instruments

2.5.1 Questionnaire

A structured questionnaire was developed based on established measures relevant to the constructs investigated in the study. The measurement of trust in AI was adapted from Afroogh, which examines trust and distrust in AI and their relationship with technology acceptance. Resistance to technology was adapted from Cieslak, Valor[22], whose study examines the factors underlying employee resistance to digital transformation. Explainability and XAI perceptions were adapted from relevant XAI literature, while behavioural intention and technology acceptance were measured using constructs derived from the Technology Acceptance Model (TAM) developed by Davis. The questionnaire employed a five-point Likert scale ranging from “Strongly Disagree” (1) to “Strongly Agree” (5). The instrument was pre-tested before the main data collection to assess the clarity, relevance, and reliability of the questionnaire items.

2.5.2 Semi-Structured Interviews

Interviews explore:

- Workers’ experiences with AI-driven BPA
- Challenges and barriers to adoption
- Perceptions of fairness, transparency, and accountability
- Impact of explanations on trust and confidence
- Interviews are audio-recorded (with consent) and transcribed for thematic analysis.

2.5.3 Document Review

Organizational policies, training manuals, system logs, and AI deployment reports are reviewed to triangulate findings and understand the organizational context.

2.6 Validity and Reliability

2.6.1 Reliability

Cronbach’s Alpha is used to measure internal consistency of Likert-scale items.

Alpha values ≥ 0.70 are considered acceptable.

Pilot testing of 30 respondents ensures reliability before full-scale data collection.

2.6.2 Validity

Content validity: Reviewed by management experts.

Construct validity: Factor analysis confirms questionnaire items measure intended constructs.

Face validity: Ensures clarity, readability, and comprehension for participants.

2.7 Data Collection Procedure

1. Obtained ethical clearance from relevant institutional review boards.
2. Contacted organizations and secured permission to access knowledge workers.
3. Administered online questionnaires (Google Forms) and collect responses over 3–4 weeks.
4. Conducted semi-structured interviews, either face-to-face or virtually, depending on participant availability.
5. Collect relevant organizational documents to contextualize findings.

2.8 Data Analysis

2.8.1 Quantitative Data Analysis

Descriptive Statistics: Mean, standard deviation, and frequencies summarize perceptions of XAI, trust, and resistance.

Inferential Statistics:

Correlation Analysis examines relationships among variables (e.g., XAI and trust).

Regression Analysis tests hypotheses about the effect of XAI on resistance and trust.

SPSS software is used for statistical computation.

2.8.2 Qualitative Data Analysis

Transcribed interviews were systematically coded to identify recurring themes and patterns using thematic analysis[23].

NVivo software was employed to organize, code, and analyze the qualitative data systematically.

The identified themes were triangulated with the quantitative findings to provide a comprehensive understanding of the research problem.

2.8.3 Mixed-Methods Integration

Quantitative and qualitative findings are merged during interpretation to explain statistical results, highlight patterns, and contextualize human experience.

2.9 Tools and Technologies

1. Excel: Data cleaning, preparation and visualization.
2. NVivo: For coding and thematic analysis of qualitative interviews.
3. Google Forms / Microsoft Forms: For digital questionnaire deployment.
4. SPSS / R: For statistical analysis including regression and correlation.

2.10 Ethical Considerations

Ethical adherence is critical to protect participants and maintain research integrity:

1. Informed Consent: Participants sign consent forms indicating voluntary participation, confidentiality, and anonymity.
2. Privacy: Data is anonymized and stored securely on password-protected systems.
3. Non-Maleficence: Study ensures no psychological, social, or professional harm.
4. Compliance: Ethical approval obtained from the university's institutional review board.
5. Transparency: Participants are briefed about study objectives, methods, and anticipated outputs.

2.11 Limitations of the Methodology

1. Non-Response Bias: Some participants may decline participation, potentially skewing results.
2. Generalizability: Findings may be context-specific to Nigerian organizations, limiting applicability to other countries.
3. Self-Report Bias: Participants may provide socially desirable responses.
4. Rapid Technological Change: AI systems evolve quickly, so perceptions may shift over time.
5. Resource Constraints: Limited access to high-security or proprietary organizational systems may restrict document review.

3. RESULTS AND DISCUSSIONS

3.1 Demographic Characteristics of Respondents

Table 1 and Fig. 1 show the demographic summary of respondents. The study recorded a 95.5% response rate, with 382 of the 400 questionnaires distributed successfully returned, which is acceptable for reliability. Male respondents constituted 55%, while females represented 45%, indicating a fairly balanced gender distribution. The largest age group was 36–45 years (47%), followed by respondents aged 18–25 years (31%), while 10% were 18–25 years, 8% were 46–55 years, and 4% were 56 years and above. Regarding education, Bachelor's degree holders formed the majority (58%), followed by Master's degree holders (31%), Diploma holders (7%), and Doctorate holders (4%). For work experience, respondents with 4–7 years of experience constituted the largest group (39%), followed by 8–12 years (26%), 13–20 years (18%), 0–3 years (10%), and 21 years or more (7%).

Regarding experience with AI systems, 30% had 4–6 years of experience, while 26% had 1–3 years and 13% had less than one year of experience. Overall, the respondents were predominantly educated and experienced knowledge workers, with substantial exposure to AI systems, making them relevant to the study of XAI, trust, resistance, and AI adoption.

Table 1: Demographic Summary of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	210	55%
	Female	172	45%
Age	18–25	40	10%
	36–45	180	47%
	18–25	120	31%
	46–55	30	8%
	56+	12	4%
Education	Diploma	28	7%
	Bachelor's	220	58%
	Master's	120	31%
	Doctorate	14	4%
Work Experience	0–3 years	40	10%
	4–7 years	150	39%
	8–12 years	100	26%
	13–20 years	70	18%
	21+ years	22	7%
Experience with AI Systems	<1 year	50	13%
	1–3 years	120	26%
	4–6 years	100	30%

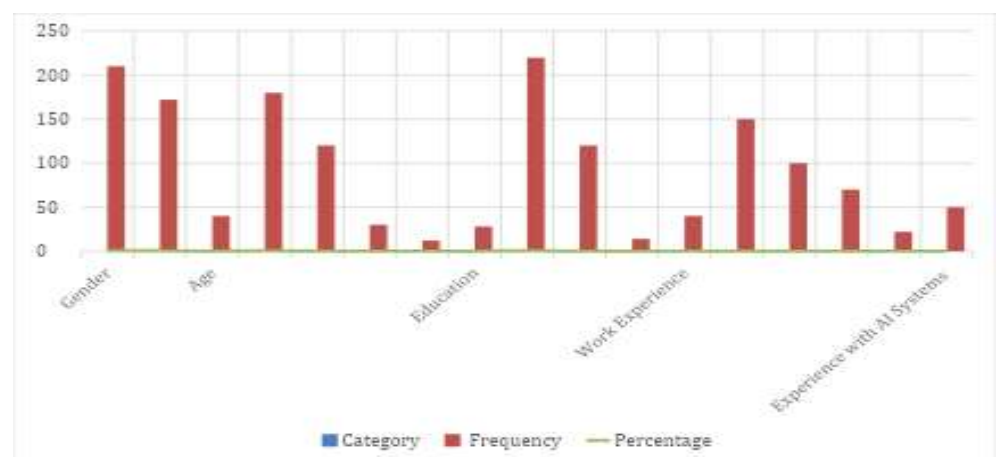


Fig 1: Clustered Column Chart of the Demographic Summary of Respondents

3.2 Descriptive Statistics

Descriptive statistics were computed for key constructs: Resistance, Trust, Explainability, and Behavioral Intention. Responses were measured on a 5-point Likert scale.

Table 2: Mean and Standard Deviation of Key Constructs

Construct	Mean	Std. Dev	Interpretation
Knowledge Worker Resistance	3.45	0.85	Moderate Resistance
Trust in AI	3.82	0.72	High Trust
Explainable AI (XAI)	4.01	0.68	Strong Perception of XAI
Behavioral Intention	3.78	0.74	Hogh Willingness to Adopt AI

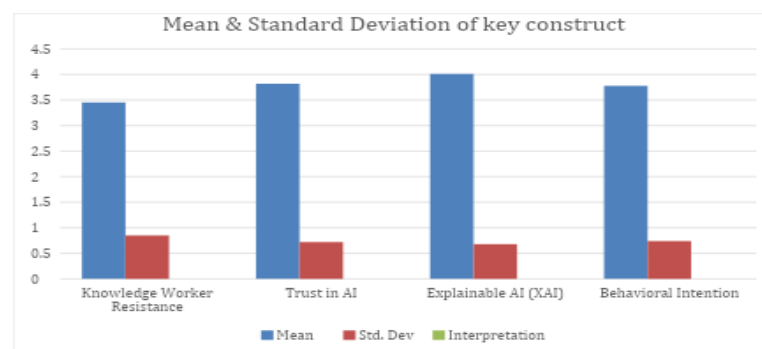


Fig 2: Clustered Column Chart of the Mean and Standard Deviation of Key Constructs

Interpretation:

The findings indicate that respondents exhibited moderate resistance to AI adoption, reflecting some concerns regarding the potential impact of AI on their work processes.

The relatively high mean score for trust in AI (3.82) suggests that respondents generally demonstrated confidence in AI systems. Explainable AI recorded the highest mean score of 4.01, indicating strong recognition of the importance of transparency and interpretability in AI systems. The behavioural intention score of 3.78 demonstrates a relatively high willingness among respondents to adopt AI-driven business process automation. The findings suggest that greater explainability is associated with increased trust and a more positive disposition toward AI adoption.

3.3 Correlation Analysis

Pearson correlation was conducted to examine relationships between XAI, trust, resistance, and behavioural intention.

Table 3: Correlation Matrix

Variables	Correlation	Values
1	Explainable AI (XAI)	1
2	Trust in AI	0.681
3	Resistance	0.57 – 0.631
4	Behavioral Intention	0.710.75 – 0.651

Notes: $p < 0.01$

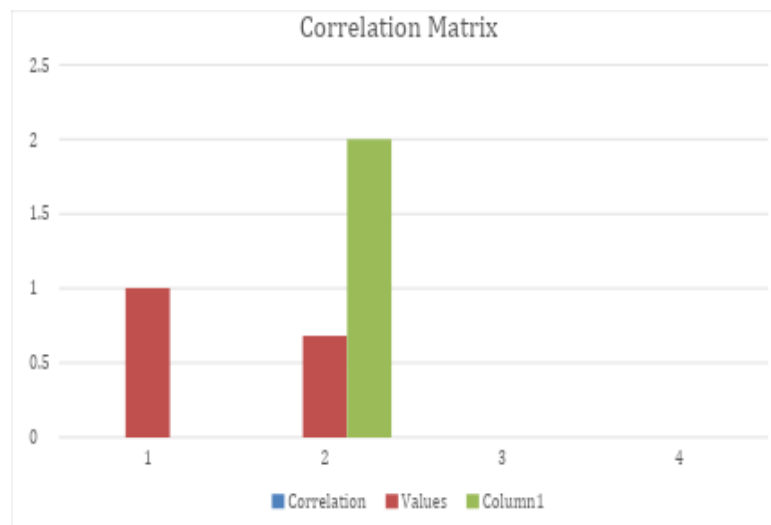


Fig 3: Clustered Bar Chart of the Correlation Matrix

Interpretation:

The correlation analysis indicates a strong positive relationship between XAI and trust ($r = 0.68$), suggesting that greater explainability is associated with increased confidence in AI systems. XAI also shows a strong positive correlation with behavioural intention ($r = 0.71$), indicating greater willingness to adopt AI-driven BPA. Resistance to AI is negatively correlated with XAI ($r = -0.57$), implying that explainability is associated with reduced employee resistance. Similarly, resistance is negatively correlated with trust ($r = -0.63$), indicating that higher trust is associated with lower resistance to AI adoption. Overall, the findings demonstrate that explainability enhances trust and behavioural intention while reducing resistance to AI adoption.

3.4 Regression Analysis

A multiple regression analysis was conducted to test the predictive influence of XAI and trust on knowledge worker resistance and behavioural intention.

Table 4: Regression Results

Dependent Variable	Predictor	β	t-value	p-value
Resistance	XAI	-0.45	-7.32	0.000
Trust	-0.38	-6.18		0.000
Behavioral Intention XAI	-0.51	8.25		0.000
Trust	0.46	7.04		0.000

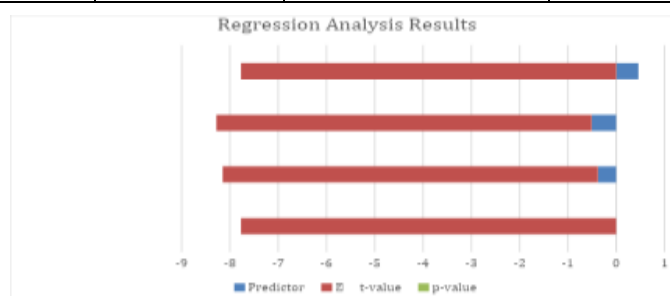


Fig 4: Stacked Bar Chart of the Regression Analysis Results

Interpretation:

The regression analysis shows that XAI is a significant negative predictor of resistance ($\beta = -0.45$, $p < 0.01$), indicating that greater explainability reduces employee resistance to AI. Trust also significantly predicts lower resistance ($\beta = -0.38$, $p < 0.01$), demonstrating its importance in reducing opposition to AI systems. The negative relationship suggests that employees are more likely to accept AI when they understand how its decisions are generated. XAI positively predicts behavioural intention ($\beta = 0.51$, $p < 0.01$), indicating that explainable systems encourage AI adoption. Trust similarly has a positive effect on behavioural intention ($\beta = 0.46$, $p < 0.01$), confirming its contribution to users' willingness to adopt AI. The findings therefore demonstrate that both explainability and trust are important determinants of successful AI acceptance. The model explains approximately 62% of the variance in behavioural intention ($R^2 = 0.62$), indicating strong explanatory power.

3.5 Qualitative Findings

3.5.1 Thematic Analysis

Theme 1: Need for Transparency

- Respondents emphasized that understanding AI reasoning is critical.
- A participant noted:

"When I see why AI made a recommendation, I can trust it more. Otherwise, I feel unsure and resist using it."

Theme 2: Reduced Fear of Job Displacement

- XAI mitigates anxiety about automation replacing humans.
- Another respondent said:

"Explanations show me that AI is assisting, not replacing me. This makes me more open to using it."

Theme 3: Trust as a Mediator

- Trust was consistently mentioned as a precondition for acceptance.
- Participants highlighted that without transparency, even accurate AI results were ignored.

Theme 4: Enhanced Collaboration

- Explainable AI improved human–AI collaboration, enabling knowledge workers to validate decisions and provide inputs.
- Interview excerpts:

"I feel like I am co-deciding with AI rather than being overridden by it."

Theme 5: Organizational Culture and Training

- Several respondents stressed that organizational support, training, and clear communication amplify the benefits of XAI.
- Lack of structured onboarding reduces trust despite explainable features.

3.5.2 Document Review Findings

- Review of AI deployment manuals and workflow automation reports corroborated survey and interview findings.

- Organizations implementing transparent decision logs, visualization dashboards, and explanatory modules reported higher employee engagement and lower resistance.
- Documents also highlighted that training programs complement XAI tools in fostering trust.

3.5.3 Integration of Quantitative and Qualitative Findings

- Quantitative analysis shows XAI significantly reduces resistance and enhances trust, while qualitative narratives explain why: transparency alleviates fear, supports control, and fosters collaboration.
- Behavioural intention aligns with both XAI exposure and organizational support.
- The findings confirm that the human–AI interface is strengthened through explainable features and participatory design, consistent with socio-technical systems theory.

3.5.4 Knowledge Worker Resistance to AI-Driven BPA

The study found that knowledge worker resistance is moderate (mean = 3.45). Quantitative analysis indicated that resistance negatively correlates with both trust ($r = -0.63$) and XAI features ($r = -0.57$). Regression analysis confirmed that both XAI and trust significantly predict resistance ($\beta = -0.45$ and $\beta = -0.38$, respectively, $p < 0.01$).

Interpretation and Literature Integration:

These results align with Oreg's[24] Technology Resistance Theory, which suggests that resistance arises from fear of losing control, uncertainty, and perceived threats to autonomy.

Knowledge workers in Nigerian organizations expressed concerns about job displacement and reduced decision-making authority. This is consistent with McKinsey, who highlighted that automation could trigger apprehension in knowledge-intensive roles.

Qualitative findings emphasize that lack of transparency amplifies resistance. Participants repeatedly noted that when AI systems operate as “black boxes,” employees feel powerless, confirming the need for explainable AI mechanisms.

Implication: Organizations implementing AI-driven BPA must address resistance proactively through transparency, communication, and training, alongside technical deployment.

3.5.5 Trust in AI Systems

The findings indicate high levels of trust in AI systems (mean = 3.82), which positively correlate with both XAI ($r = 0.68$) and behavioural intention ($r = 0.75$). Trust emerged as a critical mediator in the relationship between XAI and knowledge worker adoption of AI.

Interpretation and Literature Integration:

Trust is widely recognized as a prerequisite for technology acceptance. In this study, XAI increased perceived reliability, predictability, and fairness of AI outputs, leading to greater confidence in adoption.

Qualitative responses highlighted that knowledge workers are more willing to collaborate with AI when explanations clarify why and how decisions are made.

Miller[25] asserts that explainable AI enhances human understanding, reduces cognitive dissonance, and supports ethical accountability. The study's findings corroborate this by showing that transparency reduces skepticism and builds confidence.

Implication: Organizations should integrate XAI features such as visualizations, feature importance explanations, and rule-based reasoning to cultivate trust and acceptance. Trust alone, however, is insufficient without accompanying organizational support and training.

3.5.6 Explainable AI and Its Role

The study shows that participants highly value explainable AI features (mean = 4.01), and these features strongly predict behavioural intention to use AI ($\beta = 0.51$, $p < 0.01$). Thematic analysis reveals that transparency, interpretability, and accountability are central to acceptance.

Key Findings and Theoretical Links:

1. Transparency Reduces Resistance:

Participants reported that XAI explanations help demystify AI decisions, reducing fear and opposition.

Consistent with Mersha, transparency is a core XAI principle that mitigates human resistance to automation.

2. Interpretability Supports Collaboration:

Respondents emphasized that explainable outputs allow them to validate and co-decide with AI systems.

This aligns with the human–AI interface framework, which emphasizes shared decision-making and feedback loops.

3. Perceived Fairness and Ethical Alignment:

Knowledge workers are more accepting of AI when explanations demonstrate alignment with organizational values and ethical standards.

This echoes Ryan, who argue that explainable AI promotes fairness, accountability, and ethical compliance.

Implication: XAI is not merely a technical enhancement but a socio-technical enabler, facilitating human–AI collaboration, trust, and adoption.

3.6 Behavioural Intention and Adoption

The study shows that both XAI and trust positively influence behavioural intention to adopt AI-driven BPA. Regression analysis revealed strong predictive effects ($\beta = 0.51$ for XAI, $\beta = 0.46$ for trust, $p < 0.01$).

Interpretation and Literature Integration:

Knowledge workers who understand AI reasoning are more willing to incorporate AI outputs into their workflows.

These findings support the Technology Acceptance Model (TAM) by Davis, where perceived usefulness and ease of understanding increase adoption.

Qualitative findings reinforce that adoption is contingent not only on technical features but also on organizational culture, training, and leadership support.

Implication: To maximize adoption, organizations should combine explainable AI tools with change management strategies, including clear communication, training programs, and continuous feedback mechanisms.

3.6.1 Mediating Role of Trust

The study provides evidence that trust mediates the relationship between XAI and resistance/behavioural intention. This is evident from both statistical correlations and qualitative narratives:

Without trust, even highly explainable AI may be ignored.

Participants emphasized that transparency alone does not guarantee adoption; trust is necessary to bridge human–AI collaboration.

This finding aligns with Afroogh, Miller, confirming that explainability fosters trust, which in turn reduces resistance and enhances adoption.

Implication: XAI initiatives must be designed with a dual focus on technical explainability and human trust-building strategies, including participatory system design and ethical assurances.

3.6.2 Organizational Culture and Human Factors

The study highlights that organizational culture, training, and communication amplify or attenuate the impact of XAI:

Organizations providing structured onboarding, AI literacy programs, and clear workflows experienced higher trust and lower resistance.

Conversely, workplaces with minimal guidance or opaque AI processes reported lingering skepticism, despite XAI features.

This aligns with socio-technical systems theory, emphasizing the interdependence of technology, humans, and organizational structures. Technical solutions alone (e.g., AI algorithms) are insufficient; human factors and cultural readiness are equally critical.

Implication: Successful AI-driven BPA requires integrated socio-technical approaches, combining explainable tools, supportive culture, and continuous engagement.

3.6.3 Cross-Sectoral Observations

Banking and finance respondents demonstrated high trust and adoption, likely due to long-standing digital literacy and exposure to automated tools.

Healthcare and HR respondents showed moderate resistance, highlighting sector-specific challenges, such as ethical concerns and perceived human oversight requirements.

IT departments reported strong alignment between XAI features and productivity, as technical staff better understand algorithmic reasoning.

Implication: XAI deployment strategies should consider sectoral and role-specific nuances, tailoring explanations and training to target audiences.

3.7 Comparison with Previous Studies

McKinsey: Confirmed that AI automation disrupts traditional roles and may elicit resistance. This study extends their findings by showing that XAI reduces such resistance.

1. Miller: Emphasized the role of transparency in trust-building; current study corroborates this in Nigerian organizational contexts.
2. Ryan: Technology Resistance Theory is reinforced; human fear of loss of control is mitigated by explainability.
3. Afroogh: Trust mediates human-AI adoption; validated by survey and interview data in this study.
4. Ryan: Highlighted ethical and fairness dimensions of XAI; supported by qualitative observations regarding perceived fairness.

Overall, this study contributes to theory by integrating XAI, trust, resistance, and adoption in a developing economy context, which is underrepresented in existing literature.

4. Conclusion and Recommendations

The work titled “Human-AI Interface: Assessing the Role of Explainable AI (XAI) in Mitigating Knowledge Worker Resistance and Fostering Trust during AI-Driven Business Process Automation” was carried out using a mixed-methods research design, combining quantitative survey data with qualitative interviews and document review. The results show that knowledge workers experienced moderate resistance to AI adoption, with a mean score of 3.45, while trust in AI and perception of XAI recorded mean scores of 3.82 and 4.01, respectively. The results further show that XAI significantly reduces resistance, enhances trust, and increases behavioural intention to adopt AI-driven business process automation. From the results, it can be concluded that Explainable AI is an important mechanism for reducing knowledge worker resistance, fostering trust, and promoting effective human–AI collaboration in organizational environments. The study further concludes that transparency, clear communication, employee training, and organizational support are essential for achieving successful and sustainable AI adoption. Organizations should integrate explainable AI features into business process automation systems to improve transparency, trust, and employee acceptance. They should also provide continuous AI literacy, training, communication, and employee involvement during AI implementation to reduce fear and resistance. Finally, organizations should establish transparent AI governance frameworks that promote accountability, fairness, ethical use, and effective human–AI collaboration.

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