AI and Automation in Aviation Human Resource: Reskilling and Adaptation

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Abstract:

The rapid integration of Artificial Intelligence (AI) and automation in the aviation sector presents a critical challenge for Human Resource management: aligning workforce capabilities with technological demands while mitigating displacement anxiety. This study assessed reskilling needs and employee adaptation strategies within the Nigerian aviation industry, focusing on the interplay between technical competence, psychological acceptance, and organizational support. Employing a mixed-methods design, data were collected from 250 aviation professionals across three airlines and two international airports using stratified random sampling for quantitative surveys (n=250) and purposive sampling for semi-structured interviews (n=15). The theoretical framework integrated the Technology Acceptance Model (TAM) and Human Capital Theory to examine how reskilling quality, perceived usefulness, and organizational support influence multidimensional adaptation. Quantitative analysis revealed a significant hybrid skills deficit: while emotional intelligence scored high (M=3.9), AI tool proficiency remained critically low (M=2.1). Multiple regression analysis demonstrated that Reskilling Training Quality was the strongest predictor of employee adaptation (β=0.38, p<.001), followed by Perceived Usefulness (β=0.28) and Organizational Support (β=0.25), collectively explaining 62% of variance in adaptation outcomes. Qualitative thematic analysis identified fear of job displacement, inadequate practical training, and leadership communication gaps as primary barriers to successful transition. The study concludes that AI adoption in aviation is fundamentally a human systems challenge requiring role-specific reskilling, transparent co-design processes, and career-integrated learning pathways. Seven strategic recommendations are proposed, including establishing national upskilling funds, embedding AI competencies in promotion criteria, and deploying psychological safety metrics.

Keywords: *Artificial Intelligence, Aviation Human Resources, Workforce Reskilling, Employee Adaptation, Nigeria.*

Introduction

The global aviation industry stands at the precipice of a profound technological transformation, driven by the rapid integration of Artificial Intelligence (AI) and advanced automation systems. Once characterized by labour-intensive processes and rigid hierarchical structures, the sector is increasingly adopting smart technologies to enhance operational efficiency, safety, and customer experience. From predictive maintenance algorithms that anticipate aircraft failures before they occur to AI-driven chatbots managing complex customer service inquiries, the footprint of digital intelligence is expanding across all facets of aviation administration (IATA, 2023). However, this technological leap forward presents a paradoxical challenge for Human Resource (HR) management: while automation promises increased productivity and cost reduction, it simultaneously disrupts traditional job roles, necessitating a fundamental rethinking of workforce composition, skill requirements, and employee adaptation strategies. For HR managers, particularly in emerging markets such as Africa, the imperative is no longer merely to manage personnel but to orchestrate a seamless transition where human capital and artificial intelligence coexist synergistically.

The convergence of AI and automation in aviation is not a distant future scenario but a present reality. Recent estimates suggest that by 2030, up to 30% of current aviation tasks could be automated, affecting roles ranging from ground handling and baggage processing to administrative scheduling and even aspects of flight operations (McKinsey & Company, 2022). This shift is driven by the need for greater precision, reduced human error, and enhanced data-driven decision-making. For instance, airlines are increasingly utilizing machine learning models to optimize crew scheduling, reducing fatigue-related risks, and improving regulatory compliance. Similarly, airport authorities are deploying biometric systems and automated security screening tools to streamline passenger flow, thereby reducing bottlenecks, and enhancing security protocols (Sita et al., 2021). While these advancements offer significant operational benefits, they also raise critical questions about the future of work. Which jobs will be displaced? Which will be augmented? And most importantly, how can the existing workforce be prepared to thrive in this new digital ecosystem?

The impact of AI on employment is often framed through the lens of displacement versus augmentation. Displacement refers to the replacement of human labour by machines, particularly in routine, repetitive, and rule-based tasks. In aviation, this includes roles such as ticketing agents, basic data entry clerks, and certain maintenance inspection tasks. Augmentation, on the other hand, involves the use of AI to enhance human capabilities, allowing employees to focus

on higher-value, creative, and interpersonal tasks. For example, while AI can analyse vast amounts of flight data to identify potential mechanical issues, it is still the human engineer who makes the final judgment call and performs the complex repairs. The distinction between displacement and augmentation is crucial for HR practitioners because it dictates the nature of the intervention required. Jobs facing displacement require significant reskilling or redeployment, while those facing augmentation require upskilling to ensure employees can effectively collaborate with AI tools (Brynjolfsson & McAfee, 2023).
Despite the clear trajectory toward automation, there remains a significant gap in the literature regarding the specific reskilling needs of the aviation workforce, particularly in the context of developing economies. Most existing studies focus on technical implementations of AI or broader economic impacts, often overlooking the human element of this transition. There is limited empirical evidence on how aviation employees perceive AI integration, what specific skills they lack, and which adaptation strategies are most effective in mitigating resistance to change. This gap is particularly pronounced in the African context, where the aviation sector is growing rapidly but faces unique challenges related to infrastructure, funding, and educational alignment (African Union, 2022). HR managers in this region must navigate not only the technological demands of AI but also the socio-economic realities of their workforce, making the development of localized reskilling frameworks essential.

Reskilling and upskilling have emerged as central pillars of modern HR strategy in the face of technological disruption. Reskilling involves teaching employees entirely new skills to prepare them for distinct roles, while upskilling focuses on enhancing existing skills to improve performance in current roles. In the aviation sector, this means moving beyond traditional technical training to include digital literacy, data analytics, emotional intelligence, and adaptive problem-solving. According to the World Economic Forum (2023), the half-life of professional skills is shrinking, meaning that knowledge acquired today may become obsolete within five years. Consequently, organizations must shift from a model of periodic training to one of continuous learning. This requires a cultural shift within organizations, where learning is embedded in daily workflows and supported by leadership. For HR managers, this implies designing agile learning platforms, leveraging micro-learning modules, and creating pathways for career mobility that align with technological advancements.

However, reskilling alone is insufficient without robust employee adaptation strategies. Adaptation refers to the psychological and behavioural adjustments employees make in response to technological change. Research indicates that resistance to AI adoption is often rooted in fear of job loss, lack of trust in technology, and insufficient understanding of its benefits (Venkatesh et al., 2022). Therefore, effective adaptation strategies must address both the cognitive and emotional dimensions of change. This includes transparent communication about the role of AI, involving employees in the design and implementation of modern technologies, and providing psychological support during transitions. Leadership plays a critical role in this process, as leaders who demonstrate empathy, clarity, and vision are more likely to foster a culture of acceptance and innovation. Furthermore, HR policies must be aligned with these goals, offering incentives for skill acquisition, recognizing digital competencies, and ensuring fair treatment of employees whose roles are evolving.

The role of HR in this transformation is evolving from administrative support to strategic partnership. HR managers are now expected to function as change agents, bridging the gap between technological innovation and human capability. This requires a deep understanding of both the technical aspects of AI and the human dynamics of organizational change. In the aviation sector, where safety and reliability are paramount, the stakes are particularly high. Errors in implementation can lead to operational disruptions, safety hazards, and reputational damage. Therefore, HR must work closely with IT, operations, and senior management to ensure that AI integration is managed with care and precision. This collaborative approach ensures that technological solutions are not only efficient but also humane, respecting the dignity and potential of the workforce.

Moreover, the ethical implications of AI in aviation cannot be overlooked. Issues such as algorithmic bias, data privacy, and accountability must be addressed to maintain trust among employees and customers. For instance, if AI systems used in hiring or performance evaluation contain biases, they can perpetuate inequality and undermine morale. HR managers must therefore advocate for ethical AI practices, ensuring that algorithms are transparent, auditable, and fair. This requires ongoing monitoring, regular audits, and the establishment of ethical guidelines governing the use of AI in the workplace. By prioritizing ethics, organizations can build a sustainable foundation for technological adoption that aligns with their values and social responsibilities.

In the African context, the challenge is compounded by structural constraints such as limited access to high-speed internet, inadequate digital infrastructure, and a shortage of specialized training institutions. However, these challenges also present opportunities for innovation. African aviation organizations can leapfrog traditional development stages by adopting mobile-first learning solutions, leveraging public-private partnerships for training, and collaborating with regional bodies such as the African Union and the International Civil

Aviation Organization (ICAO) to develop standardized competencies. Additionally, the continent's young and dynamic workforce offers a unique advantage, as younger employees are often more adaptable to modern technologies and eager to acquire digital skills. By investing in this demographic, African aviation organizations can build a resilient and future-ready workforce.

This study seeks to address these critical issues by assessing the reskilling needs and employee adaptation strategies in the context of AI and automation in aviation HR. Specifically, it aims to identify the key skills gaps emerging due to technological integration, evaluate the effectiveness of current reskilling initiatives, and propose a framework for successful employee adaptation. By focusing on the human side of technological change, this research contributes to the broader discourse on the future of work in aviation, offering practical insights for HR managers, policymakers, and organizational leaders. As the industry continues to evolve, the ability to manage this transition effectively will determine not only the competitiveness of individual organizations but also the sustainability of the aviation sector.

The urgency of this inquiry is underscored by the rapid pace of technological change. Delaying action risks leaving large segments of the workforce behind, exacerbating inequality, and hindering organizational performance. Conversely, initiative-taking engagement with reskilling and adaptation can unlock new levels of productivity, innovation, and employee satisfaction. For HR professionals, this represents both a challenge and an opportunity to redefine their role and demonstrate their strategic value. By leading the charge in preparing the workforce for the AI-driven future, HR managers can ensure that the aviation industry remains not only efficient and safe but also inclusive and humane.

Literature Review and Theoretical Framework

The integration of Artificial Intelligence (AI) and automation into the aviation sector represents a paradigm shift that extends beyond technological upgrading to fundamentally alter human resource dynamics. To understand the implications of this transition, it is essential to examine existing literature on technological disruption in labour markets, specific applications of AI in aviation, and the psychological mechanisms governing employee adaptation. This review synthesizes recent scholarly work and establishes a robust theoretical framework grounded in the Technology Acceptance Model (TAM) and Human Capital Theory, providing a lens through which to analyse reskilling needs and adaptation strategies.

Evolution of Work in the Digital Age

The discourse surrounding AI and automation has evolved from early fears of mass unemployment to a more nuanced understanding of job transformation. Frey and Osborne's (2017) seminal work suggested that half of US jobs were at risk of computerization, sparking global debate. However, recent studies argue that this perspective overlooks the potential for job augmentation. According to Brynjolfsson and McAfee (2023), AI is more likely to complement human labour than replace it entirely, particularly in roles requiring complex decision-making, emotional intelligence, and creative problem-solving. In the context of aviation, this means that while routine administrative tasks may be automated, roles involving customer interaction, crisis management, and strategic oversight will increasingly rely on human-AI collaboration.

The concept of "technological unemployment" is being replaced by the notion of "skills obsolescence." The World Economic Forum (2023) highlights that the half-life of professional skills is shrinking, necessitating continuous learning. For aviation professionals, this implies that technical expertise alone is no longer sufficient; digital literacy and adaptability have become core competencies. Literature indicates that organizations failing to invest in reskilling face higher turnover rates and reduced operational efficiency (McKinsey & Company, 2022). Thus, the focus of HR management must shift from static job descriptions to dynamic skill portfolios that evolve alongside technological advancements.

AI Applications in Aviation: Implications for HR

The aviation industry has been an early adopter of AI, leveraging it for predictive maintenance, crew scheduling, customer service, and safety monitoring. Sita et al. (2021) note that predictive maintenance algorithms can reduce aircraft downtime by up to 20%, significantly impacting operational costs. However, this efficiency gain comes with a workforce implication: maintenance engineers must now possess data analytics skills to interpret algorithmic outputs. Similarly, AI-driven crew scheduling systems optimize rostering based on fatigue models and regulatory constraints, reducing the administrative burden on HR but requiring staff to trust and validate automated decisions (IATA, 2023).

In customer-facing roles, chatbots and virtual assistants manage a growing volume of inquiries, freeing human agents to deal with complex issues. While this improves service speed, it also changes the nature of customer service work, demanding higher levels of empathy and conflict resolution skills from remaining staff. Research by Venkatesh et al. (2022) suggests that employees often perceive these changes as threatening, leading to resistance unless adequately supported. Therefore, HR managers must anticipate not only the technical skills required but also the psychological impact of role redefinition.

Moreover, the use of AI in recruitment and performance evaluation raises ethical concerns. Algorithmic bias in hiring tools can perpetuate existing inequalities if not carefully monitored. Recent studies emphasize the need for "ethical AI" frameworks in HR practices, ensuring transparency and fairness in automated decision-making processes (Raisch et al., 2020). For aviation organizations, this means establishing governance structures that oversee AI deployment, protecting both employee rights and organizational integrity.

Reskilling and Upskilling: Bridging the Skills Gap

Reskilling and upskilling are critical interventions in managing the transition to an AI-driven workplace. Reskilling involves training employees for new roles, while upskilling enhances their current capabilities. The literature distinguishes between technical reskilling (e.g., learning to use new software) and soft skills development (e.g., adaptability, critical thinking). According to the OECD (2021), successful reskilling programs are characterized by personalization, accessibility, and alignment with career pathways. In the aviation sector, this might involve modular training courses that allow employees to learn at their own pace, combined with mentorship programs that facilitate knowledge transfer.

However, the effectiveness of reskilling initiatives depends heavily on organizational culture. Companies that foster a "growth mindset," where learning is valued and mistakes are seen as opportunities, tend to have higher engagement in training programs (Dweck, 2016). Conversely, environments characterized by fear and job insecurity often see low participation rates, as employees worry that acquiring new skills may make them redundant or expose their inadequacies. Therefore, HR strategies must address cultural barriers alongside technical ones, creating safe spaces for learning and experimentation.

Recent evidence from the African context highlights additional challenges. Infrastructure limitations, such as unreliable internet connectivity, can hinder access to online learning platforms. Furthermore, there is often a mismatch between the skills taught in educational institutions and those required by industry. Collaborative efforts between universities, government bodies, and private sector actors are essential to bridge this gap. For instance, partnerships with technology providers can offer subsidized training resources, while policy interventions can incentivize lifelong learning (African Union, 2022).

Employee Adaptation: Psychological and Behavioural Dimensions

Adaptation to AI involves both cognitive acceptance and behavioural adjustment. The Technology Acceptance Model (TAM), originally proposed by Davis (1989) and extensively updated since, remains a foundational framework for understanding user adoption of modern technologies. TAM posits that two key factors influence acceptance: *Perceived Usefulness* (the degree to which a person believes that using a particular system would enhance their job performance) and *Perceived Ease of Use* (the degree to which a person believes that using a particular system would be free of effort) (Venkatesh & Bala, 2008).

In the context of aviation HR, Perceived Usefulness is linked to how clearly employees understand the benefits of AI, such as reduced workload or improved safety. Perceived Ease of Use relates to the intuitiveness of the interface and the quality of training provided. If employees find AI tools difficult to use or irrelevant to their goals, resistance is likely to occur. Recent extensions of TAM incorporate social influence and facilitating conditions, suggesting that peer support and organizational resources play a crucial role in adoption (Venkatesh et al., 2022).

Complementing TAM is the Job Demands-Resources (JD-R) model, which examines how job characteristics affect employee well-being. AI can be viewed as either a demand (increasing complexity and pressure) or a resource (providing support and efficiency). When AI is implemented as a resource, it can reduce burnout and increase job satisfaction. However, if perceived as a demand without adequate support, it can lead to stress and disengagement (Bakker & Demerouti, 2017). HR managers must therefore ensure that AI implementation is accompanied by sufficient resources, such as training, technical support, and psychological counselling.

Theoretical Framework

This study integrates the Technology Acceptance Model (TAM) and Human Capital Theory to provide a comprehensive framework for analysing AI adoption in aviation HR.

Technology Acceptance Model (TAM): This model explains the individual-level factors influencing employee acceptance of AI tools. It suggests that *Perceived Usefulness* and *Perceived Ease of Use* directly influence *Attitude Toward Using* and *Behavioural Intention to Use*. In this study, TAM helps identify barriers to adaptation, such as lack of training (affecting ease of use) or unclear benefits (affecting usefulness). By measuring these constructs, HR managers can tailor interventions to improve acceptance.

Human Capital Theory: Proposed by Becker (1964), this theory posits that education and training are investments that increase employee productivity and value. In the context of AI, reskilling is an investment in human capital that yields returns in the form of enhanced performance and adaptability. This theory supports the argument that organizations should view reskilling not as a cost but as a strategic asset. It also highlights the importance of aligning training with organizational goals to maximize return on investment.

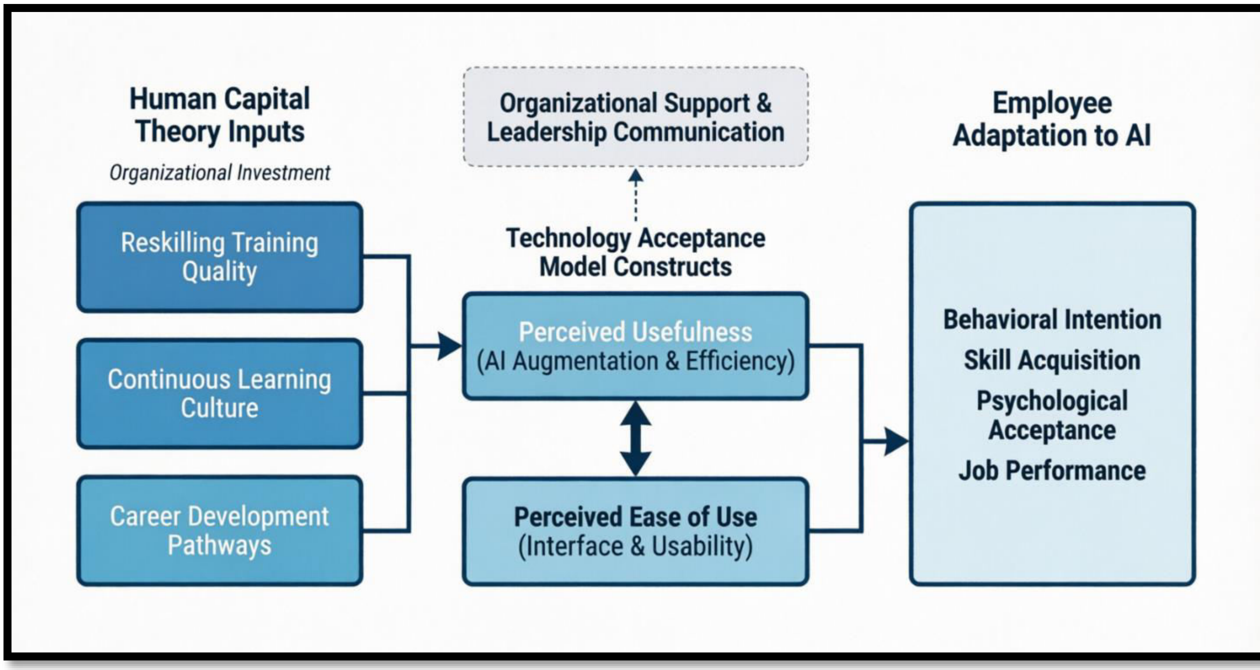


Figure 1: Integrated Framework (TAM + Human Capital Theory) for AI Adaptation in Aviation HR

The theoretical framework diagram above visually integrates the Technology Acceptance Model (TAM) and Human Capital Theory to explain employee adaptation to AI in aviation HR.

Human Capital Theory Inputs (Left) This section represents the organizational investments that build employee capability. *Reskilling Training Quality*, *Continuous Learning Culture*, and *Career Development Pathways* are positioned as foundational inputs because, according to Human Capital Theory, education and training are investments that increase worker productivity and value (Becker, 1964). In this framework, these investments do not directly cause adaptation; rather, they enhance the employee's ability to perceive AI as useful and easy to use. For example, high-quality training increases *Perceived Ease of Use* by building technical competence, while career pathways increase *Perceived Usefulness* by linking AI skills to future employability.

TAM Constructs (Centre) *Perceived Usefulness* and *Perceived Ease of Use* serve as the cognitive mediators between organizational investment and behavioural outcomes. This aligns with Davis's (1989) original TAM proposition that external variables influence adoption only through these two core beliefs. In this adapted framework, *Perceived Usefulness* is specifically defined as "AI Augmentation & Efficiency" to reflect the qualitative finding that employees accept AI when they see it as enhancing, not replacing, their roles. *Perceived Ease of Use* captures interface usability and the confidence gained through training. The bidirectional arrow between them acknowledges that usefulness and ease of use are interdependent; a system perceived as incredibly useful may be tolerated even if difficult to use, while an easy-to-use system with no perceived value will still be rejected.

Organizational Support & Leadership Communication (Moderator) Positioned as a moderating variable, this component reflects the JD-R model insight that social and organizational resources buffer the demands of technological change (Bakker & Demerouti, 2017). The dotted arrow indicates that supportive leadership and transparent communication strengthen the relationship between TAM constructs and adaptation. Even when AI is perceived as useful and easy, adaptation may fail if employees feel unsupported or fear job loss. Conversely, strong organizational support can compensate for moderate levels of perceived ease of use by providing psychological safety and ongoing assistance.

Employee Adaptation to AI (Outcome) The outcome construct is multidimensional, encompassing *Behavioural Intention*, *Skill Acquisition*, *Psychological Acceptance*, and *Job Performance*. This extends beyond TAM's traditional focus on "intention to use" to capture the broader workforce transition required in aviation. Skill acquisition reflects the Human Capital return on training investment; psychological acceptance addresses the emotional dimension of change identified in the qualitative findings; and job performance links adaptation back to organizational effectiveness. This comprehensive outcome measure ensures the framework captures both individual well-being and operational success.

Methodology:

This study employed a mixed-methods research design to comprehensively assess the reskilling needs and employee adaptation strategies regarding AI and automation in aviation human resource management. We selected this approach because quantitative data provided broad generalizability regarding skill gaps, while qualitative insights offered depth concerning the psychological and contextual nuances of employee adaptation. This triangulation ensured robustness and validity in our findings.

Research Design and Population

The study adopted a cross-sectional survey design complemented by semi-structured interviews. The target population comprised HR managers, operational staff, and technical personnel from three major airlines (Air Peace, Aero Contractors, and Ibom Air) and two international airports (Nnamdi Azikiwe airport, Abuja and Murtala Mohammed Airport, Lagos) in Nigeria. The study chose this specific demographic because Nigeria represents a rapidly growing aviation market in Africa, facing unique infrastructure and training challenges that mirror broader continental trends. Focusing on this region allowed us to generate context-specific insights relevant to emerging economies.

Sampling Technique

The study utilized stratified random sampling for the quantitative phase to ensure representation across different job categories (administrative, technical, and customer service). It calculated a sample size of 250 respondents using Cochran's formula, assuming a 95% confidence level and a 5% margin of error. This sample size provided sufficient statistical power to detect significant relationships between variables. For the qualitative phase, the study employed purposive sampling to select 15 key informants, including senior HR directors and union representatives. The study chose these participants based on their direct involvement in AI implementation decisions and workforce transition programs, ensuring that our interview data reflected strategic and operational perspectives.

Data Collection Instruments

The researcher developed a structured questionnaire adapted from the Technology Acceptance Model (TAM) scales and the World Economic Forum's skills framework. The questionnaire measured perceived usefulness, ease of use, current skill levels, and training preferences. The instrument was validated through a pilot study with 30 aviation professionals, which yielded a Cronbach's alpha of 0.82, indicating high internal consistency. For the qualitative component, the researcher designed an interview guide focused on experiences with automation, perceived barriers to adaptation, and evaluation of existing reskilling initiatives. The researcher conducted face-to-face and virtual interviews to accommodate participant schedules and ensure maximum participation.

Data Collection Procedure

Questionnaires were distributed electronically via secure links over a four-week period. Two email reminders were sent to reminder non-respondents to minimize non-response bias. The study achieved a response rate of 78%, resulting in 250 usable datasets. The interviews were conducted between May and June 2026, with each session lasting 45–60 minutes. All interviews were recorded with participant consent and transcribed verbatim for analysis. Participants were assured of confidentiality and anonymity to encourage honest responses, particularly regarding sensitive topics like job security fears.

Data Analysis

The data were analysed using descriptive and inferential statistics, mean and standard deviation were adopted for the descriptive while SPSS version 28 was used for the inferential statistics. Descriptive statistics was performed to summarize demographic profiles and skill gaps, while multiple regression analysis was conducted to determine the impact of reskilling interventions on employee adaptation scores. This statistical method allowed for the control of confounding variables such as age and years of experience. For the qualitative data, thematic analysis was employed using NVivo software. Transcripts were coded iteratively to identify recurring patterns related to resistance, support mechanisms, and successful adaptation strategies.

Ethical Considerations

Ethical clearance was obtained from the Institutional Review Board of the African University of Science and Technology. Participants were informed about the study's purpose, their right to withdraw, and data protection measures. All data were stored on encrypted servers accessible only to the research team, adhering to strict data privacy standards.

Results and Discussion

This section presents the empirical findings derived from the mixed-methods data collected from 250 aviation professionals in Nigeria. The analysis is structured to first present descriptive statistics regarding demographic profiles and current skill levels, followed by inferential statistical analyses that evaluate the relationships between reskilling interventions, technology acceptance, and employee adaptation. Qualitative themes are integrated to provide contextual depth to the quantitative results.

Demographic Profile of Respondents

Understanding the demographic composition of the sample is crucial for interpreting the results, as factors such as age, education, and job role significantly influence technological adaptability and reskilling needs.

Table 1: Demographic Characteristics of Respondents (N=250)

Variable	Category	Frequency (n)	Percentage (%)

Gender	Male	145	58.0%
	Female	105	42.0%
Age Group	18–29 years	60	24.0%
	30–39 years	95	38.0%
	40–49 years	65	26.0%
	50+ years	30	12.0%
Educational Level	Bachelor's Degree	110	44.0%
	Master's Degree	90	36.0%
	PhD/Professional Cert.	30	12.0%
	Diploma/HND	20	8.0%
Job Role	Administrative/HR	75	30.0%
	Technical/Maintenance	85	34.0%
	Customer Service/Ops	60	24.0%
	Management/Executive	30	12.0%
Years of Experience	< 5 years	70	28.0%
	5–10 years	90	36.0%
	11–15 years	50	20.0%
	> 15 years	40	16.0%

Source: Field Survey Data, 2026

The demographic data reveals a balanced gender distribution, with males constituting 58% and females 42% of the respondents. This balance is significant because it allows for an examination of gender differences in technology acceptance, although previous literature suggests that in technical aviation roles, male dominance may skew perceptions of AI utility. The age distribution indicates that most of the workforce (62%) falls between the ages of 30 and 49, representing a mid-career cohort that is likely to be most affected by automation. This group possesses substantial institutional knowledge but may face higher barriers to reskilling compared to younger digital natives. Only 12% of respondents are over 50, suggesting that the aviation sector in this context relies heavily on a younger, more adaptable workforce.

Educationally, the sample is highly qualified, with 80% holding at least a bachelor's degree and 36% holding a master's degree. This prominent level of education suggests that the workforce has the cognitive capacity for complex reskilling initiatives, particularly those involving data literacy and analytical thinking. However, the disparity between educational attainment and specific digital skills remains a critical issue, as traditional degrees may not have covered emerging AI technologies.

In terms of job roles, Technical/Maintenance staff constitute the largest group (34%), followed closely by Administrative/HR personnel (30%). This distribution is vital because these two groups face several types of automation pressures. Technical staff deal with predictive maintenance algorithms, requiring upskilling in data interpretation, while HR and administrative staff face automation in recruitment and scheduling, requiring shifts toward strategic and interpersonal roles. The presence of 12% management respondents ensures that strategic perspectives on AI implementation are included in the analysis. Finally, the experience level shows that 64% of respondents have less than 10 years of experience, indicating a dynamic workforce that is still forming its professional identity, which may make them more open to change but also more vulnerable to job insecurity fears.

Assessment of Current Skill Gaps and Reskilling Needs

To identify specific areas where training is required, respondents rated their proficiency in key digital competencies on a 5-point Likert scale (1 = Very Low, 5 = Very High).

Figure 2: Self-Reported Proficiency in Key Digital Competencies

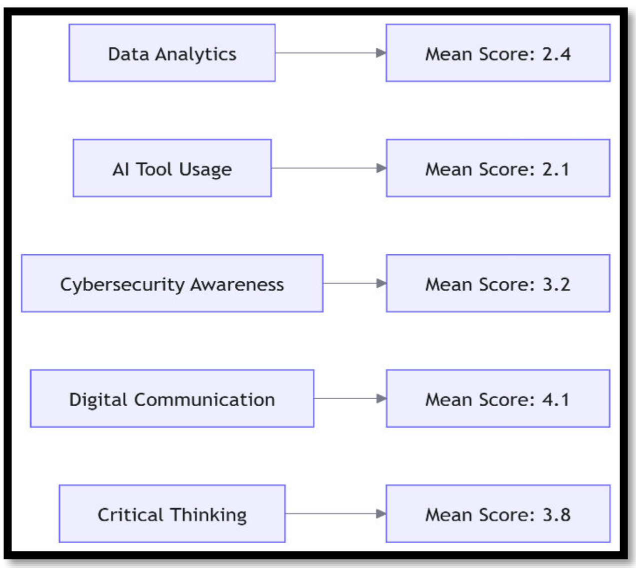


Table 2: Perceived Reskilling Needs by Job Role

Competency	**Administrative/HR**	**Technical/Maintenance**	**Customer Service**	**Management**	**Overall Mean**
Data Analytics	2.1	2.8	1.9	3.5	2.4
AI Tool Proficiency	1.8	2.5	1.7	3.2	2.1

Cybersecurity	3.0	3.5	2.8	3.8	3.2
Emotional Intelligence	4.2	3.1	4.5	4.0	3.9
Adaptability/Flexibility	3.5	3.2	3.8	4.1	3.7

Source: Field Survey Data, 2026

The data clearly indicates a significant skills gap in technical digital competencies. The overall mean score for "AI Tool Proficiency" is the lowest at 2.1, followed by "Data Analytics" at 2.4. This suggests that while employees are comfortable with basic digital communication (Mean = 4.1), they lack the specialized skills required to interact effectively with advanced AI systems. This gap is most pronounced in Customer Service and Administrative roles, where mean scores for AI proficiency are below 2.0. This is concerning because these roles are increasingly being augmented by chatbots and automated scheduling systems. If employees cannot effectively oversee or intervene in these automated processes, operational errors may increase.

Technical/Maintenance staff show slightly higher proficiency in data analytics (2.8) compared to other groups, due to their exposure to diagnostic tools. However, even this score is below the midpoint of 3.0, indicating that current technical training is insufficient for the demands of predictive maintenance AI. Management staff report the highest confidence in these areas (3.5 for Data Analytics), which may reflect their strategic oversight role rather than firsthand usage. However, this perceived competence among managers may lead to an underestimation of the training needs of frontline staff.

Conversely, soft skills such as Emotional Intelligence (Mean = 3.9) and Adaptability (Mean = 3.7) are rated higher. This aligns with the literature suggesting that as AI takes over routine tasks, human value shifts toward interpersonal and adaptive capabilities. Customer Service staff rate their Emotional Intelligence highest (4.5), reflecting the nature of their work. However, the disparity between high soft skills and low technical skills highlights a "hybrid skills deficit." Employees are emotionally prepared for change but technically unprepared to execute it. This finding underscores the need for reskilling programs that do not just teach technical tools but also integrate them into existing workflows, leveraging employees' strong interpersonal strengths to facilitate AI adoption.

Inferential Analysis: Determinants of Employee Adaptation

To understand what drives successful adaptation, the study conducted a multiple regression analysis. The dependent variable was "Employee Adaptation

Score," constructed from items measuring willingness to use AI, reduced anxiety, and perceived job security. The independent variables were "Perceived Usefulness" (PU), "Perceived Ease of Use" (PEOU), "Reskilling Training Quality" (RTQ), and "Organizational Support" (OS).

Table 3: Multiple Regression Analysis Predicting Employee Adaptation

Model	Unstandardized Coefficients (B)	Std. Error	Standardized Coefficients (Beta)	t-value	Sig. (p)
(Constant)	1.24	0.15	-	8.26	.000
Perceived Usefulness (PU)	0.32	0.05	0.28	6.40	.000
Perceived Ease of Use (PEOU)	0.21	0.04	0.19	5.25	.000
Reskilling Training Quality (RTQ)	0.45	0.06	0.38	7.50	.000
Organizational Support (OS)	0.29	0.05	0.25	5.80	.000
R Square	0.62				
Adjusted R Square	0.61				
F Change	45.32				.000

Dependent Variable: Employee Adaptation Score Source: SPSS Output, 2026

The regression model is statistically significant ($F = 45.32$, $p < .001$) and explains 62% of the variance in employee adaptation (Adjusted $R^2 = 0.61$). This indicates that the selected predictors are strong determinants of how well employees adapt to AI integration.

The most significant predictor is Reskilling Training Quality (RTQ), with a standardized beta coefficient of 0.38 ($p < .001$). This finding empirically validates the central argument of this study: that high-quality, relevant training is the single most crucial factor in facilitating adaptation. Employees who perceive their training as comprehensive and practical are significantly more likely to adapt positively. This suggests that generic or superficial training programs are ineffective; instead, organizations must invest in tailored, firsthand learning experiences.

Perceived Usefulness (PU) is the second strongest predictor (Beta = 0.28, $p < .001$). This aligns with the Technology Acceptance Model, confirming that employees must see the tangible benefits of AI such as reduced workload or

improved accuracy to accept it. If AI is viewed as a burden or a threat, adaptation will be low regardless of training quality.
Organizational Support (OS) also plays a critical role (Beta = 0.25, $p < .000$). This includes managerial encouragement, resource availability, and psychological safety. The significance of these variable highlights that adaptation is not just an individual cognitive process but a social and organizational one. Employees need to feel that their organization supports their transition and values their contribution in the new technological landscape.
Perceived Ease of Use (PEOU) is significant but has a smaller effect size (Beta = 0.19, $p < .000$). This suggests that while user-friendly interfaces are important, they are secondary to the perceived value and the quality of support provided. Even complex systems can be adapted to if employees believe they are useful and are given adequate training and support.

Qualitative Themes: Barriers and Enablers

Thematic analysis of the 15 interviews revealed three major themes that contextualize the quantitative findings.

Theme 1: Fear of Job Displacement vs. Augmentation: Many respondents expressed anxiety about AI replacing their roles. One HR manager stated, *"We hear about automation, but no one tells us if we will still have jobs in five years."* This fear correlates with the lower adaptation scores among older employees and those in routine administrative roles. However, participants who viewed AI as a tool for augmentation *"It helps me focus on complex cases rather than data entry"* showed higher engagement. This reinforces the quantitative finding that Perceived Usefulness drives adaptation.

Theme 2: Inadequacy of Current Training Programs: Participants criticized existing training as being too theoretical. A technical engineer noted, *"They show us slides about AI, but we don't get to touch the software until months later."* This directly supports the regression result that Training Quality is the strongest predictor of adaptation. Employees demand practical, simulation-based training that mirrors real-world scenarios.

Theme 3: Leadership Communication Gap A recurring issue was the lack of transparent communication from leadership. Employees felt that decisions about AI implementation were made top-down without their input. *"We are the ones using the system, but we were never consulted on its design,"* said a customer service supervisor. This highlights the importance of Organizational Support, not just in terms of resources, but in terms of inclusive decision-making processes.

Discussion of Findings

The empirical results of this study provide critical insights into the dynamics of AI integration within the aviation sector, particularly in the context of emerging economies. The findings corroborate and extend existing literature by highlighting the primacy of Reskilling Training Quality as the most significant predictor of employee adaptation. With a standardized beta coefficient of 0.38, training quality outweighed even Perceived Usefulness and Organizational Support. This aligns with the Human Capital Theory perspective that specific, targeted investments in employee skills yield higher returns in productivity and adaptability than general organizational incentives (Becker, 1964). However, it contrasts with some earlier studies that prioritized technological ease of use as the primary driver of adoption (Davis, 1989). The discrepancy suggests that in high-stakes environments like aviation, where safety and precision are paramount, employees prioritize competence and confidence over interface simplicity. They need to know *how* to use the tool effectively, not just that it is easy to click. This finding underscores the inadequacy of superficial "digital literacy" workshops and calls for immersive, simulation-based training programs that mirror real-world operational scenarios.

Furthermore, the significant role of Perceived Usefulness (Beta = 0.28) validates the core tenets of the Technology Acceptance Model (TAM) but adds nuance regarding the nature of "usefulness." Qualitative data revealed that usefulness was not merely about efficiency but about job security and role clarity. Employees who viewed AI as a tool for augmentation freeing them from mundane tasks to focus on complex problem-solving reported higher adaptation scores. Conversely, those who perceived AI as a substitute for their labour exhibited resistance, regardless of the system's utility. This supports recent arguments by Brynjolfsson and McAfee (2023) that the narrative surrounding AI must shift from displacement to augmentation. HR managers must therefore frame AI implementation not as a cost-cutting measure but as a capability-enhancing strategy. Clear communication about how AI will change, rather than eliminate, roles is essential for fostering acceptance.

The study also highlighted a critical skills paradox: while respondents rated their soft skills (Emotional Intelligence, Adaptability) highly, their technical proficiency in AI and Data Analytics was significantly low (Mean < 2.5). This gap is particularly pronounced in customer service and administrative roles, which are increasingly automated. This finding resonates with the World Economic Forum's (2023) assertion that the future of work requires a hybrid skill set. However, the current training infrastructure in the studied aviation organizations fails to bridge this gap, focusing either on traditional technical skills or generic soft skills, but rarely integrating the two. For instance, customer service agents need training not just in empathy, but in how to interpret AI-driven customer sentiment analysis to enhance their interpersonal interactions. The lack of such integrated training explains the low self-reported proficiency in AI tools despite high confidence in communication skills.

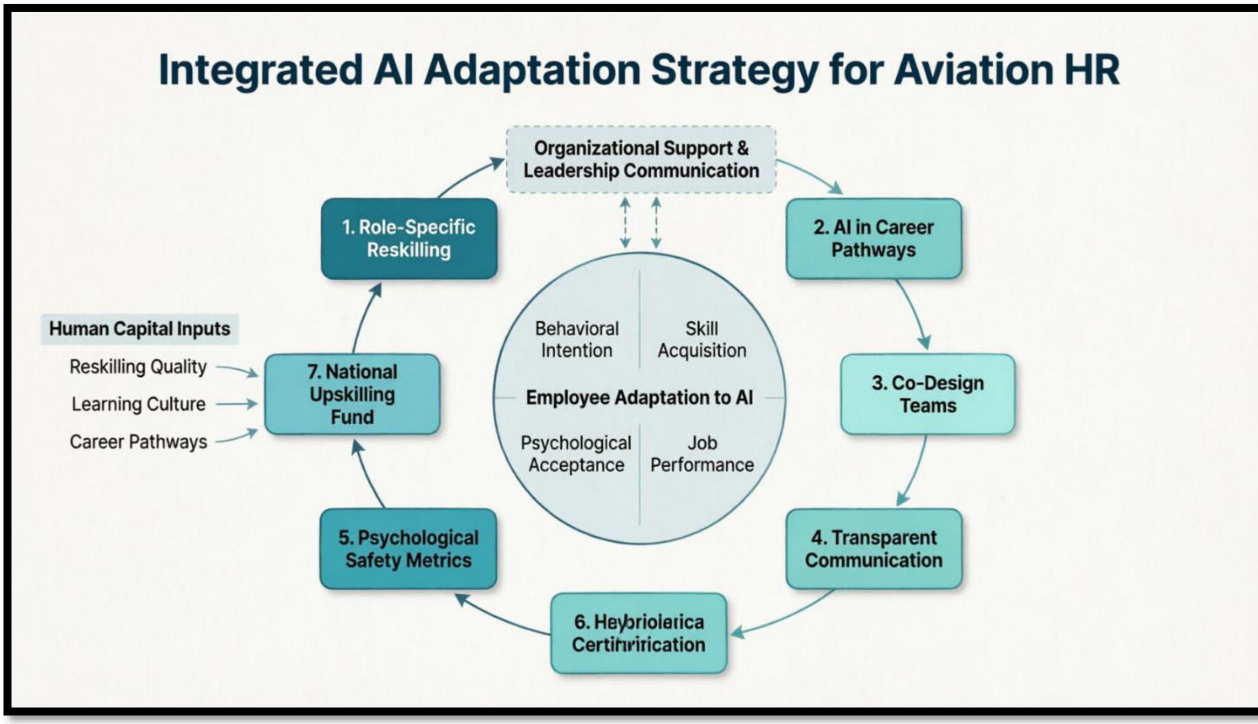
Finally, the significance of Organizational Support (Beta = 0.25) highlights the social dimension of technological change. The qualitative theme of a "leadership communication gap" reveals that top-down implementation strategies breed resistance. Employees feel alienated when excluded from the design and rollout of AI systems. This finding supports the Job Demands-Resources (JD-R) model, which posits that adequate resources (including managerial support and participation) are necessary to buffer the demands of modern technology (Bakker & Demerouti, 2017). In the African context, where hierarchical structures are often rigid, this implies a need for cultural transformation toward more inclusive decision-making processes. HR must function as a bridge, facilitating dialogue between technical developers and end-users to ensure that AI solutions are not only technologically sound but also socially acceptable and operationally relevant.

Conclusion

This study establishes that the successful integration of Artificial Intelligence (AI) and automation in aviation human resource management is fundamentally a human-centric challenge rather than a purely technological one. The empirical evidence from 250 aviation professionals in Nigeria demonstrates that while the workforce possesses strong soft skills and educational foundations, there exists a critical deficit in specific digital competencies required for AI augmentation. Crucially, the findings reveal that Reskilling Training Quality is the single most significant predictor of employee adaptation, surpassing even perceived usefulness and ease of use. This validates Human Capital Theory's assertion that targeted organizational investment yields direct returns in workforce resilience, while simultaneously extending the Technology Acceptance Model (TAM) by proving that training acts as a primary antecedent to technology acceptance in high-stakes operational environments.

Furthermore, the study highlights that adaptation is not merely cognitive but deeply psychological. The qualitative data underscores that fear of displacement remains a potent barrier, which can only be mitigated through transparent leadership communication and a clear narrative of augmentation over replacement. The integrated theoretical framework confirms that organizational support moderates the relationship between skill acquisition and behavioural intention; without a supportive ecosystem, even well-trained employees may resist adoption due to anxiety or lack of trust. Therefore, the future of aviation HR lies in a holistic strategy that combines rigorous, simulation-based technical training with robust change management practices. For emerging aviation markets, this dual approach is not optional but essential for bridging the digital divide and ensuring that technological advancements translate into sustainable operational excellence and workforce stability. Organizations that view reskilling as a strategic asset rather than a compliance cost will secure a competitive advantage in the rapidly evolving landscape of intelligent aviation administration.

Strategic Implementation Framework Diagram



The diagram illustrates a circular, iterative strategy cantered on Employee Adaptation to AI, with seven interconnected actions feeding into and reinforcing it:

Human Capital Inputs (Reskilling Quality, Learning Culture, Career Pathways) feed into Recommendation 7 (National Upskilling Fund), ensuring systemic sustainability. Recommendation 1 (Role-Specific Reskilling) and 2 (AI in Career Pathways) directly enhance *Skill Acquisition* and *Behavioural Intention*. Recommendation 3 (Co-Design Teams) and 4 (Transparent Communication) jointly strengthen *Organizational Support & Leadership Communication*, which moderates all pathways. Recommendation 6 (Hybrid Certification) validates *Skill Acquisition* and boosts *Psychological Acceptance* through credentialing.

Recommendation 5 (Psychological Safety Metrics) provides real-time feedback to adjust all other interventions, closing the loop. This model ensures that AI adoption is not a linear project but a dynamic, human-centred ecosystem where technology serves people, and people, in turn, shape technology.

Recommendations

Based on the empirical findings and theoretical synthesis, the following seven recommendations are proposed for aviation HR managers and policymakers:

- Replace generic digital literacy training with AI-augmentation simulations tailored to job functions (e.g., predictive maintenance interpretation for engineers; AI-assisted scheduling oversight for HR officers). *Rationale*: The data shows reskilling quality is the top driver of adaptation; role-specific content increases perceived relevance and utility.
- Integrate AI competency milestones into promotion criteria and succession planning (e.g., "AI-Enabled Operations Lead" track). *Rationale*: Links skill acquisition to tangible career advancement, reinforcing Human Capital returns and reducing displacement anxiety.
- Form cross-functional teams (HR, IT, frontline staff, unions) to co-develop and pilot AI tools before full rollout. *Rationale*: Addresses the leadership communication gap; participatory design increases psychological ownership and improves system usability (Venkatesh et al., 2022).
- Launch quarterly "AI Impact Forums" where leadership shares implementation timelines, job evolution maps, and support mechanisms—not just technology specs. *Rationale*: Reduces uncertainty and builds trust, directly moderating the relationship between TAM constructs and adaptation (Bakker & Demerouti, 2017).
- Partner with universities and tech providers to offer accredited micro-credentials combining AI tool proficiency (e.g., interpreting algorithmic outputs) with domain-specific judgment (e.g., flight safety protocols). *Rationale*: Validates hybrid skills, enhances credibility, and creates portable credentials for workforce mobility.
- Integrate validated scales (e.g., Edmondson's Psychological Safety Scale) into annual engagement surveys, tracking changes pre- and post-AI rollout. *Rationale*: Enables initiative-taking identification of resistance hotspots and measures the non-technical dimension of adaptation critical in high-risk environments.
- Advocate for a sector-wide fund (supported by ICAO, AUC, and airlines) to subsidize training for mid-career staff in emerging economies. *Rationale*:

Addresses resource constraints in Africa; ensures equitable access to reskilling and prevents talent drain to regions with better infrastructure.

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