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A Systematic Review of Factors Influencing the Adoption of Artificial Intelligence for Training and Development in the Nigerian Banking Sector

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Abstract

Artificial intelligence (AI) is revolutionising human resource management through automation, data-driven decisions, personalised learning, and improved skills-gap detection. Nevertheless, AI adoption in training and development (T&D) programs in the Nigerian banking sector remains low. Therefore, this situation has become a barrier to the development of human capital and to digital transformation. This systematic literature review aims to identify the factors influencing AI adoption in T&D within Nigerian banks and then to analyse the interrelationship among the constructs. This review also examines the mediating role of T&D-AI Fit between influencing factors and AI adoption in T&D. The study uses the Task–Technology Fit (TTF) model as the theoretical framework. Using the PRISMA 2020 guidelines, 46 peer-reviewed studies published between 2018 and 2025 were identified from multiple databases and analysed using thematic synthesis. The review Key enablers include training needs assessment, training design quality, AI system attributes (usability, reliability, personalisation), and individual factors (employee attitudes and digital competency). The major barriers are inadequate infrastructure, resistance to organisational change, fears of job displacement, and regulatory uncertainty. In addition, the T&D-AI fit was shown to mediate the relationship between these factors and successful AI adoption. Achieving strong task–technology alignment (T&D–AI fit) is critical for overcoming contextual barriers and maximising AI benefits in resource-constrained banking environments. This review highlights

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practical implications for digital skill-building, infrastructure improvement, and ethical AI governance while extending the TTF model to emerging economies.

Keywords: Artificial Intelligence Adoption, Training and Development, Nigerian Banking Sector, Task-Technology Fit, Digital Transformation, Workforce Upskilling.

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1.0 Introduction

Artificial intelligence (AI) is revolutionising organisational practices worldwide, including human resource management, by improving efficiency through automation, tailored learning, and analytics-driven decision-making. Training and development (T&D) are also enhanced by AI, which enables the construction of dynamically customised learning journeys, provides real-time performance feedback, and generates an automated curriculum, thereby contributing to the further growth of the workforce (Bhatt & Muduli, 2022). While high-income countries have rapidly incorporated AI into workplace learning systems, adoption in most developing countries remains low due to weak infrastructure, limited digital skills, and limited access to state-of-the-art technologies (Melkamu, 2025). In African countries, for example, the adoption of AI-driven T&D systems remains limited because there is no consistent digital landscape across the continent to support AI-based T&D implementation and institutional preparedness (Amankwah-Amoah & Lu, 2022). In Nigeria, this problem is more acute. Although banks have made efforts to adopt AI in areas such as customer experience and fraud detection, AI applications for employee T&D remain underdeveloped. At present, traditional classroom-based training remains common despite being time-proven, expensive, outdated, and not being adapted to the evolving environment (Odufisan et al., 2025).

In recent research, less than one-quarter of Nigerian banks have deployed AI-based learning tools in T&D, such as adaptive or simulation-based training, which lags global adoption patterns (Abdulquadri et al., 2021). Low digital literacy among bank personnel, infrastructure limitations, and uncertainty about regulatory guidelines also hinder progress. Although there has been an increasing reliance on data analytics, information security infrastructure, and automation in the sector, the slow adoption of AI highlights a challenge to address when evaluating the factors that affect an organisation's use of AI for T&D purposes. Furthermore, while some previous studies have focused on using AI to enhance HRM, there has been limited research on applying the Task-Technology Fit (TTF) model to explain the adoption of AI-driven T&D, particularly in developing countries. Only a cursory understanding has been gained of how training design, system characteristics, information quality, and employees' individual factors affect adoption, and how T&DAI enables effective fit and use. These gaps highlight the need to synthesise existing evidence to clarify the determinants of AI uptake in this context (Bello & Ajao, 2024).

1.1 Theoretical Framework: The Task–Technology Fit (TTF) Model

The Task–Technology Fit (TTF) forms the theoretical framework for this review by indicating how well a specific technology facilitates a user's ability to perform their task. (Goodhue & Thompson, 1995). TTF proposes that technology drives positive adoption and performance outcomes to the extent that its capabilities align with task requirements and individuals' capabilities. The original model by Goodhue and Thompson (1995), as illustrated in Figure 1, explains the interaction among five constructs: task characteristics, technology characteristics, task-technology fit, utilisation, and performance impact. This model posits that technology will only improve individual performance (‘performance impact’) if its functionalities and features (‘technology characteristics’) align with the specific tasks (‘task characteristics’) it is intended to support. It moves beyond merely measuring whether the technology is being employed (‘utilisation’) in performing the tasks, focusing instead on whether the technology matches user task needs (‘task-technology fit’).

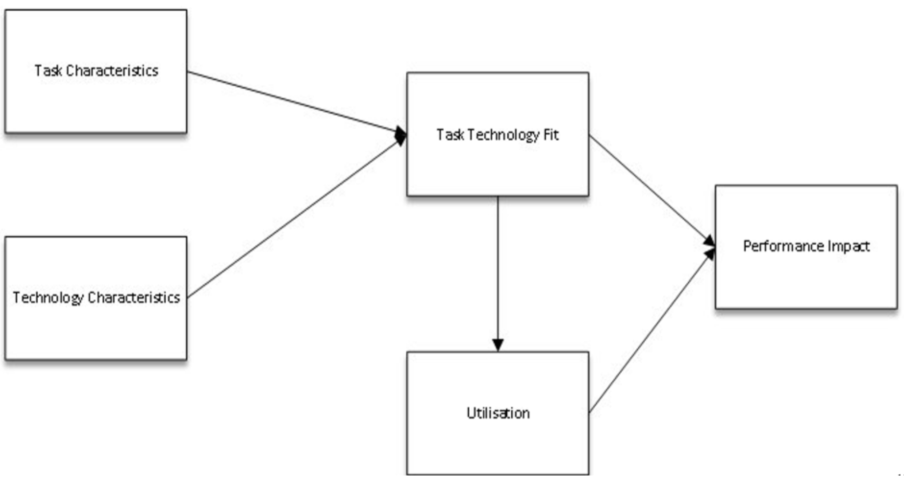

Figure 1: The Task-Technology Fit Model (Goodhue & Thompson, 1995)

Thus, the TTF model is relevant for examining the factors influencing the adoption of AI in T&D programs in the Nigerian banking sector, as digital skills, infrastructure, and training requirements may differ significantly across banks. In this study, the term ‘task characteristics’ was operationally defined as task characteristics. These include training needs assessment and the quality of training design. These elements guide the development of learning contents and modes of learning delivery (Wijayanti et al., 2024). Technology characteristics refer to ‘AI characteristics, which are the specific features and functionalities of AI tools utilised in T&D delivery. They should encompass the usability, reliability, responsiveness, accuracy, and adaptability of AI-generated training materials. These features govern whether our AI tool adequately facilitates T&D functions (Wijayanti et al., 2024). In addition, an individual characteristics construct was added to account for users' personal traits in AI adoption. This construct is vital to determine how different individual traits affect the success of AI adoption and acceptance in the Nigerian banking sector (Symasek et al., 2025). Individual characteristics capture employees' attitudes and digital skill sets, which drive users’ willingness and ability to use AI-enabled learning systems (Omotayo & Haliru, 2020). In this study, the ‘utilisation’ construct is changed to ‘adoption’ because this term best captures the process of AI integration into training and development in the Nigerian banking sector, highlighting the acceptance and adoption of AI technologies rather than their mere use (Tomczyk & Majkut, 2025). ‘Performance impact’ is not included in this study, as the main focus is on the adoption process rather than evaluating outcomes. It then becomes possible to thoroughly scrutinise the factors that influence AI adoption for T&D, as the added complications of performance measures are absent (Lampropoulos & Sidiropoulos, 2024).

In the TTF model, the task-technology fit plays a central role in mediating the relationship between the three influencing factors (T&D characteristics, AI characteristics, and individual characteristics) and AI adoption in T&D. When these three factors are properly aligned, TTF suggests the existence of a strong fit between T&D and AI (T&D–AI Fit). A proper alignment or fit between T&D and AI means that the capabilities and quality of AI technology closely match the T&D programs and individual user requirements that AI intends to support. Simply put, it is an ideal scenario when AI technology provides the right support, at the right time, and in the right way for

T&D. T&D-AI fit will facilitate the learning experience, which will be conclusively perceived as useful, user-friendly, and cost-effective (Jamal et al., 2024). Ultimately, this fit increases the likelihood of AI adoption in T&D. Conversely, misalignment and the absence of clear training objectives, system inapplicability, or digital literacy deficiencies undermine the fit and hinder AI adoption. Table 1 maps each study variable to its corresponding TTF construct and illustrates the anticipated impact of each on AI adoption in training and development. The conceptual framework guiding the systematic review is shown in Figure 2.

Table 1: TTF Constructs Mapped to Study Variables and Anticipated Impact on AI Adoption in T&D

TTF Constructs	Variables in This Review	Role in TTF Model	Expected Impact on AI Adoption in T&D
Task Characteristics (T&D Characteristics)	1. Training Needs Assessment 2. Training Design	Define T&D tasks, requirements, and learning structure	Clear T&D tasks increase fit, improve relevance, and support higher adoption
Technology Characteristics (AI Characteristics)	1. System Quality 2. Information Quality	Determine how well AI tools support T&D tasks	High-quality systems strengthen fit, build trust, and increase intention to use AI
Individual Characteristics	1. Attitude Toward AI 2. Digital Skills	Represent user capability and willingness to use AI	Positive attitudes and sufficient skills enhance perceived fit and engagement
T&D–AI Fit (Mediator)	1. Alignment between T&D and AI capabilities	Integrates task, technology, and user readiness	High fit strengthens the effect of enablers and reduces the impact of barriers
Adoption	1. Adoption of AI for T&D	Behavioural intention and actual use	Adoption increases when tasks, technology, and user readiness align.

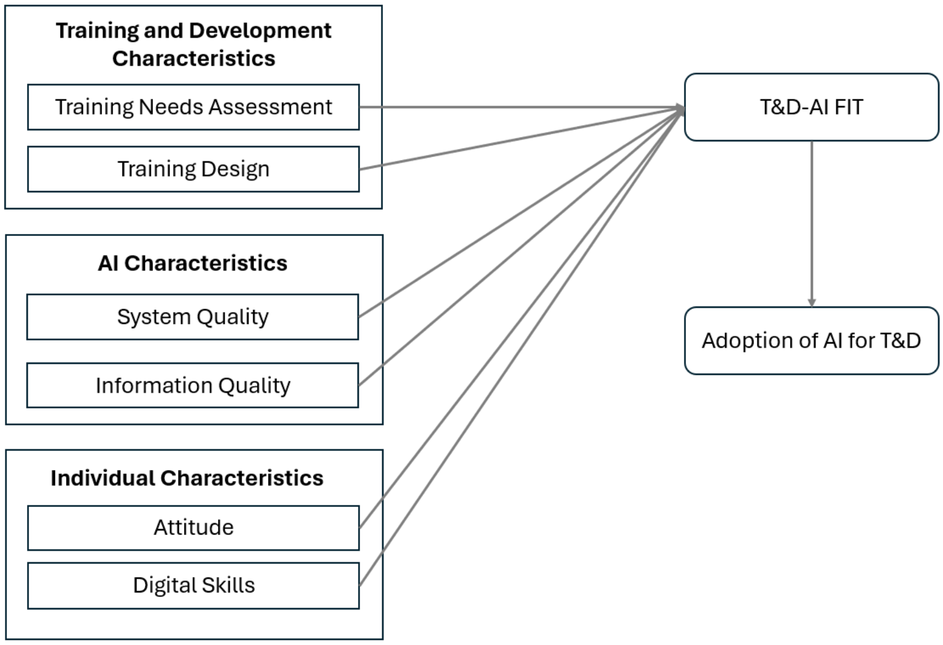

Figure 2: Conceptual Framework

Although TTF serves as the primary theoretical framework for this review, it is also important to note that more recent research has suggested integrated models such as TTF–UTAUT, which integrate user-focused acceptance drivers with task-technology alignment. The significance of digital skills, enabling circumstances, and performance expectations in comprehending AI adoption in resource-constrained settings like Nigeria is further reinforced by these hybrid models (Ismail et al., 2024; Aziz et al., 2025). Based on the above discussion, this study is guided by these research objectives:

1. Identify the factors influencing the adoption of AI for T&D in the Nigerian banking sector.
2. Examine how these factors relate to the adoption of AI for T&D.
3. To examine whether T&D–AI fit mediates the relationship between influencing factors and AI adoption for T&D.

2.0 Methodology

To achieve the research objectives above, this study adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and reproducibility. The PRISMA 2020 27-item checklist (Page et al., 2021) and a four-phase flow diagram (Emily Jones, 2020) guide the review process. A PRISMA flow diagram was used across three stages: identification, screening, and inclusion, and Appendix A provides the complete PRISMA 2020 checklist used in this review.

2.1 Search Strategy

The systematic review began with a search strategy to collect peer-reviewed articles and conference papers across disciplines on AI in T&D, with the Nigerian banking sector as the central context of study. A total of eight databases were searched to ensure the widest coverage. The databases used were Scopus, Web of Science, IEEE Xplore, Emerald Insight, Wiley Online Library, ScienceDirect, MDPI, and ResearchGate. These databases were selected to ensure comprehensive access to all required information on AI, human resource management, training and development, and other relevant areas. These articles were published between January 2018 and 23 June 2025. Boolean operators (AND, OR, NOT) and truncation (like "train*", "bank*") were used to maximise the search. Key terms included "artificial intelligence" OR AI OR "machine learning" OR "generative AI," paired with ("training and development" OR T&D OR upskilling OR reskilling OR "human resource development"), ("banking sector" OR bank* OR "financial sector"), and Nigeria OR "Nigerian banks.". Therefore, a summary of the search strings is presented in Table 2.

Table 2: Adapted Search Strings Used Across Databases

Database	Search Fields	Search String	Year Range
Scopus	Title, Abstract, Keywords	("artificial intelligence" OR AI OR "machine learning") AND ("training and development" OR T&D OR upskilling) AND ("banking sector" OR bank*) AND Nigeria	2018–2025
Web of Science	Topic	("artificial intelligence" OR AI) AND ("training and development" OR T&D) AND (bank* OR "banking sector") AND Nigeria	2018–2025

Database	Search Fields	Search String	Year Range
IEEE Xplore	All fields	("artificial intelligence" OR AI) AND ("training" OR "development" OR T&D) AND (banking OR bank) AND Nigeria	Journals & conferences, 2018–2025
Emerald Insight	All fields	("artificial intelligence" OR AI) AND ("training and development" OR T&D) AND (banking OR bank*) AND Nigeria	2018–2025
Wiley Online Library	Title, Abstract, Keywords	("artificial intelligence" OR AI) AND ("training and development" OR T&D) AND (banking OR Nigeria)	2018–2025
ScienceDirect	Title, Abstract, Keywords	("artificial intelligence" OR AI) AND ("training and development" OR T&D) AND (banking OR bank* OR Nigeria)	2018–2025
MDPI	Full text	("artificial intelligence" OR AI) AND ("training and development" OR T&D) AND (banking OR Nigeria)	2018–2025
ResearchGate	Full text	("AI" AND "training and development" AND banking AND Nigeria) OR ("artificial intelligence" AND T&D AND bank* AND Nigeria)	Sorted by relevance, 2018–2025

The use of this multi-database strategy yielded 1,238 unique records after duplicates were removed, providing a high-quality evidence base covering HRM, education, management, and AI technology. Subscription-based databases (such as Scopus, Web of Science, and ScienceDirect) and open-access platforms (such as MDPI and ResearchGate) complement each other, providing a fair representation of peer-reviewed and emerging literature. Following PRISMA guidelines, this study screened 1,238 titles and abstracts, assessed 162 full-text articles, and ultimately selected 46 papers for inclusion in the review. Table 3 on the next page summarises the overall search strategy for this review.

Table 3: Summary Of Search Strategy Designed to Capture Studies On (AI) Applications In (T&D) Within the Banking Sector, With A Focus on Nigeria

Component	Details
Databases	Scopus: Interdisciplinary coverage. IEEE Xplore: AI Tech Advancements. Emerald Insight: HRM/management studies.

Component	Details
	Web of Science: High-impact, peer-reviewed. ResearchGate: Emerging HRM/AI works.
Search Terms	Combinations: "Artificial Intelligence," "AI," "Training and Development," "T&D," "Banking Sector," "Nigeria," "Task-Technology Fit," "Technology Acceptance Model," "Diffusion of Innovations."
Search Operators	Boolean: AND, OR. Truncation: e.g., "train*," "develop*." Proximity: e.g., "AI NEAR/5 training."
Time Frame	January 2018 to June 23, 2025 (AI emergence in T&D).
Filters	English only; peer-reviewed/articles/conferences/reports; foundational theories pre-2018 included for relevance; excluded non-AI/non-banking T&D. Included foundational theoretical studies pre-2018 (e.g., TAM, TTF, DOI) for framework relevance. Excluded non-AI or non-banking T&D studies.
Number of Records	1,238 unique after deduplication; 46 included post-PRISMA.

2.2 Inclusion and Exclusion Criteria

The specific criteria to determine the eligibility of the articles are as follows:

Inclusion criteria

This study examined `how’, `where’, or `what’ AI or other technologies (e.g., machine learning, intelligent tutoring systems, adaptive learning platforms) may be used, applied, or adopted in employee training and development or other related learning activities.

a) It was carried out in the banking/financial sector or in organisational environments that are easily transferable.
b) Presented empirical results, case studies, or content conceptual/theoretical evidence on drivers of adoption, obstacles, or task-technology fit.
c) It was published as peer-reviewed journal articles, conference papers, or reliable industry/government reports.
d) Published in English.
e) Publication date 1 January 2018 to 23 June 2025 (date of final search)

Exclusion criteria

a) Concentrated on AI usage not related to T&D (e.g. recruitment, payroll, fraud detection only)

b) Not available in English
c) Non-peer-reviewed editors, commentaries, magazine articles or student theses.
d) Published before the year 2018 or beyond the search cut-off date.

2.3 Data Extraction

Data extraction from the 46 studies was conducted using a standardised template. This helped not only capture the study's features but also obtain details on AI, research findings, and factors affecting task-technology fit. Data extraction was completed by two reviewers, who meticulously reviewed all articles and resolved any disagreements. The inter-rater reliability was robust, with Cohen's kappa of 0.82 for abstract screening and 0.79 for full-text eligibility, indicating a high level of agreement. The study did not use any automated software, and any data not reported (for example, AI specifics) were marked as unspecified. Table 4 on the next page illustrates an overview of the data extraction process.

The wide-ranging differences in study designs, methods, and results prevented a quantitative meta-analysis. Instead, thematic and narrative syntheses (Thomas & Harden, 2008) were employed, guided by the Task-Technology Fit (TTF) framework. The synthesis progressed in three phases. First, inductive methods and line-by-line coding were performed on the findings from all 46 studies. Second, codes were assigned to various variables such as digital literacy, infrastructure challenges, resistance to change, system usability, and T&D-AI fit. Third, analytical themes were generated that closely matched the three research objectives (Research Objective 1: influencing factors; Research Objective 2: relationships between AI and T&D; Research Objective 3: the mediating role of T&D-AI fit). By taking this route, this study can explain how and why T&D-AI fits as a mediator for the adoption of AI in banks.

Table 4: Data Extraction Process

Category	Description	Specifics Captured	Quality Control	Synthesis Approach
Data Extraction	Systematic extraction from 46 studies.	Outcomes on AI in T&D/banking.	Standardised template.	Narrative with thematic grouping (e.g., effectiveness, fit, barriers).
Captured Information	Key data points from each study.	(1) Characteristics: Author/year/design. (2) Tech: AI type/platform. (3) Context: Banking role/T&D focus. (4) Outcomes: Effectiveness/adoption/ barriers. (5) Fit: Task-technology details.	Two reviewers; consensus on discrepancies (kappa=0.80).	No meta-analysis due to heterogeneity.
Goal	Distil findings for research focus.	AI's impact on T&D.	Bias minimization via independent review.	Evaluate AI trends in banking T&D.
Presentation	Extracted data in results.	Tabular summaries.	Cross-referenced protocols for reporting bias.	Clear communication of findings.

2.4 Quality Assessment

The quality of the 46 studies was assessed to determine the robustness of evidence supporting the use of AI for T&D in banks. The assessment of the strengths and weaknesses of these studies (either empirical or theoretical in nature) was guided by the PRISMA 27-point checklist (Page et al., 2021). The assessment criteria include the following:

a) Did the study have clear research objectives?
b) Was the study methodology a good fit for this research?

c) Were these results reliable and easy to follow?

d) Was the research relevant to the topic `AI in T&D in banks?

e) Had the researchers acknowledged the limitations of their study?

Based on the criteria above, all 46 studies were assigned a score of either high quality, moderate, or low quality. These quality scores were used to determine the weight assigned to each study in our conclusions about AI adoption in T&D. Table 5 presents the quality assessment rubrics of the reviewed studies.

Table 5: Quality Assessment Rubric for Included Studies

Criterion	Description	Score 0	Score 1	Score 2
Clarity of Research Objectives	Whether aims and research questions are clearly stated	Not stated	Partly stated	Clearly stated
Methodological Appropriateness	Suitability of study design (survey/experiment/case study) for the stated objectives	Inappropriate	Partially appropriate	Fully appropriate
Data Quality & Rigor	Adequacy of sample size, analysis, and reporting transparency	Weak/ inadequate	Moderate rigor	Strong rigor, clearly reported
Relevance to AI–T&D in Banks	How directly does the study address AI in T&D?	Low relevance	Partial relevance	High relevance
Consideration of Limitations	Whether limitations are acknowledged and discussed	None	Mentioned briefly	Clearly acknowledged with implications

Scoring Interpretation: 0–4 = Low Quality, 5–7 = Moderate Quality,8–10 = High Quality. This rubric supports the High/Moderate/Low ratings used in the synthesis and ensures transparency in the evaluation process.

2.5 Summary of Included Studies

This section summarises the 46 studies included in the systematic review, as shown in Table 6, and identifies thematic categories relevant to this study's research objectives. This summary provides key insights into the evidence regarding the use of AI in T&D in the global and Nigerian banking sectors. By breaking the research into relevant categories, this review can present the variation in AI applications and highlight some key emerging trends in AI and T&D.

Table 6: Summary of 46 Included Review Papers

No.	Author & Year	Category	Research Focus
1	Abdulquadri et al. (2021)	T&D in Banking	Chatbot adoption for financial services T&D in Nigeria; highlights digital barriers.
2	Adeniwura et al. (2025)	T&D in Banking	Comparative AI role in addressing skill gaps in Nigerian vs. UK commercial banks.
3	Amankwah-Amoah and Lu (2022)	Contextual Factors	AI drivers and challenges for business/T&D in Africa, including Nigeria.
4	An et al. (2024)	Contextual Factors	Human AI skills and digital culture moderating innovation in organizational T&D.
5	Awotunde and Aregbeshola (2024)	T&D in Banking	Intrapreneurship T&D for future workplace performance; AI implications in banking.
6	Bhatt and Muduli (2022)	T&D in Banking	Systematic review of AI in learning and development; foundational for banking applications.
7	Boonmee et al. (2025)	Contextual Factors	AI adoption barriers/enablers among SMEs; transferable to Nigerian banking infrastructure issues.
8	Budhwar et al. (2022)	T&D in Banking	AI challenges/opportunities in international HRM and T&D.
9	Choi and Park (2024)	T&D in Banking	Trends in learning needs assessment; supports AI-driven skill-gap detection in banking.
10	Al Dari et al. (2020)	Contextual Factors	Organisational culture and tech capabilities influencing learning/T&D adoption.
11	Davis (1989)	Task-Technology Fit Frameworks	TAM foundations for perceived usefulness/ease in AI-T&D system adoption.
12	Dishaw and Strong (1999)	Task-Technology Fit Frameworks	Extending TAM with TTF for better AI-task alignment in T&D.
13	Dulloo (2024)	T&D in Banking	AI revolution mapping automation, skills, and roles in HR/T&D landscape.
14	Goodhue and Thompson (1995)	Task-Technology Fit Frameworks	Core TTF theory for aligning AI technology with T&D tasks and user performance.

No.	Author & Year	Category	Research Focus
15	Hidayat et al. (2021)	Task-Technology Fit Frameworks	Review of contemporary TTF studies; applications to AI in T&D systems.
16	Ismail et al. (2024)	Task-Technology Fit Frameworks	Investigating TAM, TTF, and UTAUT for digital/AI transformation in T&D.
17	Jamal et al. (2024)	T&D in Banking	Job redesign, reskilling/upskilling via AI for 15ersonalizatio agility in banking.
18	Khan et al. (2021)	T&D in Banking	Training needs assessment and effectiveness, relevant to AI-driven T&D in emerging contexts.
19	Madanchian and Taherdoost (2025)	Contextual Factors	Organisational/technological barriers/enablers of AI in HRM/T&D.
20	Maity (2019)	T&D in Banking	Opportunities for AI evolution in T&D practices; applicable to banking upskilling.
21	Melkamu (2025)	Contextual Factors	AI implementation challenges in industries; developing countries (incl. Nigeria) perspectives.
22	Murire (2024)	Contextual Factors	AI shaping 15ersonalizatio work practices and culture; implications for T&D.
23	Nair et al. (2025)	T&D in Banking	Barriers to AI adoption among banking professionals using the TISM approach.
24	Ni et al. (2025)	T&D in Banking	Data-driven AI frameworks for business processes, relevant to banking T&D evaluation.
25	Odebode and Ogunbayo (2025)	T&D in Banking	Digital technology's potential to improve 15ersonalizatio performance and T&D in banking.
26	Odufisan et al. (2025b)	T&D in Banking	AI/ML for fraud detection; transferable to simulation-based T&D in Nigeria.
27	Ogundele et al. (2025b)	T&D in Banking	AI advancing sustainable banking and efficiency; Nigerian institutions focus.
28	Okoro (2024)	T&D in Banking	Digital HR practices and employee development in Nigerian banking sector.
29	Omotayo and Haliru (2020)	Task-Technology Fit Frameworks	Perception of TTF in digital systems; implications for AI-T&D fit.
30	Ononiwu et al. (2024)	T&D in Banking	Digital transformation impact on banking operations/T&D in developing economies.
31	Patre et al. (2023)	AI-only Tools	Enablers/barriers in upskilling/reskilling via professional programs on EdTech platforms.

No.	Author & Year	Category	Research Focus
32	Rahman et al. (2024)	T&D in Banking	Effective training design for bank managers; AI-adaptive implications.
33	Ramachandran et al. (2024)	AI-only Tools	Developing AI-powered programs for employee upskilling/reskilling.
34	Simbolon et al. (2025)	Contextual Factors	Overcoming AI adoption challenges (security, regulation, infrastructure) in banking.
35	Sposato (2024)	T&D in Banking	Leadership T&D in the age of AI; relevant to Nigerian banking.
36	Stofkova et al. (2022)	Contextual Factors	Digital skills as key factor in HR development and AI-T&D adoption.
37	Suhail et al. (2024)	Task-Technology Fit Frameworks	UTAUT2/TTF integration for AI/robot adoption in learning systems.
38	Tusquellas et al. (2024)	T&D in Banking	AI potential for professional development and talent management.
39	Udodiugwu et al. (2024)	T&D in Banking	AI enhancing performance in Nigerian banks; direct T&D implications.
40	Vitezić and Perić, (2024)	Contextual Factors	Digital skills role in AI acceptance; barriers in banking T&D.
41	Wijayanti et al. (2024)	Task-Technology Fit Frameworks	TTF application in 16ersonalizat systems; extendable to AI-T&D tools.
42	Zeng et al. (2022)	Contextual Factors	AI adoption and innovation, moderated by training protocols/digital resilience.
43	Alhusban et al. (2025)	T&D in Banking	Generative AI integration challenges in 16ersonalizatio learning/T&D.
44	Chitranshi et al. (2024)	AI-only Tools	AI is transforming/replacing traditional employee T&D.
45	Frenkenberg and Hochman (2025)	Contextual Factors	Psychological dimensions (anxiety, dependency) in AI adoption for T&D.
46	Panda et al. (2023)	Contextual Factors	AI enablers for HR resiliency; past/future directions in T&D.

3.0 Results and Discussions

This section explains the study selection procedure and highlights the key findings of the included studies. The PRISMA flow diagram depicts the study selection process. The subsequent section presents the key results and synthesis, anchored in the research objectives.

3.1 Study Selection Flow Diagram

Figure 3 on the next page presents the PRISMA flow diagram, visually outlining the number of studies identified, screened, excluded, and included at each stage of the review process. The selection procedure consists of the following three major stages:

a) **Identification**: Records retrieved from database searches (e.g., Scopus, ResearchGate, Emerald, IEEE, Web of Science)
b) **Screening**: Records were assessed for relevance through title and abstract evaluations.
c) **Inclusion**: Studies were selected for qualitative and quantitative syntheses.

Nevertheless, it is important to note that while the selection process resulted in a total of 46 studies, there is a risk that the process is prone to publication bias towards positive results of AI, which might not reflect failure in the adoption of T&D.

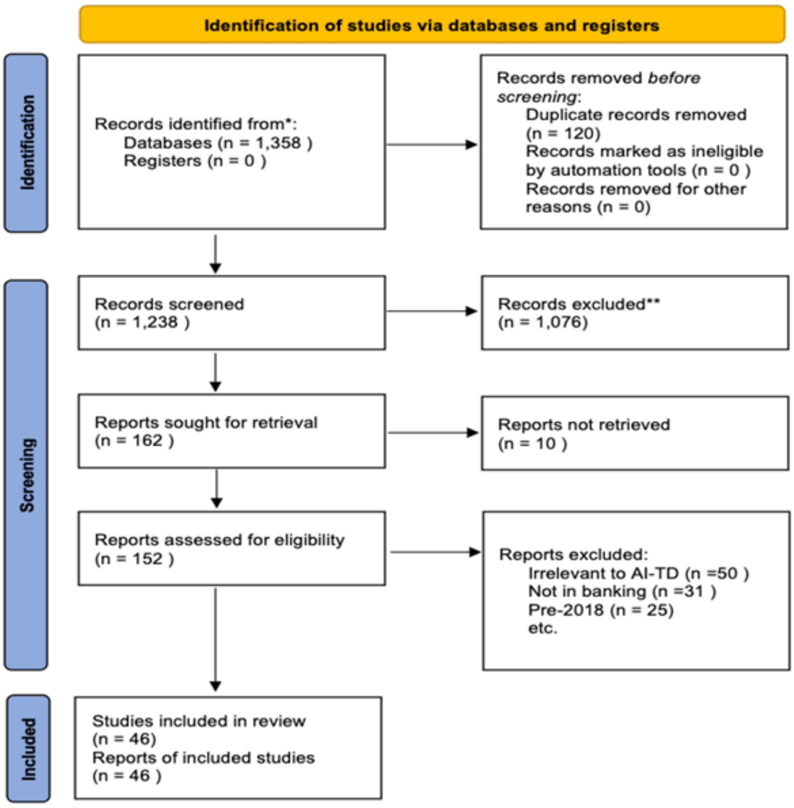

Figure 3: PRISMA Flow Diagram (Emily Jones, 2020)

3.2 Summary of Key Findings

This section summarises the key findings of the 46 studies included in the review. It provides an overview of the main results reported in these studies, but offers no detailed interpretation or integration. The summary (Table 7) highlights the primary focus areas and outcomes examined across the selected studies, which align with the research objectives. These findings reveal some clear trends: strong factors like well-structured training programs, a supportive workplace culture, user-friendly systems, and positive employee mindsets that really help boost AI adoption in T&D. However, inadequate digital skills, lack of proper infrastructure, and change resistance are among the factors that still limit the progress made towards the use of AI T&D. Moreover, one cannot deny that it is mainly the alignment between T&D and AI that determines the interaction of these dynamics, as most studies acknowledge.

3.3 Synthesis of Results

The data from these studies were thematically 18ersonaliza through a dynamic coding process. The synthesis analyses and interprets the identified themes to determine the extent to which i) they align with or diverge from the Task–Technology Fit (TTF) theory and ii) they address the research objectives. Three broad thematic clusters are proposed and discussed in subsequent sections.

3.3.1 Factors Influencing AI Adoption in T&D in the Banking Sector

This section presents the findings and addresses the first research objective: to identify the key factors influencing the adoption of AI for T&D in the Nigerian banking sector. The thematic synthesis outlines three dimensions of factors that affect AI adoption in banks: (i) T&D characteristics, (ii) AI characteristics, and (iii) individual characteristics. These themes are not mutually exclusive; they reinforce or undermine one another and are essential for explaining the variation in AI adoption in T&D (Chitranshi et al., 2024). The T&D characteristics, namely training needs assessment and training design, were found in 24 completed studies under the "skill gaps" category.

Table 7: Summary of Key Findings (n = 46)

No	Author(s) (Year)	Country / Focus	Study Type	AI Technology in T&D	Key Enablers	Key Barriers	Link to T&D–AI Fit / TTF
1	Abdulquadri et al. (2021)	Nigeria	Empirical	Chatbot for financial services training	Perceived usefulness, leadership support	Digital literacy gaps, infrastructure	Fit improves with perceived ease in task alignment
2	Adeniwura et al. (2025)	Nigeria & UK	Comparative	AI addressing skill gaps in commercial banks	Personalisation, analytics	Regulatory differences, skills shortage	Strong fit closes skill gaps in Nigerian banks
3	Amankwah-Amoah and Lu (2022)	Africa (incl. Nigeria)	Review	AI for business/T&D development	Innovation drivers, policy support	Infrastructure, access barriers	Fit constrained in low-resource African contexts
4	An et al. (2024)	Global → Organizational	Quantitative	Human AI skills for innovation/training	Digital 19ersonalizatio culture	Low digital maturity	Culture moderates T&D–AI fit
5	Awotunde and Aregbeshola (2024)	Global → Banking relevance	Conceptual	Intrapreneurship T&D with AI implications	Training design quality	Resistance to change	Fit enhances performance in the future workplace
6	Bhatt and Muduli (2022)	Global	Systematic Review	AI in learning and development	Adaptive paths, automation	Skills gaps	TTF is foundational for AI-task alignment
7	Boonmee et al. (2025)	Thailand → Emerging economies	Qualitative	AI adoption in SMEs training	Top management support	Infrastructure, regulation	Fit mediates barriers in resource-constrained settings

No	Author(s) (Year)	Country / Focus	Study Type	AI Technology in T&D	Key Enablers	Key Barriers	Link to T&D–AI Fit / TTF
8	Budhwar et al. (2022)	International HRM	Review	AI challenges/opportunities in HRM/T&D	Personalisation	Ethical concerns, job displacement	Fit is critical for international adoption
9	Choi and Park (2024)	Global	Review	AI for learning needs assessment	Accurate gap detection	Data quality issues	Fit improves assessment-task alignment
10	Al Dari et al. (2020)	Global → Organizational	Quantitative	Tech capabilities in 20ersonalizatio learning	Supportive culture	Hierarchical structures	Culture influences T&D–AI fit
11	Davis (1989)	Foundational	Theoretical	TAM for technology acceptance in T&D	Perceived usefulness/ease	—	Baseline for perceived fit in AI adoption
12	Dishaw and Strong (1999)	Foundational	Theoretical	Extending TAM with TTF	Task-tool alignment	Misalignment	Core extension linking task to AI fit
13	Dulloo (2024)	Global → HR	Conceptual	AI revolution in HR automation/skills	Automation efficiency	Emerging role shifts	Fit maps new AI roles in T&D
14	Goodhue and Thompson (1995)	Foundational	Theoretical	Original TTF model	Task-technology alignment	Misalignment	Core foundation for T&D–AI fit
15	Hidayat et al. (2021)	Global	Review	Contemporary TTF studies	System usability	Complexity	Fit reviews support AI-T&D applications
16	Ismail et al. (2024)	Global	Empirical	TAM, TTF, UTAUT for digital transformation	Performance expectancy	Resource limits	Integrated models strengthen T&D–AI fit
17	Jamal et al. (2024)	Global → Organizational	Quantitative	AI for reskilling/upskilling	Job redesign	Readiness gaps	Fit drives organizational agility
18	Khan et al. (2021)	Pakistan → Transferable	Quantitative	Training needs assessment effectiveness	Work passion	Low assessment quality	Fit via accurate needs-task matching

No	Author(s) (Year)	Country / Focus	Study Type	AI Technology in T&D	Key Enablers	Key Barriers	Link to T&D–AI Fit / TTF
19	Madanchian and Taherdoost (2025)	Global → HRM	Critical Analysis	AI in HRM/T&D barriers/enablers	Organizational support	Technological factors	Fit mediated by organizational readiness
20	Maity (2019)	Global	Conceptual	AI opportunities in T&D evolution	Personalisation	Traditional resistance	Fit identifies evolution opportunities
21	Melkamu (2025)	Developing countries	Prospective	AI implementation in industries/T&D	Policy frameworks	Infrastructure, skills	Poor fit in developing contexts
22	Murire (2024)	Organizational	Conceptual	AI shaping work practices/culture in T&D	Adaptive culture	Resistance to change	Culture moderates T&D–AI fit
23	Nair et al. (2025)	Banking professionals	Modelling (TISM)	AI adoption barriers in banking T&D	System reliability	Security, regulation	Fit overcomes structured barriers
24	Ni et al. (2025)	Commercial banks	Framework	Data-driven AI for process/T&D evaluation	Hybrid analytics	Data quality	Fit via multi-dimensional alignment
25	Odebode and Ogunbayo (2025)	Nigeria relevance	Conceptual	Digital tech improving performance/T&D	Digital integration	Access barriers	Fit enhances 21ersonalizatio outcomes
26	Odufisan et al. (2025b)	Nigeria	Empirical	AI/ML for fraud prevention → simulation T&D	Analytics accuracy	Implementation costs	Fit in simulation-based training
27	Ogundele et al. (2025b)	Nigeria	Assessment	AI for sustainable banking efficiency/T&D	Service personalisation	Infrastructure shortcomings	Fit advances sustainable T&D
28	Okoro (2024)	Nigeria	Empirical	Digital HR practices in banking T&D	Supportive culture	Hierarchical resistance	Fit improves with digital practices

No	Author(s) (Year)	Country / Focus	Study Type	AI Technology in T&D	Key Enablers	Key Barriers	Link to T&D–AI Fit / TTF
29	Omotayo and Haliru (2020)	Nigeria	Quantitative	TTF perception in digital systems	User readiness	Digital competency gaps	Direct TTF link to AI-T&D readiness
30	Ononiwu et al. (2024)	Developing economies/Nigeria	Mixed	Digital transformation impact on T&D	Employee engagement	Infrastructure	Poor fit in regional banks
31	Patre et al. (2023)	EdTech platforms	Empirical	AI in professional upskilling/reskilling	Platform usability	Skill shortages	Fit via enablers overcoming barriers
32	Rahman et al. (2024)	Indonesia → Banking	Qualitative	Effective training design for managers	Leadership support	Resistance	Fit with managerial task needs
33	Ramachandran et al. (2024)	Global	Conceptual	AI-powered programs for upskilling	Adaptive content	Digital divide	Fit 22ersonalizat employee learning
34	Simbolon et al. (2025)	Banking sector	Empirical	Overcoming AI challenges in banking T&D	Reliable systems	Security, regulation, infrastructure	Fit mediates adoption challenges
35	Sposato (2024)	Global → Leadership	Conceptual	AI in leadership training/development	Personalisation	Acceptance anxiety	Fit enhances leadership T&D
36	Stofkova et al. (2022)	Global → HR	Empirical	Digital skills for HR development	Training protocols	Skill deficits	Skills enable stronger T&D–AI fit
37	Suhail et al. (2024)	General → Learning systems	Quantitative	UTAUT2/TTF for AI robots in T&D	Perceived ease	Complexity	Integrated fit model for adoption
38	Tusquellas et al. (2024)	AyypuGlobal	Systematic Review	AI for professional development/talent 22erso.	Adaptive tools	Accessibility	Fit supports talent management

No	Author(s) (Year)	Country / Focus	Study Type	AI Technology in T&D	Key Enablers	Key Barriers	Link to T&D–AI Fit / TTF
39	Udodiugwu et al. (2024)	Nigeria	Survey	AI enhancing bank performance/T&D	Digital competency	Job displacement fear	Fit mediates performance outcomes
40	Vitezić and Perić (2024)	Cross-national	Quantitative	Digital skills in AI acceptance	Skills (70% variance)	Cultural resistance	Skills moderate T&D–AI fit
41	Wijayanti et al. (2024)	Microfinance → Transferable	Empirical	TTF in 23ersonalizat systems	Usability, reliability	System inapplicability	Direct TTF application extendable to AI
42	Zeng et al. (2022)	Global	Quantitative	AI adoption is moderated by training/resilience	Training protocols	Low resilience	Training moderates T&D–AI fit
43	Alhusban et al. (2025)	Organizational	Conceptual	Generative AI in learning/development	Innovation potential	Integration challenges	Fit addresses generative AI implications
44	Chitranshi et al. (2024)	Global → Employees	Conceptual	AI transforming traditional T&D	Automation, replacement efficiency	Resistance to change	Fit in transformation/replacement
45	Frenkenberg and Hochman (2025)	Psychological	Empirical	AI adoption anxiety/dependency	Motives	Fear/anxiety	Psychological factors moderate fit
46	Panda et al. (2023)	HR resiliency	Review	AI enablers for HR/T&D resiliency	Past literature insights	Future gaps	Fit builds resiliency in T&D

These T&D features emphasise clear learning objectives and relevant content, as well as learner-centred delivery approaches that consistently increase engagement and prepare employees to effectively leverage AI-assisted learning tools (Faisal-E-Alam, 2024; Maity, 2019; Rahman & Putranto, 2024; Yaqub & Singh, 2021). Assessing training needs further strengthens this by identifying specific competency gaps that AI solutions can address. "AI-driven analytics personalise learning, closing to 60% of identified skill gaps in Nigerian banks (Budhwar et al., 2022; Choi & Park, 2024; Cotes & Ugarte, 2019; Khan et al., 2021; Mahmud et al., 2019; Nor 2025; Robert & Mori, 2024)

These characteristics reinforce AI's capabilities, thereby enabling its adoption in T&D. AI features such as usability, interface reliability, and information accuracy were identified in 22 articles coded as "usability" (Elmunsyah et al., 2023). Nineteen studies emphasise system quality, while ten highlight information quality; both contribute to the trustworthiness of AI platforms and to their sustained application in the field (Sabeh et al., 2021; Yoon & Kim, 2023). Rulinawaty et al. (2024) argue that reliable AI systems enhance learning consistency and increase the likelihood of improving T&D by 40%-50%. These AI system characteristics must align with the T&D design, because well-structured training programs will create minimal value if the system is unusable. The third theme is individual characteristics, which reflect readiness at both the individual and contextual levels. A key indicator of individual and contextual preparedness, which is coded as "attitudes/digital literacy," was identified in 30 studies. Positive attitudes, perceived usefulness, and digital skills are also strong predictors of employees' willingness to utilise AI-enabled training. Stofkova et al. (2022) and Vitezić and Perić (2024) find that digital skills facilitate a 70% increase in the 24ersonaliza of AI-supported T&D, with readiness as one of their key determinants. However, the extent of readiness varies across these studies. When younger digital native employees readily embrace AI, their confidence increases swiftly compared to older generations who do not adopt this technology. A clear indication of this generational gap in AI adoption emerges in the reviewed studies (Cetindamar et al., 2021; Odebode & Ogunbayo, 2025; Weritz, 2022).

There are reports of good T&D results when deploying AI in well-resourced, culturally adapted urban banks with appropriate infrastructure and data-literate staff. In comparison, research in low-resource or regional banking contexts shows little benefit due to weak internet connectivity, outdated hardware, and relatively low digital literacy, which hinder the success of AI products. From the TTF perspective, these contradictions indicate a mismatch among training types, user capabilities, and technology features. Even well-designed AI tools will make little difference if the infrastructural and skill structures are insufficient (Hidayat et al., 2021; Yuce et al., 2019). This highlights the context-specific discrepancy that warrants attention to achieve widespread acceptance (Maity, 2019). Table 8 summarises the evidence weight of each factor and indicates that digital skills is an under-investigated, however important driving force in the Nigerian banking context, as well as an under-researched antecedent of employees' T&D attributes and system quality.

Table 8: Factors Influencing AI Adoption in the Banking Sector

Factor	Description (Aligned with Themes)	No. of Studies	Evidence Strength
Training Needs Assessment	Identifies specific competency gaps that AI tools can address; supports 25ersonalization and readiness.	24	High (empirical banking-focused studies).
Training Design	Structured learning objectives, relevant content, and learner-centred delivery that enhance engagement with AI systems.	24	Moderate (mix of conceptual and empirical studies).
System Quality	Usability, interface reliability, and responsiveness that increase trust and encourage sustained adoption.	19	High (technology-focused evaluations).
Information Quality	Accuracy, relevance, and real-time adaptability of AI-generated training content.	10	Moderate (limited but consistent findings).
Attitude Towards AI	Employee openness, perceived usefulness, and motivation to adopt AI-based learning tools.	23	High (survey-based perceptual studies).
Digital Skills	Baseline technical skills needed to effectively engage with AI-enabled T&D platforms.	11	Low (underexplored in Nigerian banks).

3.3.2 Relationships Between the Influencing Factors and AI Adoption in T&D

This section discusses the findings that address the second research objective, which is to examine how the identified factors relate to AI adoption in T&D. In the thematic synthesis of 35 Nigeria-related studies, the three factors identified in section 3.2.1, interact with contextual barriers in ways that either drive or hinder AI adoption for T&D (Alhusban et al., 2025; Niraula et al., 2025). These relationships do not operate independently; they show how institutional, technological, and individual influences interact with each other to shape and influence AI adoption. Resistance to change, a common relational barrier, was found in 19 studies (Code: “fear of redundancy”) (Frenkenberg & Hochman, 2025; López-Rodríguez et al., 2024). Employees who perceive that AI threatens job security become less inclined to engage with AI-supported learning, especially if they have low awareness about AI’s role. Marocco et al. (2025) highlight that anxiety regarding job relevance prevents AI use, particularly in non-urban banks.

Attitudes can shape institutional communication in ways that negatively affect AI adoption (Bedué & Fritzsche, 2021; Kaya et al., 2022). Factors such as limited infrastructure, as identified in 14 analyses, can exacerbate resistance by restricting access to AI-powered training (Simbolon et al., 2025). The quality of bandwidth, age of hardware, and unstable Internet systems in local (and regional) lending or microfinance banks also disrupt learning platforms and erode trust in AI offerings (Arora & Mittal, 2024; Gkinko & Elbanna, 2023). Inadequate digital tools were found to hinder 50–70% of workforce readiness in Nigerian banking (PwC Nigeria AI Whitepaper, 2025). More recent studies in this region reveal that the effect of digital skills and organisational culture strongly influences the adoption of AI for T&D in the banking industry in Nigeria (An et al., 2024; Al Dari et al., 2020; Deep, 2023; Joseph & Ravikumar, 2024) Upon looking through the latest reports by the Nigeria Inter-Bank Settlement System (2024) and the Central Bank of Nigeria (Agboola, 2022), lack of workforce digital competence remains a major barrier in adoption. This is most common amongst mid-sized and microfinance banks (Agboola, 2022). Organisational culture also influences banks' adoption of AI-enabled learning tools. Innovative cultures that favour collaboration are increasingly deploying this technology. In contrast, banks driven by hierarchies and compliance may struggle with use cases (Nair et al., 2025; Ni et al., 2025). Nigerian empirical studies (Okoro, 2024; Ononiwu et al., 2024; Udodiugwu et al., 2024) also indicate that a favourable learning culture, employee engagement, and management acceptance of digital transformation significantly enhance the acceptance of AI-driven T&D initiatives.

The review findings indicate that infrastructure limitations reduce system usability, shape workers' attitudes, and ultimately lead to low adoption rates. Job dislocation (11 studies) and regulatory indecision (9 studies) have almost the same impact. Insufficient data security regulation leads to the perception that technological advancement in the T&D sector is an organisational risk. As a result, employees have limited opportunities to engage productively with AI (Bagherifam et al., 2025; Sposato, 2024). Shittu et al. (2024) suggest that unclear data privacy and security regulations are discouraging banks from investing further in AI-based staff training. This demonstrates a series of connections in which policy uncertainty causes investment to decline, which in turn reduces exposure and eventually lowers employee acceptance. Conflicting results across studies demonstrate the importance of institutional context. Some well-resourced urban banks cite the benefits of AI-enabled training for themselves (e.g., enhanced engagement in personalised simulations), whereas less empowered institutions have found it difficult.

The Task–Technology Fit (TTF) model suggests that an alignment between training tasks, user capabilities, and AI tools increases adoption. In contrast, inadequate infrastructure or skills leads to lower adoption. This provides further evidence that contextual readiness moderates the interaction among individual, system, and organisational factors, either positively or negatively (Abed Alkarim Ayyoub et al., 2023). In conclusion, these data demonstrate that environmental barriers, specifically infrastructure, attitudes, and the regulatory void, collectively hinder adoption outcomes. The summary of the contextual barriers is presented in Table 9.

Table 9: Nigeria-Specific Contextual Barriers

Factor	Description	No. of Studies	Evidence Strength
Resistance to Change	Fear of redundancy and limited awareness about AI's role in T&D.	19	Moderate (qualitative studies)
Infrastructure Gaps	Limited internet access, outdated systems, and inconsistent digital tools.	14	High (industry reports, empirical data)
Job Displacement Fear	Concerns that AI may replace traditional roles, reducing engagement in AI-based learning.	11	Moderate
Regulatory Constraints	Policy gaps and weak data-protection frameworks are affecting investment in AI-T&D systems.	9	High (policy analyses)

3.3.3 Mediating Role of T&D-AI Fit

This section discusses the findings that address the third research objective, which is to examine whether T&D–AI fit mediates the relationship between the influencing factors and the adoption of AI for T&D. Thematic synthesis from approximately 20 studies (See Table 7) shows that T&D-AI Fit is the mediating variable that plays the most crucial role. Specific factors such as system quality, training design, and digital literacy can thus be viewed as contributing factors to the successful implementation of AI adoption and training outcomes in T&D. According to the Task–Technology Fit (TTF) theory (Goodhue & Thompson, 1995; Dishaw & Strong, 1999), these antecedents do not directly lead to adoption; instead, they influence it indirectly through the alignment (or fit) of training tasks, AI capabilities, and user maturity. When alignment is high, the benefits are magnified (i.e., greater perceived usefulness and engagement). However, a low fit can diminish or even prevent these advantages, regardless of antecedent strength. Adeniwura et al. (2025), Ogundele et al. (2025), and Ohiani (2020) reported that AI tools in Nigerian banks increased operational efficiency up to 50%; however, this was true only when the technology was properly aligned with the supported tasks. Even when it is at its strongest, good infrastructure can have only a limited effect if the T&D–AI fit is low. This implies that fitness acts as a mediator, reducing barriers to digital literacy and improving the effectiveness of AI use.

Binsaeed et al. (2023), Vitezić and Perić (2024), and Zeng et al. (2022) found that digital skills explained about 70% of the variation in employees' acceptance of AI. Perceived fit acted as the key mediator when employees with stronger digital skills experienced better alignment between tasks and AI tools, which increased adoption. In contrast, cultural resistance weakened this fit and reduced its indirect influence on adoption. Furthermore, Murire (2024) and Ramachandran et al. (2024) reported that personalised AI learning paths improved upskilling effectiveness, but this mediation happened through well-designed training and dependable AI features fostered alignment, indirectly enhancing adoption intentions in settings with limited resources. Adeyemo and Obafemi (2024) provided indirect evidence in fraud detection systems that AI was more effective when task-technology alignment was strong, indicating that fit mediates the relationship between system quality and user outcomes, leading to performance gains.

The evidence clearly shows that the T&D and AI fit plays a significant role in both driving and hindering progress. For example, a high-quality system, coupled with expertly designed training, can effectively present the fit that improves adoption. Conversely, limitations such as limited digital literacy or underdeveloped infrastructure can be lessened to some extent if a good fit is established, for instance, by simplifying tasks and keeping learners engaged. Nevertheless, there are very few studies that statistically test these mediation effects in the context of Nigerian T&D. Most research is conceptual and focuses on fit, thus not conducting formal mediation analysis, such as structural equation modelling (SEM). This highlights the urgent need for new research to measure indirect effects in the banking sector, particularly as adoption rates of T&D-specific AI tools remain unacceptably low at below 25%, while other banking functions are more readily adopting these technologies.

4.0 Conclusion

This section presents the study's limitations, its theoretical and practical implications, and directions for future research.

4.1 Limitations of the study

A key limitation of this review is the lack of research on AI in Nigeria's banking sector's T&D. Consequently, much of the evidence is based on general AI applications, which may reduce accuracy and relevance to specific contexts. The studies used (e.g. surveys and theoretical/practical analyses) did not allow a meta-analysis, thus limiting the quantitative strength. The underreporting of negative results may further contribute to publication bias, as studies with positive outcomes are more likely to be published, making the overall findings appear more favourable than they actually are. Excluding studies published in languages other than English may omit key research findings from Africa, thereby reducing the scope and relevance of the review.

4.2 Theoretical Implications

This study shows that while AI has enormous potential to personalise learning and close existing skill gaps, it also faces major challenges in emerging geographical contexts. This study contributes to the theory by positioning the current research within the TTF model for testing in African contexts. This is an area often overlooked by dominant models such as the Technology Acceptance Model (TAM), which tends to underrepresent cultural and infrastructural differences. Integrating TTF theory with Nigerian-specific constraints, such as low literacy levels that affect task–technology alignment, helps adapt TTF constructs to low-resource environments. This highlights the critical need for contextual adaptation, extending technology adoption theories beyond Western-centric frameworks and enhancing their broader applicability.

4.3 Practical Implications

Given the massive investments in AI technologies, it is only prudent for Nigerian banks to initially focus on specific T&D programs to raise awareness of AI's broader roles. These T&D modules need to be developed through a comprehensive training needs analysis and delivered through user-friendly learning systems. It is equally vital to invest in digital literacy to reduce employee resistance and enable the efficient use of AI. Public-private partnerships, particularly with fintech companies, may help get pilot AI projects in banking off the ground. Recent results from applying AI in banking and related areas have shown that productivity can be improved by 40–60% when AI tools are well-suited to the tasks.

Nigeria's problems are similar to those of many African economies. AI adoption can be hampered by several factors, namely, unfavourable organisational culture, inadequate infrastructure, and a shortage of skilled workers. Global statistics indicate that AI could raise Africa's GDP by up to $1.5 trillion by 2035 (Balogun, 2026). However, for Nigeria to realise some of these gains, it will require targeted investments in institutional readiness, capacity building, and ethical governance. The ethical guidelines in Nigerian banking need to be centred on justice, minimising bias, and enabling comprehensive participation in AI-enabled T&D. In this way, the benefits can flow to underrepresented populations, including workers in rural or disadvantaged regions. Such a strategy is critical if we are to avert the kinds of inequalities that AI might accelerate, as some have raised as a concern based on technological changes observed in African economies more broadly.

4.4 Future Research

After reviewing the literature, it's clear that there are significant gaps in our understanding of how Nigerian banks use AI for training and development. These gaps highlight a real opportunity for future research. Moving forward, it would be beneficial for researchers to focus on conducting empirical studies in the Nigerian banking sector rather than relying on findings from non-Nigerian or broader regional contexts. This approach will likely enhance the relevance and applicability of the new research outcomes to Nigeria's unique environment. The future research needs to capitalise on quantitative research methodologies like large-scale survey research to collect concrete empirical evidence regarding how the variables of training and development (T&D), the nature of the AI system, and individual variables play a part in influencing the acceptance as well as adoption of AI among the consumers of banks in Nigeria.

The third research point requiring deeper analysis is the compatibility between T&D and AI variables. While there is some truth to the proposition that users' individual needs must match the AI system's offering, very little empirical research has been conducted in this area, especially in a developing economy. Future research needs to capitalise on sophisticated methods, such as SEM modelling, to link variables. Instead of just focusing on why users might want to adopt new tools or technology, we should really dive into what happens after they make that leap. It’s crucial to explore the effects that come after adoption. Longitudinal studies could shed light on how effective an AI-powered training and development tool is over time, particularly its impact on learning effectiveness, skill development, performance, and overall organisational outcomes.

Looking ahead, future research should pay more attention to the context and equity factors at play. Several variables can affect how banks adopt AI, including the institution's size, organisational culture, existing infrastructure, and varying levels of employees' digital skills. These aspects haven’t been thoroughly explored in existing literature. Lastly, using qualitative and mixed-methods approaches can shed light on the social, cultural, and ethical issues associated with AI in training and development (T&D). These methods can also benefit market segments that are often overlooked, such as microfinance and smaller banks. By following the path outlined in this article, future research can contribute to the growing knowledge base on AI-supported T&D in the Nigerian banking sector. This, in turn, can help develop theories and practices that will drive improvements in developing countries.

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APPENDIX A: PRISMA 2020 Checklist (Page et al., 2021)

Section and Topic	Item #	Checklist item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title page/Abstract (includes "systematic literature review")
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Pages 1–2 (structured abstract with background, objectives, methods, results, conclusions)
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Pages 2–7 (background, low adoption in Nigeria/Africa, practical and theoretical gaps)
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Page7, Section 1.2. Three research objectives are explicitly listed.
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Pages 10-11, Section 2.2: Inclusion and exclusion criteria
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Pages 8–11, Section 2.1: Search Strategy. Page 30-41, References
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Pages 8–11, Section 2.1: Search Strategy.
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if	Page 8-12, Section 2.1: Search Strategy. Section 2.2: Data Extraction

Section and Topic	Item #	Checklist item	Location where item is reported
		applicable, details of automation tools used in the process.	
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Page 11-12, Section 2.2: Data Extraction
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Pages 13–26 (factors: enablers/barriers, TTF constructs, adoption outcomes)
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Pages 13-26 (contextual factors, study characteristics)
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Pages 14–15 (Section 2.4: independent review, consensus to mitigate bias)

Section and Topic	Item #	Checklist item	Location where item is reported
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Not applicable (thematic synthesis, no quantitative meta-analysis)
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Pages 13-26 (thematic synthesis aligned with RO1–RO3 and TTF)
	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Pages 13-26 (line-by-line coding, inductive themes)
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Pages 15–17 + Figure (PRISMA flow diagram) + Tables (e.g., Table 1, Table 6 in Appendix A)
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Pages 15–17 (thematic synthesis following Thomas & Harden, 2008)
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Pages 28–32 (narrative discussion of contextual differences)
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	None (not conducted, qualitative synthesis)

Section and Topic	Item #	Checklist item	Location where item is reported
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	None (publication bias not formally assessed)
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Pages 14–15 (quality weighting in synthesis; no formal GRADE)
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Pages 17–18 + Figure (PRISMA flow diagram: ~1,300 → 46 included)
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Pages 17–18 (reasons recorded; summarised, not listed individually)
Study characteristics	17	Cite each included study and present its characteristics.	Appendix A (Table 6: Summary of 46 studies)
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Pages 14–15 (independent review and consensus)
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimates and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Pages 19–28 (Sections 3.2.1–3.2.3: thematic results)
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Pages 28–32 (weighted by quality)
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical	Not applicable (thematic/narrative synthesis)

Section and Topic	Item #	Checklist item	Location where item is reported
		heterogeneity. If comparing groups, describe the direction of the effect.	
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Pages 28–32 (contextual barriers/enablers discussed)
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	None
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	None
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Pages 28–32 (evidence synthesis weighted by quality)
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Pages 15-26
	23b	Discuss any limitations of the evidence included in the review.	Section 4.1, page 27
	23c	Discuss any limitations of the review processes used.	Section 4.1, page 27
	23d	Discuss implications of the results for practice, policy, and future research.	Pages 27-29 (Theoretical and practical implications, future directions)
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	Not registered
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	Protocol not prepared

Section and Topic	Item #	Checklist item	Location where item is reported
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	Not applicable
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	No funding received (Funding Statement)Page 3o
Competing interests	26	Declare any competing interests of review authors.	No competing interests (Conflict of Interest Statement) page 30
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Not applicable