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A Systematic Review of Knowledge Management Practices as Antecedents of Artificial Intelligence Adoption in Nigerian SMEs

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Abstract

Research on artificial intelligence adoption among Nigerian small and medium enterprises is young and fragmented, and studies that pair knowledge management practices with an artificial intelligence adoption outcome are rare. This systematic review takes stock of that evidence and asks which knowledge management practices are plausible antecedents of artificial intelligence adoption in this setting. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 guidelines, Google Scholar, Scopus, Web of Science and ResearchGate were searched using database-specific Boolean strings, yielding 1,286 records. After removing 274 duplicates, screening 1,012 titles and abstracts and assessing 171 full texts against two-tier eligibility criteria, 21 studies were included: three from Nigeria, three from wider African settings and 15 international comparative studies. Study quality was appraised with the Mixed Methods Appraisal Tool and Joanna Briggs Institute checklists. Thematic synthesis identified four themes: knowledge sharing culture, absorptive capacity, digital leadership and structural constraints. Only four studies examined knowledge management directly, while most measured proxy constructs such as digital leadership, human capital or dynamic capabilities, and no Nigerian study measured knowledge management and artificial intelligence adoption together. The review concludes with a conceptual framework and seven testable propositions, alongside low-cost knowledge management interventions for small firms and recommendations for national digital transformation agencies.

Keywords: Knowledge Management, Artificial Intelligence Adoption, Small and Medium Enterprises, Nigeria, Absorptive Capacity, Systematic Literature Review.

Introduction

Artificial intelligence has moved from a specialised research pursuit to a mainstream organisational capability that is reshaping how firms compete, learn and create value (Ayinaddis, 2025; Rajaram & Tinguely, 2024). Organisations that integrate artificial intelligence into decision-making, customer engagement and operational processes report measurable gains in efficiency and competitiveness (Wamba-Taguimdje et al., 2020). Small and medium enterprises occupy a distinctive position in this transformation. They lack the financial reserves, dedicated data science teams and formal governance structures that large firms use to absorb new technology, yet they represent the overwhelming majority of firms and employment in most economies, including Nigeria, where they account for a substantial share of gross domestic product and non-oil employment (Small and Medium Enterprises Development Agency of Nigeria [SMEDAN], 2023). Understanding what enables or constrains artificial intelligence adoption within this segment is therefore a matter of direct economic consequence.

A growing body of research treats knowledge management, rather than infrastructure or finance alone, as a proximate determinant of technology adoption (Alavi & Leidner, 2001; Davenport & Prusak, 1998; Jarrahi et al., 2023). Artificial intelligence systems depend on organisational data, codified procedures and the tacit expertise of employees who understand how a business actually operates (Nonaka & Takeuchi, 1995). A firm that has built routines for acquiring, sharing and applying knowledge is better positioned to recognise the value of an external technology, absorb it into existing workflows and exploit it for commercial ends, a capability Cohen and Levinthal (1990) term absorptive capacity. Firms without such routines may hold the same financial resources and still fail to adopt or benefit from artificial intelligence (Iaia et al., 2024). This knowledge-centred explanation has been examined extensively in Europe, North America and East Asia, but far less within Nigeria.

Nigerian small and medium enterprises operate under well-documented constraints, including unreliable electricity, limited access to credit and a persistent digital skills gap (Adegbuyi et al., 2024; Awotunde et al., 2024; Uwagaba et al., 2023), and available evidence confirms that artificial intelligence adoption lags global benchmarks (Nwagbala et al., 2025; Organisation for Economic Co-operation and Development [OECD], 2025). It would be premature, however, to frame the question as though direct evidence on how knowledge conditions drive adoption in these firms were already available. Local research on the topic is nascent and fragmented across disciplines. Studies of Nigerian small and medium enterprises tend to examine information and communication technology adoption broadly rather than artificial intelligence specifically (Ahmadu, 2025; Awotunde et al., 2024), and the few that isolate artificial intelligence adoption examine leadership, infrastructure or awareness rather than knowledge management practices as such (Adegbuyi et al., 2024; Idowu & Babalola, 2026). Meanwhile, the international literature connecting knowledge management to artificial intelligence outcomes has been developed largely outside African contexts (Ayinaddis, 2025; Jarrahi et al., 2023; Okechukwu et al., 2026). This review is therefore positioned explicitly as a systematic stocktaking exercise. Rather than claiming to establish how knowledge management drives artificial intelligence adoption in Nigerian firms, it maps what the available evidence does and does not show, distinguishes Nigerian from comparative evidence, separates studies that measure knowledge management directly from those that measure proxy constructs, and converts the resulting synthesis into propositions that primary

research can test. A systematic design suits this purpose because it applies an explicit, reproducible search and screening protocol and produces a transparent account of how much direct evidence exists (Page et al., 2021). This matters for a topic in which the temptation to substitute adjacent, more abundant literature, such as general digital transformation studies, for the narrower pairing of knowledge management and artificial intelligence is real.

The review pursues four objectives: to identify the knowledge management practices, including acquisition, sharing, creation and application, that have been associated with artificial intelligence or closely related technology adoption in small and medium enterprises; to establish the mechanisms, particularly absorptive capacity and digital leadership, through which these practices are argued to operate; to determine how much of this evidence derives from Nigeria as opposed to other African or international settings, and whether it measures knowledge management directly or through proxies; and to synthesise the evidence into a conceptual framework and testable propositions for a subsequent Nigerian study. The paper first reviews the theoretical foundations and empirical literature, then sets out the methodology, presents and discusses the findings, and closes with recommendations, limitations and directions for future research.

Literature Review

Knowledge-Based Theory and the Organisational Knowledge Base

The knowledge-based view treats knowledge, rather than physical or financial capital, as the firm's most strategically important resource, and treats the firm as an institution for integrating specialised individual knowledge into productive activity (Grant, 1996). Davenport and Prusak (1998) argue that organisations that deliberately manage knowledge, making it visible, codifying it and building infrastructure for its exchange, outperform those that leave it implicit and person-bound. Alavi and Leidner (2001) distinguish knowledge creation, storage, transfer and application as the core processes any knowledge management system must support. These contributions matter here because artificial intelligence adoption is at heart a knowledge integration problem: a firm must recognise the external knowledge embedded in the technology, combine it with internal process knowledge and apply the result to a specific business function.

Nonaka and Takeuchi's (1995) SECI model describes organisational knowledge creation as a spiral of socialisation, externalisation, combination and internalisation between tacit and explicit knowledge, building on Nonaka's (1994) dynamic theory of knowledge creation. The spiral explains concretely how the tacit know-how of a small firm becomes usable by artificial intelligence tools. In socialisation, experienced staff share know-how through observation and joint work, for example how a sales team qualifies a lead or how a workshop schedules production. Externalisation then converts that know-how into explicit artefacts such as written standard operating procedures, decision rules, process maps and worked examples of correct and incorrect decisions. Combination assembles these artefacts with transaction records into structured, machine-readable forms, namely consistently coded spreadsheets, customer and inventory databases, labelled examples and data dictionaries, which are precisely the inputs that predictive models, chatbots and generative tools require for training, configuration and prompting (Jarrahi et al., 2023). Internalisation completes the cycle when employees learn from artificial intelligence outputs and refine their own practice. A firm whose operational knowledge never passes through externalisation and combination has, in effect, no data from which artificial intelligence can learn, which is why knowledge codification is a precondition for adoption rather than a by-product of it.

Absorptive capacity, introduced by Cohen and Levinthal (1990) and reconceptualised by Zahra and George (2002) as a dynamic capability comprising acquisition, assimilation, transformation and exploitation, provides the most direct theoretical bridge between knowledge management and technology adoption. Its central claim is that a firm's ability to recognise, assimilate and commercially exploit new external knowledge, such as an artificial intelligence capability, is a function of its prior related knowledge stock rather than its financial resources alone. Barney's (1991) resource-based view and Teece et al.'s (1997) dynamic capabilities framework reinforce this logic by positioning internal capabilities, including knowledge management routines, as the mechanism through which external resources become sustained advantage.

Technology Adoption Theory

The review uses Tornatzky and Fleischer's (1990) technology, organisation and environment framework as its principal adoption lens, because it accommodates knowledge-related organisational factors, such as staff expertise and management support, alongside technological and environmental ones, and because it dominates the studies included in this review (Ayinaddis, 2025; Baabdullah et al., 2021; Badghish & Soomro, 2024). Rogers' (1995) diffusion of innovations theory adds the perceived attributes of an innovation, such as relative advantage and compatibility, that shape willingness to adopt. In small firms the adoption decision is usually made by the owner-manager, so individual-level acceptance models remain relevant. Davis's (1989) technology acceptance model and the unified theory of acceptance and use of technology (Venkatesh et al., 2003) explain intention through perceived usefulness, ease of use and performance expectancy. Rather than treating these models as background, this review integrates them into its conceptual framework as the cognitive channel through which organisational absorptive capacity is expected to translate into the owner-manager's adoption intention. DeLone and McLean's (1992, 2003) information systems success model is retained only as a post-adoption extension, linking adoption to use and net benefits, because none of the included studies measured post-adoption success.

Knowledge Management and Artificial Intelligence Adoption in the International Literature

An international literature examines the knowledge management and artificial intelligence relationship directly, although mostly conceptually. Jarrahi et al. (2023) characterise artificial intelligence and knowledge management as a partnership between human and machine intelligence, arguing that deployments succeed where knowledge codification practices are mature enough to supply the structured data and process documentation that artificial intelligence requires. Iaia et al. (2024) adopt a knowledge management perspective on implementing artificial intelligence in business communication and argue that knowledge management practices actively shape whether implementation succeeds. Cristache et al. (2025), surveying 528 managers and staff in Romania, find that knowledge creation, integration and sharing predict innovation, which in turn predicts organisational performance, although their outcome is innovation rather than artificial intelligence adoption. Okechukwu et al. (2026), in a comparative systematic review of artificial intelligence as an information and knowledge management capability, report differences in managerial impacts between African and European organisations.

Other studies examine knowledge-related capabilities rather than knowledge management itself. Wamba-Taguimdje et al. (2020), analysing 500 vendor-documented artificial intelligence projects, show that the business value firms extract depends on complementary organisational capabilities rather than on the technology alone. Han et al. (2025) examines organisational learning capability in 1,657 Chinese specialised and innovative enterprises and report that it conditions the effect of artificial

intelligence technology on innovation performance, although the direction of their moderating effect is reported inconsistently across their results and conclusions.

Determinants of Artificial Intelligence Adoption in Small and Medium Enterprises

A larger literature examines artificial intelligence adoption determinants in small and medium enterprises without foregrounding knowledge management. Baabdullah et al. (2021), surveying 392 business-to-business small and medium enterprises in Saudi Arabia, find that technology roadmapping, attitude, infrastructure and awareness significantly predict acceptance of artificial intelligence practices, whereas professional expertise does not, a result that cautions against assuming that existing staff expertise automatically drives adoption. Badghish and Soomro (2024), applying the technology, organisation and environment framework to 220 Saudi small and medium enterprises, find that sustainable human capital, alongside relative advantage, compatibility, customer demand and government support, significantly predicts adoption, which in turn improves operational and economic performance. Chaudhuri et al. (2022) report from 343 small and medium enterprise managers that organisational, technological and individual characteristics shape the use of artificial intelligence for sustainability, with leadership support acting as a moderator. Cimino et al. (2025), studying 210 Italian innovative start-ups, extend a dynamic capability framework to explain artificial intelligence adoption for sustainable growth, and Drydakis (2022) finds among 317 London small and medium enterprises that artificial intelligence tools were associated with reduced pandemic business risk, interpreting the effect through dynamic capabilities. Kukanja (2024) shows, from 287 hospitality managers, that entrepreneurial orientation, self-efficacy and perceived performance shape attitudes towards artificial intelligence, attributes closely tied to managers' own knowledge and confidence.

Systematic and bibliometric reviews corroborate the pattern. Ayinaddis (2025), reviewing 78 studies, identifies skills, competencies and functional knowledge as recurring determinants that distinguish small from large firms. Yesuf and Fields (2025), reviewing 63 studies, list human capital and digital literacy among adoption enablers and note that Africa receives little attention in the literature. Kasigit et al. (2025), reviewing 32 studies from developing countries, identify knowledge gaps as a constraint distinct from financial and technological barriers. At policy level, the OECD (2025) identifies skills as one of four enabling conditions for artificial intelligence adoption by small and medium enterprises, alongside connectivity, data and finance. Related work on generative artificial intelligence emphasises that firms lacking internal expertise to evaluate and govern its use adopt more cautiously (Rajaram & Tinguely, 2024; Rana et al., 2024), and Hokmabadi et al. (2024) show that capability development underpins small and medium enterprise resilience through digital transformation.

Digital Leadership and Managerial Knowledge Capability

A related stream examines digital leadership as both a carrier of organisational knowledge and an influence on artificial intelligence adoption. Yu et al. (2025), analysing more than 27,000 firm-year observations from Chinese listed companies, find that executives with a digital background are associated with greater artificial intelligence utilisation, positioning leader-level knowledge as an upstream determinant of firm behaviour. Tigre et al. (2025) operationalise digital leadership as a four-dimensional construct spanning strategic, delivery-related, interpersonal and personal-attribute capabilities, several of which map onto knowledge sharing and continuous learning. Abbu et al. (2022) distinguish character-related from competency-related dimensions of digital leadership, including digital literacy and knowledge sharing, and Brunner et al. (2021) show that digital leadership competences and information technology capabilities jointly affect an organisation's ability to

transform digitally and adopt new technologies. Hossain et al. (2025) argue that artificial intelligence-driven capabilities are reshaping what responsible leadership requires. Upper echelons theory explains why leadership belongs upstream: top managers' knowledge, values and experience shape the strategic choices and learning routines of their organisations (Hambrick & Mason, 1984). At the individual level, Scott and Bruce's (1994) model of innovative behaviour describes how knowledge-sharing climates translate into innovation-supportive behaviour, and Zeike et al. (2019) show that digital leadership skills carry consequences beyond the immediate technology decision.

Nigerian and Sub-Saharan African Evidence

Evidence specific to Nigeria and Sub-Saharan Africa is sparse and more often framed around general technology or digital transformation adoption than around knowledge management and artificial intelligence. SMEDAN (2023) documents that small and medium enterprises constitute the overwhelming majority of registered Nigerian businesses and are concentrated in sectors with low digital maturity. Adegbuyi et al. (2024) examine the role of artificial intelligence in small and medium enterprise management in south-west Nigeria, and Awotunde et al. (2024) show that digital marketing significantly influences small and medium enterprise performance in Nigeria. Uwagaba et al. (2023), reviewing the Sub-Saharan literature, identify limited technical knowledge and skills shortages as primary constraints alongside cost and infrastructure, and Nwagbala et al. (2025) document opportunities and persistent structural challenges in African small and medium enterprises. Idowu and Babalola (2026), surveying 306 owner-managers in south-west Nigeria, provide the most direct evidence: strategic, interpersonal and personal-attribute digital leadership capabilities predict artificial intelligence adoption intention, whereas delivery-related capability does not, with organisational innovation climate partially mediating these effects. Arakpogun et al. (2021) argue at continental level that institutional and knowledge infrastructure gaps shape adoption as much as financial constraint, a framing consistent with the knowledge-based lens adopted here, while Ahmadu (2025) and Agbaakin (2025) discuss technology adoption by small firms in terms broad enough to include, but not measure, knowledge-related factors.

Synthesis and Conceptual Gap

Read together, this literature supports a theoretically grounded expectation that knowledge management practices, operating through absorptive capacity and shaped by digital leadership, are antecedents of artificial intelligence adoption readiness in small and medium enterprises. The expectation rests largely on conceptual and international work (Iaia et al., 2024; Jarrahi et al., 2023; Okechukwu et al., 2026) and finds only indirect support in Nigeria, through studies of leadership, awareness and general technology adoption (Adegbuyi et al., 2024; Idowu & Babalola, 2026). The gap is therefore not one of theory but of direct, Nigeria-specific empirical testing, and the following sections establish how wide that gap is.

Methodology

Research Design

This review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement (Page et al., 2021), which requires an explicit, auditable account of search, screening and exclusion decisions. The review protocol, comprising the eligibility criteria, search strings and extraction form, was defined before searching began.

Eligibility Criteria

Eligibility criteria followed a population, concept and context structure, which suits a question about an organisational determinant relationship rather than a treatment effect. Because the review set out to compare Nigerian evidence with the wider literature, context eligibility was defined in two tiers, and this distinction governs every screening decision reported below. Tier 1 admitted any study conducted in Nigeria that met the population and concept criteria. Tier 2 admitted studies from other African and international settings only when they met a stricter comparative standard: an organisational or small and medium enterprise unit of analysis, an explicit knowledge management or knowledge-related capability construct, and an artificial intelligence adoption, use or value outcome, or a systematic review of artificial intelligence adoption in small and medium enterprises. Non-Nigerian studies that failed this comparative standard were excluded, and these are the exclusions labelled as non-Nigerian studies failing the comparative criteria in Figure 1. Table 1 presents the full criteria.

Table 1: **Inclusion and Exclusion Criteria**

Criterion	Inclusion	Exclusion
Population	Small and medium enterprises or their owners and managers; for Tier 2, organisations of any size where the unit of analysis is organisational	Individual consumers or public agencies with no organisational unit of analysis
Concept	A knowledge management practice or knowledge-related capability examined in relation to artificial intelligence or closely related digital technology adoption, use or value	No knowledge management or knowledge-related construct, or no technology adoption, use or value outcome
Context, Tier 1	Studies conducted in Nigeria	Not applicable
Context, Tier 2	Studies from other African and international settings meeting the comparative standard: organisational unit, explicit knowledge-related construct and artificial intelligence outcome, or a systematic review of artificial intelligence adoption in small and medium enterprises	Non-Nigerian studies failing any element of the comparative standard
Publication type	Peer-reviewed journal articles, conference proceedings, and institutional or policy reports with analysable evidence	Opinion pieces, editorials and unreviewed web content
Language and period	English; 1990 to 2026	Non-English sources without translation

Note. Tier 1 = Nigerian evidence; Tier 2 = comparative evidence from other settings.

Search Strategy

Four sources were searched: Google Scholar, Scopus, Web of Science and ResearchGate. Google Scholar and ResearchGate index grey literature and Africa-based journals that Scopus and Web of Science under-index, while the latter two provide more reliable citation metadata. Each search combined three concept blocks, covering knowledge management, artificial intelligence adoption and small and medium enterprises, adapted to the syntax of each source. A fourth block of Nigerian and African terms was run as a supplementary query in each source, and its results are included in the counts reported. The searches were run between 14 July and 18 August 2026, and the final search of each source was completed on 18 August 2026. Table 2 reports the exact strings and the records each source returned.

Table 2: **Database-Specific Search Strings and Records Identified**

Source	Search string as executed	Records
Scopus	TITLE-ABS-KEY (("knowledge management" OR "knowledge sharing" OR "knowledge acquisition" OR "knowledge creation" OR "absorptive capacity" OR "organi?ational learning") AND ("artificial intelligence" OR "AI adoption" OR "machine learning" OR "generative AI" OR "digital technology adoption") AND ("small and medium enterprise*" OR "small and medium-sized enterprise*" OR SME* OR "small business*")) AND PUBYEAR > 1989 AND PUBYEAR < 2027 AND LANGUAGE (English)	290
Web of Science Core Collection	TS=(("knowledge management" OR "knowledge sharing" OR "knowledge acquisition" OR "knowledge creation" OR "absorptive capacity" OR "organi?ational learning") AND ("artificial intelligence" OR "AI adoption" OR "machine learning" OR "generative AI" OR "digital technology adoption") AND ("small and medium enterprise*" OR "small and medium-sized enterprise*" OR SME* OR "small business*")); timespan 1990–2026; language English	276
Google Scholar	"knowledge management" ("artificial intelligence" OR "AI adoption") (SME OR SMEs OR "small and medium enterprises"); 1990–2026; first 520 results by relevance screened	520
ResearchGate	knowledge management AND artificial intelligence adoption AND (SME OR small and medium enterprises); first 200 results by relevance screened	200
Supplementary block (all sources)	AND (Nigeria OR Nigerian OR "sub-Saharan Africa" OR Africa*), run as an additional query in each source; results included in the counts above	Included above
Total identified		1,286

Note. Google Scholar and ResearchGate do not support full Boolean nesting or wildcards, so simplified equivalents were used and screening was limited to the most relevant results. The * symbol denotes truncation and ? a single-character wildcard.

Study Selection Process

Study selection followed the four PRISMA stages shown in Figure 1. At identification, 1,286 records were retrieved and 274 duplicates removed, leaving 1,012 records for title and abstract screening. Screening excluded 782 records that were unrelated to knowledge management or artificial intelligence (n = 436), not focused on small and medium enterprises (n = 218) or lacking any organisational technology adoption context (n = 128). Of 230 full texts sought, 59 could not be retrieved, leaving 171 assessed against the two-tier criteria. Of these, 150 were excluded because they examined no knowledge management or knowledge-related capability construct (n = 52), had no artificial intelligence or closely related technology adoption outcome (n = 38), were non-Nigerian studies that failed the Tier 2 comparative criteria (n = 32), offered opinion without analysable evidence (n = 18) or reported insufficient methodological detail (n = 10). Twenty-one studies were included: three from Nigeria under Tier 1 and 18 comparative studies under Tier 2, three of which are from other African settings. Foundational theoretical works cited in the literature review informed the framework but were not counted among the included studies.

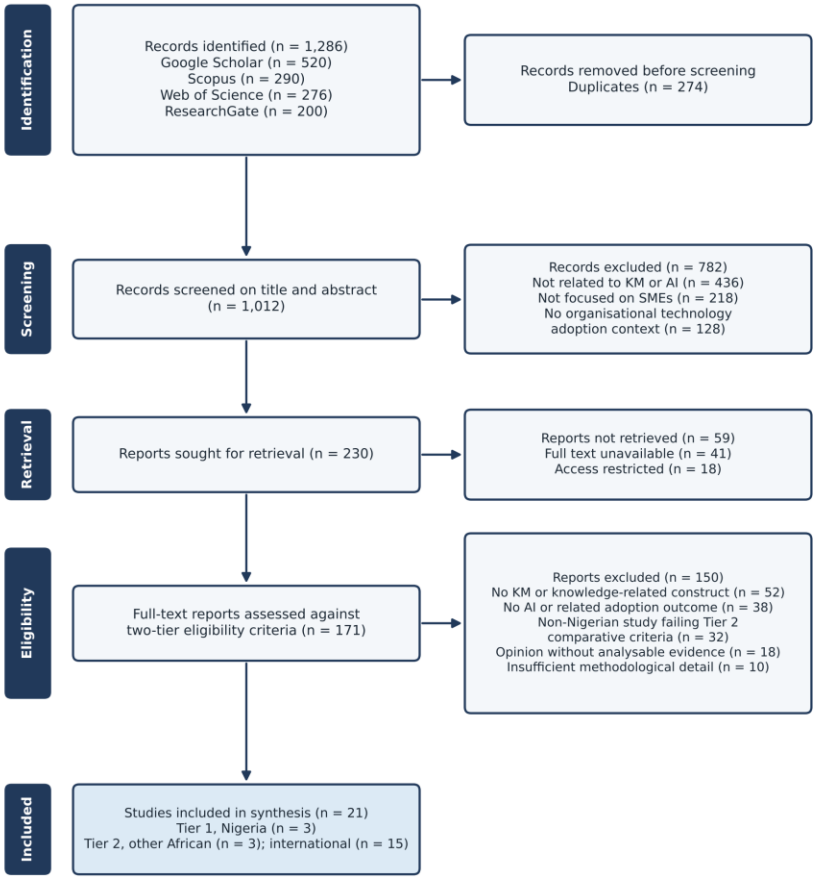


Figure 1: **PRISMA 2020 Flow Diagram of Study Identification, Screening, Eligibility and Inclusion**

Data Extraction and Quality Appraisal

A standardised extraction form, summarised in Figure 2, recorded each study's author and year, context, theoretical framework, sample and method, knowledge management construct, adoption outcome and the direction of any reported relationship. Each construct was also coded as either a direct knowledge management measure, such as knowledge sharing or creation, or a proxy construct, such as digital leadership, human capital or dynamic capability. The form was piloted on five studies to catch inconsistent construct labelling before full application.

Quality was appraised with design-appropriate tools rather than a single score. Empirical studies were appraised with the Mixed Methods Appraisal Tool (MMAT), version 2018 (Hong et al., 2018), which provides design-specific criteria for quantitative, qualitative and mixed-methods research. Systematic, bibliometric and narrative reviews were appraised with the Joanna Briggs Institute checklist for systematic reviews and research syntheses (Aromataris et al., 2015), and conceptual papers with the Joanna Briggs Institute checklist for text and opinion (McArthur et al., 2015). Appraisal informed the weight given to each study in the synthesis rather than serving as an exclusion criterion, consistent with recommended practice for reviews spanning mixed designs.

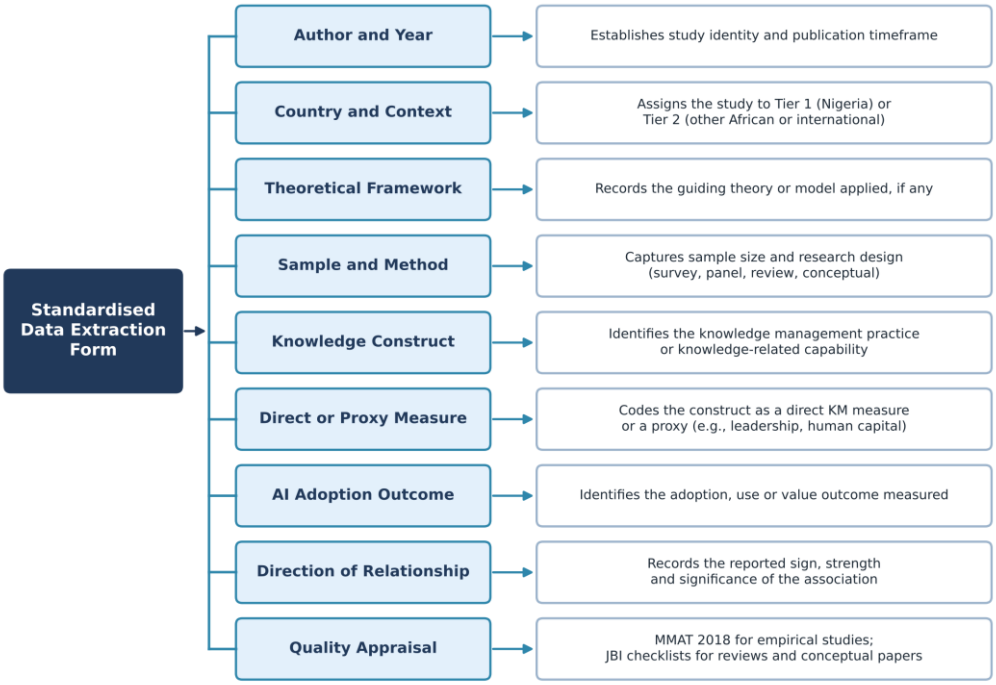


Figure 2: **Data Extraction Framework Applied to Each Included Study**

Characteristics of the Included Studies

Table 3 presents the full matrix of the 21 included studies, reporting each study's context, sample, design, knowledge management construct and adoption outcome. Two features stand out. First, only three studies are Nigerian, and none of them measures a knowledge management practice together with an artificial intelligence adoption outcome. Second, only four studies examine knowledge management directly (Cristache et al., 2025; Iaia et al., 2024; Jarrahi et al., 2023; Okechukwu et al., 2026), and only one of these collects primary data, with an outcome of innovation rather than artificial intelligence adoption. The remaining 17 studies measure proxy constructs, most often digital leadership, human capital, skills or dynamic capabilities. Figure 3 summarises the geographic scope and research designs of the included studies.

Table 3: **Matrix of the 21 Included Studies**

Study	Context	Sample	Design	Knowledge construct (type)	Adoption-related outcome and finding
Tier 1: Nigeria					
Adegbuyi et al. (2024)	Nigeria (south-west), SMEs	NR	Questionnaire survey	Awareness and technical skills (proxy)	Role of AI in SME management; skills and cost barriers reported
Awotunde et al. (2024)	Nigeria, SMEs	NR	Questionnaire survey, regression	Digital marketing capability (proxy)	Digital marketing significantly improves SME performance
Idowu and Babalola (2026)	Nigeria (south-west), SMEs	306 owner-managers	Survey, PLS-SEM	Digital leadership capabilities (proxy)	Strategic, interpersonal and personal-attribute capabilities predict AI adoption intention; $R^2 = .418$

Study	Context	Sample	Design	Knowledge construct (type)	Adoption-related outcome and finding
Tier 2: Other African settings					
Nwagbala et al. (2025)	Africa, SMEs	Documents	Narrative review	Skills and knowledge (proxy)	AI adoption opportunities alongside structural challenges
Okechukwu et al. (2026)	Africa and Europe	21 studies	Systematic review	AI as information and knowledge management capability (direct)	Differences in managerial impacts of AI between regions
Uwagaba et al. (2023)	Sub-Saharan Africa, SMEs	Literature and reports	Narrative review	Technical knowledge (proxy)	Knowledge and skills shortages are primary barriers to AI adoption
Tier 2: International comparative					
Ayinaddis (2025)	Global, SMEs and large firms	78 studies	Systematic and bibliometric review	Skills and competencies (proxy)	Functional knowledge and skills distinguish SME from large-firm adoption
Baabdullah et al. (2021)	Saudi Arabia, B2B SMEs	392 SMEs	Survey, SEM	Professional expertise (proxy)	Roadmapping, attitude, infrastructure and awareness significant; expertise not significant
Badghish and Soomro (2024)	Saudi Arabia, SMEs	220 managers	Survey, PLS-SEM	Sustainable human capital (proxy)	Human capital predicts AI adoption (β = .223); adoption improves performance
Chaudhuri et al. (2022)	Not specified, SMEs	343 managers	Survey, PLS-SEM	Organisational and individual characteristics (proxy)	Shape AI use for sustainability; leadership support moderates
Cimino et al. (2025)	Italy, innovative start-ups	210 firms	Survey, PLS-SEM	Dynamic capabilities (proxy)	AI adoption supports sustainable growth through dynamic capabilities
Cristache et al. (2025)	Romania, organisations	528 respondents	Survey, PLS-SEM	Knowledge creation, integration and sharing (direct)	Predict innovation, which mediates performance; AI not measured
Drydakis (2022)	United Kingdom (London), SMEs	317 SMEs	Longitudinal survey	Dynamic capabilities (proxy)	AI use associated with reduced COVID-19 business risk
Han et al. (2025)	China, listed innovative firms	1,657 firms	Firm-level panel regression	Organisational learning capability (proxy)	Conditions AI effect on innovation; moderation direction reported inconsistently
Iaia et al. (2024)	Not specified, organisations	Not applicable	Conceptual	Knowledge management practices (direct)	Knowledge management shapes successful AI implementation in business communication
Jarrahi et al. (2023)	Global	Not applicable	Conceptual	Knowledge management and codification (direct)	Mature codification enables productive AI deployment
Kasigit et al. (2025)	Developing countries, SMEs	32 studies	Systematic review	Knowledge gaps (proxy)	Knowledge gaps constrain AI adoption alongside other barriers
Kukanja (2024)	Slovenia, hospitality SMEs	287 managers	Survey, SEM	Self-efficacy and entrepreneurial orientation (proxy)	Shape managers' attitudes towards AI adoption
Wamba-Taguimdje et al. (2020)	Global, multi-sector	500 vendor case studies	Archival case analysis	Complementary IT capabilities (proxy)	AI business value depends on complementary capabilities
Yesuf and Fields (2025)	Global, SMEs	63 studies	Systematic and bibliometric review	Human capital and digital literacy (proxy)	Skills enable adoption; Africa under-studied
Yu et al. (2025)	China, listed firms	About 27,000 firm-years	Panel regression	Executives' digital background (proxy)	Associated with greater AI utilisation

Note. NR = not reported in the accessible record; AI = artificial intelligence; SEM = structural equation modelling; PLS = partial least squares; SME = small and medium enterprise; B2B = business to business. Direct = knowledge management practice measured or theorised explicitly; proxy = related construct.

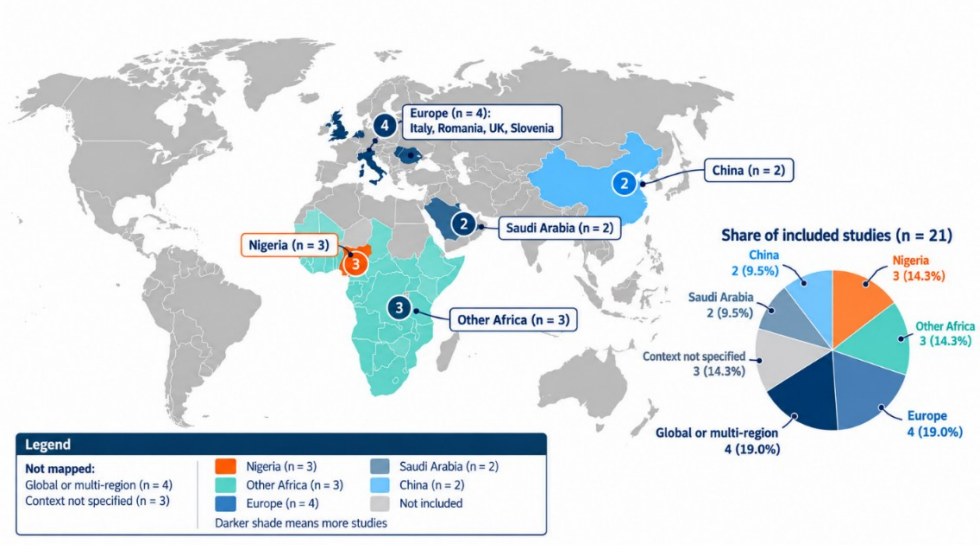


Figure 3: **Geographic Scope and Research Design of the 21 Included Studies**

Findings and Discussion

Thematic analysis identified four recurring themes: knowledge sharing culture and organisational readiness, absorptive capacity as the mediating mechanism, digital leadership as an upstream knowledge-carrying construct, and structural constraints specific to Nigeria. Table 4 summarises the themes, and Figure 4 maps the theoretical foundations onto them.

Table 4: **Thematic Summary of Findings**

Theme	Included studies	Key insight	Evidence type
Knowledge sharing culture and readiness	Jarrahi et al. (2023); Iaia et al. (2024); Cristache et al. (2025); Idowu and Babalola (2026)	Codified, shared knowledge is a precondition for productive artificial intelligence use, not a by-product of it	Mainly direct, but conceptual or non-AI outcome
Absorptive capacity as mechanism	Badghish and Soomro (2024); Cimino et al. (2025); Baabdullah et al. (2021); Han et al. (2025); Adegbuyi et al. (2024)	Routines that mobilise prior knowledge matter more than the stock of expertise alone	Proxy
Digital leadership as upstream carrier	Idowu and Babalola (2026); Yu et al. (2025); Chaudhuri et al. (2022); Kukanja (2024)	Strategic and interpersonal leadership knowledge shapes learning climate and adoption intention	Proxy
Structural constraints in Nigeria	Uwagaba et al. (2023); Nwagbala et al. (2025); Awotunde et al. (2024)	Infrastructure and finance compound, rather than replace, knowledge-related barriers	Proxy, mainly narrative

Note. Direct = knowledge management practice measured or theorised explicitly; proxy = knowledge-related construct such as leadership, human capital or dynamic capability.

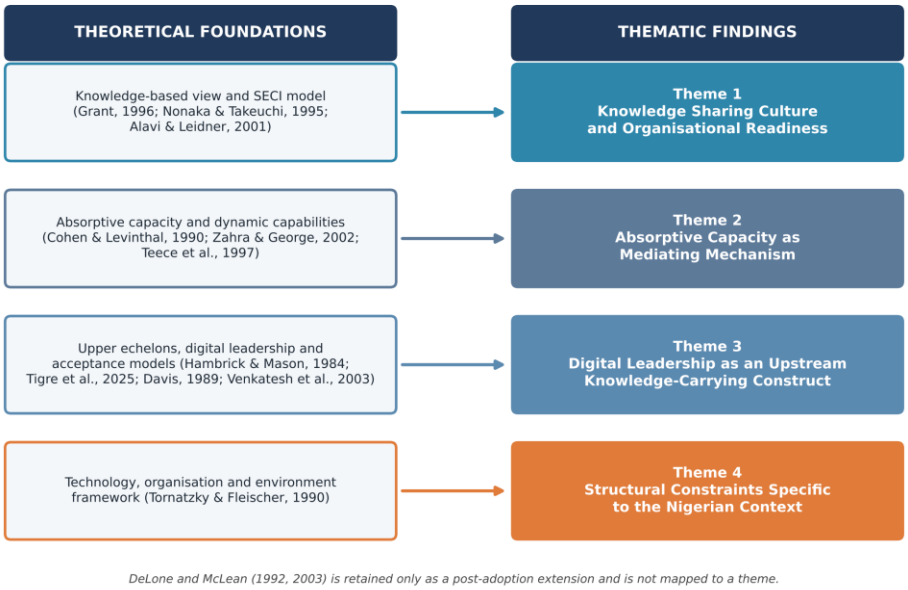


Figure 4: **Mapping of Theoretical Foundations onto Thematic Findings**

Theme One, Knowledge Sharing Culture and Organisational Readiness

The most consistent finding is that internal knowledge sharing and codification function as a precondition for productive artificial intelligence adoption rather than a consequence of it. Jarrahi et al. (2023) argue that artificial intelligence systems are only as useful as the organisational knowledge fed into and structured around them, and Iaia et al. (2024) argue that knowledge management practice shapes whether implementation succeeds. Cristache et al. (2025) provide the only primary evidence in the included set that measures knowledge management practices directly, showing that knowledge creation, integration and sharing drive innovation. This pattern matches the SECI account set out earlier: artificial intelligence adoption requires tacit operational know-how to be externalised and combined into codified, machine-readable form. Within Nigeria the theme appears only indirectly. Idowu and Babalola's (2026) finding that interpersonal digital leadership capability, which includes fostering knowledge exchange around new technology, predicts adoption intention is consistent with the knowledge sharing argument, even though the study does not frame its constructs in knowledge management terms. No Nigerian study measures knowledge sharing culture and artificial intelligence adoption as paired constructs.

Theme Two, Absorptive Capacity as the Mediating Mechanism

The second theme concerns the mechanism connecting knowledge management to adoption, and the literature converges on absorptive capacity. Cohen and Levinthal's (1990) claim that a firm's capacity to exploit external knowledge depends on its prior related knowledge is consistent with Cimino et al.'s (2025) dynamic capability account of artificial intelligence adoption in start-ups and with Badghish and Soomro's (2024) finding that human capital predicts adoption alongside technological and environmental factors. Zahra and George's (2002) distinction between potential and realised absorptive capacity helps explain why Nigerian owner-managers report awareness of artificial intelligence without converting it into adoption (Adegbuyi et al., 2024): awareness reflects potential capacity, whereas

adoption requires realised capacity built through prior knowledge and routine. The evidence also contains a caution. Baabdullah et al. (2021) found that professional expertise did not significantly predict acceptance of artificial intelligence practices, suggesting that a stock of expertise matters less than the routines that mobilise it, which is precisely the distinction absorptive capacity theory draws. Han et al.'s (2025) inconsistent moderation results reinforce the need for primary studies that model learning capability carefully.

Theme Three, Digital Leadership as an Upstream Knowledge-Carrying Construct

The third theme identifies digital leadership as the level at which managerial knowledge most visibly converts into an adoption decision. Yu et al. (2025) finds that executives with a digital background are associated with greater artificial intelligence utilisation, and Tigre et al. (2025) and Abbu et al. (2022) both build knowledge sharing and continuous learning into the definition of digital leadership. The clearest Nigerian evidence comes from Idowu and Babalola (2026), whose strategic and interpersonal capabilities predict adoption intention while delivery-related capability does not at the pre-adoption stage. This suggests that cognitive and relational capability matters more for the adoption decision than technical execution skill, which becomes relevant only at implementation.

These findings also justify placing digital leadership upstream in the conceptual framework rather than downstream of absorptive capacity. In small firms the owner-manager typically decides what knowledge is captured, which routines are formalised and whether time is set aside for learning, so leadership is better understood as an antecedent that fosters knowledge management practices and the learning routines that constitute absorptive capacity (Hambrick & Mason, 1984; Tigre et al., 2025). Idowu and Babalola's (2026) finding that innovation climate mediates the effect of leadership on adoption intention supports this ordering, because it places an organisational learning condition between leadership and adoption. Leadership may also act directly on adoption intention through the owner-manager's own perceptions of usefulness and ease of use, the channel described by individual acceptance models (Davis, 1989; Venkatesh et al., 2003).

Theme Four, Structural Constraints Specific to the Nigerian Context

The fourth theme captures the structural constraints that the Nigerian and African literature reports alongside, rather than instead of, knowledge-related barriers. SMEDAN (2023) documents the sector's exposure to unreliable electricity, limited credit and low digital infrastructure, conditions that Uwagaba et al. (2023) and Awotunde et al. (2024) connect to constrained technology adoption. Nwagbala et al. (2025) describe a compounding set of barriers in which limited knowledge and skills interact with financial and infrastructural limitation. It would be a mistake to read this evidence as showing that knowledge management does not matter because infrastructure and finance are cited more often. A more accurate reading, consistent with Arakpogun et al. (2021), is that existing Nigerian studies have rarely isolated knowledge management from infrastructure and finance, so their relative weight cannot yet be determined.

Conceptual Framework and Research Propositions

Considered together, the four themes suggest a causal chain that no included study tests in full: digital leadership fosters knowledge management practices, these practices build absorptive capacity, absorptive capacity shapes the owner-manager's perceptions of artificial intelligence and the firm's adoption decision, and structural constraints condition whether that decision can be realised. Figure 5

presents this chain as a conceptual framework, and the following propositions formalise it so that it can be operationalised in structural equation models.

P1: Digital leadership capability in Nigerian small and medium enterprises is positively associated with the intensity of knowledge management practices (acquisition, sharing, creation and application).

P2: Knowledge management practices are positively associated with absorptive capacity.

P3: Absorptive capacity is positively associated with artificial intelligence adoption intention and adoption.

P4: Absorptive capacity mediates the relationship between knowledge management practices and artificial intelligence adoption.

P5: Owner-managers' perceived usefulness and ease of use of artificial intelligence mediate the relationship between absorptive capacity and adoption intention.

P6: Digital leadership capability has a direct positive association with artificial intelligence adoption intention, in addition to its indirect association through knowledge management practices and absorptive capacity.

P7: Structural constraints, namely unreliable infrastructure, limited finance and the digital skills gap, negatively moderate the relationship between absorptive capacity and artificial intelligence adoption.

Each construct can be measured with established instruments: knowledge management practices with scales such as those used by Cristache et al. (2025), absorptive capacity with Zahra and George's (2002) four dimensions, digital leadership with Tigre et al.'s (2025) construct as applied by Idowu and Babalola (2026), and perceptions with technology acceptance items (Davis, 1989; Venkatesh et al., 2003). The post-adoption outcome shown in Figure 5, namely use and net benefits as described by DeLone and McLean (2003), is an extension for longitudinal studies rather than a proposition tested here.

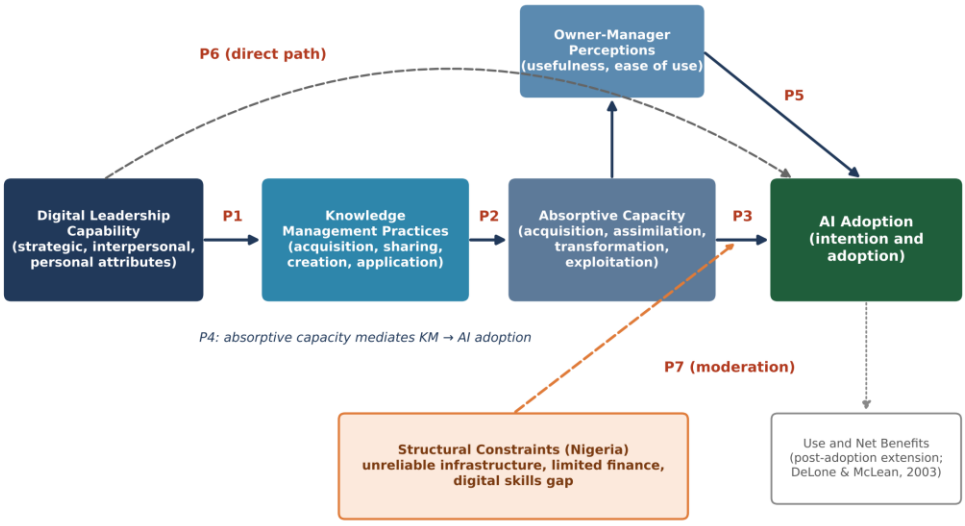


Figure 5: Proposed Conceptual Framework and Research Propositions Linking Knowledge Management Practices to Artificial Intelligence Adoption in Nigerian SMEs

Conclusion and Recommendations

This review set out to take stock of what is known about knowledge management practices as antecedents of artificial intelligence adoption among Nigerian small and medium enterprises. Following PRISMA 2020, 1,286 records were narrowed through two-tier eligibility screening to 21 studies. Knowledge acquisition, sharing, creation and application emerged as theoretically grounded antecedents of adoption readiness, with absorptive capacity as the mechanism and digital leadership as an upstream driver. The central finding, however, is the shape of the evidence: only three included studies are Nigerian, only four examine knowledge management directly, and none tests knowledge management and artificial intelligence adoption together in a Nigerian sample. The review's contribution is therefore a transparent account of that empirical void, a framework that integrates knowledge-based, absorptive capacity and technology adoption theory, and seven propositions that a primary study can test.

Although the propositions await testing, the consistent international evidence on knowledge-related capability supports low-cost interventions that Nigerian small and medium enterprises can begin immediately. Firms can codify their most important routines as short written standard operating procedures, beginning with sales, stock control and customer service, which externalises tacit knowledge and creates the structured material artificial intelligence tools need. They can use cross-functional job shadowing, in which staff spend time in other roles, so that knowledge is not held by a single person. A simple internal data audit can identify what records the firm already keeps, where they are stored and how consistently they are coded, followed by agreeing common formats for customer, sales and inventory data in free shared spreadsheets or cloud folders. Brief after-action reviews following important jobs or problems help capture lessons, and nominating one staff member as an artificial intelligence and data champion gives the firm someone responsible for testing tools and sharing what works. None of these requires new hardware or large budgets.

For policymakers, the evidence suggests that support should build knowledge readiness rather than subsidise hardware and software in isolation. The National Information Technology Development Agency (NITDA) and SMEDAN should incorporate simple knowledge management assessments, covering procedure codification, data record-keeping and knowledge sharing, into the eligibility and diagnostic stages of their digital transformation programmes. They should also set workforce data literacy benchmarks that participating firms work towards, and tie part of their support to training owner-managers and staff in data handling and in evaluating artificial intelligence tools. Pairing technology grants with these knowledge components would make it more likely that subsidised tools are actually adopted and used productively.

The review has limitations. The search covered four sources and English-language publications, so relevant Nigerian grey literature in institutional repositories or local languages may have been missed. The synthesis relies on international studies to construct its theoretical chain, a necessary but second-best solution given the scarcity of direct evidence, and the proposed causal ordering remains an inference rather than a tested finding. Future research should prioritise a survey of Nigerian small and medium enterprises that measures digital leadership, knowledge management practices, absorptive capacity, owner-manager perceptions and artificial intelligence adoption as distinct constructs, using structural equation modelling to test the seven propositions, and should extend the sample beyond south-west Nigeria.

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