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# Leadership, AI Literacy, and Organisational AI Adoption: A Systematic Literature Review and Research Agenda for Pakistan and Emerging Economies

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## Abstract

Artificial intelligence tools are being taken on by organisations at a rate that outpaces the development of leadership practices and employee literacy for using AI well, in both developed and emerging economies. The paper presents a systematic literature review of the studies on the interface of leadership, AI literacy, and organizational AI adoption, summarizing 30 empirical and review studies, 3 technology adoption theories, and the institutional context of the 2025 National AI Policy in Pakistan. Of the 30 studies, 12 (40%) explicitly model leadership as an antecedent of AI adoption or use, 6 (20%) explicitly conceptualise or measure AI literacy; and only 1 (3%) explicitly models both constructs as a formal mediation chain, although they are not located in the same model, in a 2026 mixed-methods study conducted in Vietnam. This is particularly true for AI-adoption research that focuses on Pakistan, as only five out of 30 studies are conducted in Pakistani organisations, and only one of the five contains an AI-literacy construct – whereas in other countries, such as Nigeria, China, Malaysia, South Korea, the United Kingdom, Jordan, India, and Vietnam, more than five studies contain leadership constructs. Based on the synthesis, the paper introduces a leading integrative framework that connects leadership behaviour, AI literacy and outcomes of AI adoption and outlines a five-question research agenda for empirical studies in Pakistan and similar emerging economies.

**Keywords**: artificial intelligence adoption, AI literacy, leadership, emerging economies, Pakistan, SMEs, systematic literature review

## Introduction

AI tools are coming into the everyday life of the organization at a rate far exceeding the progression of leadership skills and the capacity of employees to responsibly exercise effective control over them. In Australian organisations, only 30% reported having a policy for the use of generative AI, 57% said that their employees used AI outputs without verification, and 59% said they had made a work mistake as a result of using AI tools – explicitly identifying AI literacy gap and governance gap as likely factors of these patterns in Gillespie et al.'s (2025) global study with KPMG across 47 countries. Alongside, the Government of Pakistan has developed a National Artificial Intelligence Policy in 2025 which indicates a national policy push towards the adoption of AI across public and private institutions, which in turn will outpace organisational readiness unless leadership and literacy do so too, as in the global case. There are two groups of scholar-

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ship that address this issue but don't communicate with each other. A comprehensive literature on leadership and AI adoption, usage and/or associated employee outcomes has existed for quite some time now and has expanded across a variety of national contexts, including Nigeria (Idowu & Babalola, 2026), China (Hu et al., 2025; Wang et al., 2025; Zhang et al., 2026), South Korea (Kim et al., 2025), the United Kingdom (Fousiani et al., 2024), Jordan (Al-khatib & Bani Sakher, 2026), India (Dey & Dixit, 2025), Pakistan (Jawaid & Shoaib, 2026), United Arab Emirates (Thomas et al., 2025) and a qualitative synthesis focused on Southeast Asia (Zamir, 2025). There has been a complementary and largely psychometric literature that has created conceptual models and measurement instruments of AI literacy as a competency of the human person (Carolus et al., 2023; Liu et al., 2025; Long & Magerko, 2020). There has been limited research that views leadership behaviour and employee AI literacy as a two-way relationship and process, whereby leadership fosters the literacy which then affects uptake, instead of two antecedents studied separately. This gap is a particularly significant one, as a recent empirical literature on AI adoption exists in Pakistan, but has largely been developed from a technology- and organisation-level framework, with only one study from 2026 (Jawaid & Shoaib, 2026) starting to engage with the construct of leadership, and none yet engaging with the construct of AI literacy

SMEs make up for a vast majority of registered companies and jobs in the private sector in Pakistan and are the very organisations that don't have a technology-governance function that can take the place of those leaders. A national AI policy that achieves the goal of increasing the uptake of tools without an accompanying evidence base of how leaders can foster employee AI literacy will likely mirror the pattern identified by Gillespie et al. (2025) on a national scale of tool adoption, which far surpasses trust and competence. This paper's synthesis is provided as an initial effort to bridge that evidence gap before adoption continues to speed up. This paper has three points of focus in its three major sections and makes three contributions. In terms of methodologically paper writing, it outlines a clear and repeatable review procedure (Section 3) for finding and coding literature, which can be expanded or modified for future reviews of this rapidly changing field. Analytically, it provides a corpus-level content analysis (Section 4) of 30 studies, which is a coding of studies in terms of theoretical lens, method, geography, and construct coverage, and then presents the results of this content analysis in a summary figure, as well as quantifying the number of studies that reviewed leadership and literacy in the same study, and provide early indicators from the most recent studies that this dichotomy is beginning to disappear. In its essence it discusses in (Section 5) what this pattern implies for theory and for practice (in Pakistan specifically) before a concrete research agenda (Section 6).

## Background

Three theoretical frameworks dominate the wider organisational AI-adoption literature. The Technology Acceptance Model (TAM) (Davis, 1989) is an explanation for the adoption based on perceived usefulness and perceived ease of use. The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) expands this to include the categories of performance expectancy, effort expectancy, social influence, and facilitating conditions. The Technology-Organisation-Environment framework (Tornatzky & Fleischer, 1990) on the other hand places adoption drivers at the technological, organisational and environmental level. Three of the five Pakistan-specific studies (Jamil et al., 2025; Mirza et al., 2025; Shaikh et al., 2025) and the large-scale systematic mapping study of 256 articles on digital-transformation in SMEs by Díaz-Arancibia et al. (2024) were underpinned by these three frameworks, either individually or in

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combination ), which found TOE and TAM accounted for 33.87% and 27.02% of the theoretical lenses used across its corpus respectively.

Rather, a growing body of literature focuses specifically on leadership as a means of leading the adoption and use of AI and the associated outcomes for employees in Nigeria (Idowu & Babalola, 2026), China (Hu et al., 2025; Wang et al., 2025; Zhang et al., 2026), South Korea (Kim et al., 2025), the United Kingdom (Fousiani et al., 2024), Jordan (Al-khatib & Bani Sakher, 2026), India (Dey & Dixit, 2025), Pakistan (Jawaid & Shoaib, 2026), the United Arab Emirates (Thomas et al., 2025), and in a qualitative synthesis focused in Southeast Asia (Zamir, 2025). Conceptual frameworks for AI literacy as an individual competency have, however, emerged in a separate, largely psychometric literature (e.g., Long & Magerko, 2020) and validated measurement scales for AI literacy as an individual competency have been developed (e.g., Carolus et al., 2023; Liu et al., 2025), summarized by the review of sixteen AI measurement scales by Lintner (2024). Some studies (Kapsah, 2025, Nguyen et al., 2026, Thomas et al., 2025) are now beginning to start integrating a literacy/leadership focus into an otherwise technology-organisation-level design, suggesting a future convergence between these two literatures. In Section 4, the degree of overlap (or lack thereof) between these bodies of work in the entire set examined is explored.

## Methodology

### Review approach

The review is conducted following the systematic search and screening protocol in the tradition of PRISMA-style reporting, with a transparency limitation on the search, which was carried out using the Google Scholar and major publisher platforms (Scopus-indexed journals, MDPI, SAGE, Frontiers, Springer Nature, Nature portfolio, ScienceDirect, Taylor & Francis, and ACM) but not a full bibliographic database export via institutional access to Scopus/Web of Science. The review should therefore be read as a protocol-driven, systematic compilation of a representative sample instead of having been comprehensive (a point the paper explicitly makes, not necessarily obvious from this review).

### Search strategy

The search terms were then used in combination with "artificial intelligence" or “AI” and targeted country- and region-specific searches for “Pakistan”, “South Asia”, “Africa”, “Middle East”, “Southeast Asia”, “Latin America” and “emerging economies” / “developing countries” variants were run in eighteen distinct search sessions, between the initial scoping of the review and final corpus finalisation, which were specifically targeted to under-represented regions to expand the geographic base of the corpus. All results of each session were checked for relevance and entered into the candidate pool.

### Screening and eligibility

Peer-reviewed journal articles or equivalent (systematic review, meta-analysis, peer-reviewed conference proceeding) published in English in the years between 2015 to 2026 that engaged with AI adoption, AI literacy, or leadership as a driver of technology adoption in an organisational context (not a purely consumer-facing context) were included. Pre-2015 papers using the foundation of technology-adoption theory (Davis, 1989; Tornatzky & Fleischer, 1990; Venkatesh

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et al., 2003) were also treated as theoretical background papers, as they continue to be used as the dominant lenses in the more recent empirical literature. These papers, in which there was no organisational-behaviour angle, were purely technical/computer-science papers, opinion papers that were not peer-reviewed, and studies that had a consumer (not organisational/employee) emphasis, were excluded. In the eighteen search sessions, around 160 candidate records were found, and these candidate records were deduplicated to remove duplicate records and screened based on the inclusion criteria in the title/abstract (approx. 55 records were retained for subsequent full-text or full-abstract review). Of these, thirty were found to meet all the defining criteria and comprise the core analytic corpus reported in Table 1 and Figure 1, in addition to the three foundational theory papers and Gillespie et al. (2025)'s consumer-employee (not simply organisational-leadership) based global survey of industry and academia. These numbers reflect the scope of this review and the fact that this review was not a full database search, but rather is rather rapid/focused (Section 3.1), but they are still reported here as indicative of this review's scope, not as suggesting a precision that isn't warranted by the search process.

**Coding and Analysis**

Thirty core studies were coded for the following: publication year, geographic/national context, theoretical framework, method and sample size, leadership as a construct (explicitly modeled or not), and AI literacy as a construct (explicitly modeled or measured or not). The author used this coding scheme, and the frequencies of the corpus data in Table 2, the theoretical cross-tabulation in Table 3, and Figure 1 can be independently checked and/or recoded by other researchers as a step towards transparency in a single-author focused review, which the larger-team systematic review would normally report in dual-coder reliability checks. The analysis in this study takes place in two phases: a quantitative content analysis of the construct coverage and the geographic distribution in the corpus (Section 4); a qualitative thematic analysis of the findings of the studies included in the corpus with regard to the constructs themselves (also Section 4) that informs the Discussion (Section 5).

**Quality Considerations**

The 30 core studies consisted of most being published in internationally indexed peer-reviewed journals (including SAGE Open, Frontiers in Artificial Intelligence, Frontiers in Psychology, Scientific Reports, Behavioral Sciences, Sustainability, and Administrative Sciences, which are all Scopus- or ESCI-indexed), one ACM conference paper (Hossain & Nahid, 2024) and one arXiv preprint (Wolfe et al., 2025), which was included and indicated as such because it was the only study located using an extended UTAUT framework to AI adoption at multinational scale (N = 2,257). In the recent literature, a few studies (Dey & Dixit, 2025; Jawaid & Shoaib, 2026; Rang et al., 2025) are cited in newer journals or in journals which are focused in a particular country for which no independent confirmation of the indexing status of these journals in the major databases was possible at the time of writing; these studies were retained because they are, respectively, the only found Indian, Pakistani-higher-education, and Pakistani-banking studies to use a leadership construct in this literature, and their inclusion is made explicit here rather than assumed, in keeping with the overall transparency commitment of this review. Twenty-one of the 30 core studies report quantitative results using a validated statistical approach, such as PLS-SEM, SEM, a large-scale systematic mapping study (Diaz-Arancibia et al., 2024), a systematic scale review (Lintner, 2024), a qualitative or mixed-methods synthesis (Islam, 2026; Zamir,

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2025), or a combination of survey and interview (Nguyen et al., 2026). In almost all cases, the results presented in Section 4 are not due to small sample instability, as sample sizes for quantitative studies range from n = 100 (Jawaid & Shoaib, 2026) to n = 3,398 (pooled sample size in Pinto et al., 2025) to n = 2,257 (Wolfe et al., 2025), and thus provide a reasonable level of confidence that the results are not an artefact of small sample size. There was no formal risk-of-bias scoring tool used (e.g., the Mixed Methods Appraisal Tool) as the scope of the review indicated that it was focused rather than exhaustive as stated in Section 3.1; this is noted here as a limitation without being excluded, and it will be revisited in Section 9.

## Data Analysis

### Corpus Overview

Table 1 summarises the thirty empirical and review studies at the analytical core of this paper, ordered to group the original fifteen-study corpus (rows 1–15) alongside the fifteen studies added to extend its geographic and thematic coverage (rows 16–30).

| Study | Year | Context | Theory/lens | Method (N) | Leadership? | AI literacy? |
|---|---|---|---|---|---|---|
| **Pinto et al.** | 2025 | Multi-country meta-analysis | TOE | Meta-analysis (12 studies, n=3,398) | No | No |
| **Shaikh et al.** | 2025 | Pakistan (mfg. SMEs) | SCT / RBV / OC theory | PLS-SEM (n=427) | No | No |
| **Jamil et al.** | 2025 | Pakistan (export SMEs) | Dynamic Capabilities Theory | PLS-SEM (n=480) | No | No |
| **Díaz-Arancibia et al.** | 2024 | Global mapping (mostly Asia) | TOE / TAM / IDT | Systematic mapping (256 studies) | No | No |
| **Islam** | 2026 | Bangladesh (public sector) | PRISMA-based policy review | Qualitative SLR | No | No |
| **Idowu & Babalola** | 2026 | Nigeria (SMEs) | DOI + digital leadership model | PLS-SEM (n=306) | Yes | No |
| **Wang et al.** | 2025 | China (employees) | Social Cognitive Theory | Survey, 2-wave (n=525) | Yes | No |
| **Hu et al.** | 2025 | China (employees) | Social Cognitive Theory | Survey, 3-wave (n=364) | Yes | No |
| **Fousiani et al.** | 2024 | UK (employees) | Org. climate + power construal | Field + experiment (n=237; n=150) | Yes | No |
| **Zamir** | 2025 | Malaysia / SE Asia | Transformational/servant/adaptive leadership | Qualitative synthesis | Yes | No |
| **Kim et al.** | 2025 | South Korea (employees) | JD-R / COR theory | Survey, 3-wave (n=381) | Yes | No |
| **Lintner** | 2024 | Global (scale review) | AI literacy measurement | Systematic review (22 studies) | No | Yes |
| **Carolus et al.** | 2023 | Germany (scale dev.) | AI literacy / metacognition | Scale development & validation | No | Yes |
| **Long & Magerko** | 2020 | Conceptual | AI literacy competencies | Conceptual framework | No | Yes |
| **Gillespie et al. *** | 2025 | 47 countries (n≈48,000) | Trust in AI | Global survey | No (names gap) | Named as gap |
| **Thomas et al.** | 2025 | UAE (hospitality SMEs) | TOE / TAM | PLS-SEM (n=315) | Yes (top mgmt sup- | No |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | port) | |
| **Oleribe et al.** | 2025 | Global, 6 continents (healthcare) | None named | Cross-sectional survey (n=506) | No | No |
| **Pérez-Cepeda et al.** | 2026 | Ecuador (firms) | TAM | SEM (n=398) | No | No |
| **Liu et al.** | 2025 | China (employees) | AMO + SCT (GAIL scale dev.) | EFA/CFA (n=278; n=306) | No | Yes |
| **Nguyen et al.** | 2026 | Vietnam (marketing employees) | DOI + Institutional Theory | Mixed methods (n=699; 21 interviews) | Yes | Yes |
| **Zhang et al.** | 2026 | China (service firms) | Trait Activation + Sense-Making (paternalistic leadership) | 3-wave survey (n=633) | Yes | No |
| **Hossain & Nahid** | 2024 | Bangladesh (HR professionals) | TOE (modified) | SEM survey (n=315) | No | No |
| **Wolfe et al.** | 2025 | Global (multinational firm) | Extended UTAUT | Survey (n=2,257) | No | No |
| **Kapsah** | 2025 | Indonesia (employees) | Resource-Based View | PLS-SEM (n=200) | No | Yes (digital literacy) |
| **Mirza et al.** | 2025 | Pakistan (research scholars) | UTAUT + Innovation Resistance Theory | Survey (n=235) | No | No |
| **Rang et al.** | 2025 | Pakistan (banking) | None named | PLS-SEM (n=391) | No | No |
| **Dey & Dixit** | 2025 | India (automobile mfg.) | UTAUT + leadership mediation | SEM (n=383) | Yes | No |
| **Jawaid & Shoaib** | 2026 | Pakistan (HEIs, Lahore) | AI adoption → instructional leadership | Survey (n=100) | Yes | No |
| **Al-khatib & Bani Sakher** | 2026 | Jordan (IT sector) | RBV / Dynamic Capabilities / TOE / DOI | Survey (n=162) | Yes (entrepreneurial leadership) | No |
| **Makumbe et al.** | 2026 | South Africa (telecom HR) | UTAUT | SEM (n=500) | No | No |

** Gillespie et al. (2025) is treated as contextual background rather than part of the primary 30-study comparative corpus (see Section 3.3).*

### Corpus composition

**Figure 1 visualises the coded corpus from two angles: construct coverage (Panel A) and geographic distribution (Panel B).**

Figure 1. Composition of the reviewed corpus (n = 30 empirical/review studies)

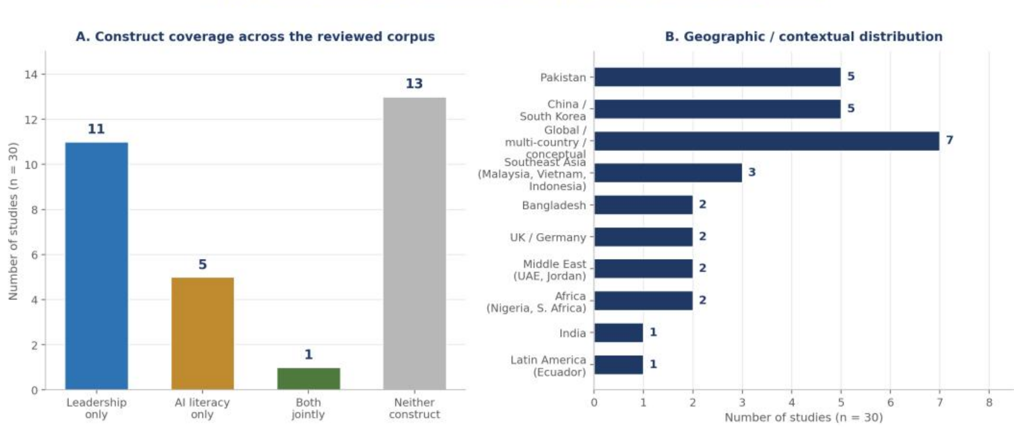

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**Table 2 reports the same construct-coverage data in numerical form, alongside the corpus's Pakistan-specific subset.**

| Corpus characteristic | Count | % of corpus (n=30) |
|---|---|---|
| **Studies explicitly modelling leadership as an antecedent** | 12 | 40% |
| **Studies explicitly conceptualising or measuring AI literacy** | 6 | 20% |
| **Studies jointly modelling leadership AND AI literacy** | 1 | 3% |
| **Studies set in Pakistan specifically** | 5 | 17% |
| **Pakistan-set studies including a leadership or literacy construct** | 1 of 5 | 20% of Pakistan subset |

The pattern in Figure 1 and Table 2 is not an artefact of any single study: leadership-inclusive and literacy-inclusive studies are each a substantial minority of the corpus (40% and 20% respectively), the two overlap in only one case out of thirty, and four of the five Pakistan-specific studies sit entirely within the technology/organisation-level tradition — the largest single bar in Figure 1, Panel A — rather than the leadership-inclusive cluster now visible in Nigeria, China, Malaysia, South Korea, the UK, Jordan, India, and Vietnam. The single exception, Jawaid and Shoaib's (2026) study of Pakistani university faculty, is discussed in Section 4.3.

### Findings of the leadership-inclusive studies

Idowu and Babalola (2026) surveyed 306 SME respondents across six Nigerian states and concluded that the digital leadership capabilities predicted the intention to use AI, with strategic capabilities being the best predictor ($\beta = 0.298$), interpersonal capabilities ($\beta = 0.245$) and personal attributes ($\beta = 0.129$); however, the delivery-related capabilities were not significant and the strategic and interpersonal pathways were partially mediated by the organisational innovation climate. In surveying 525 workers in China with a two-wave design, Wang et al. (2025) reported that both transformational leadership and perceived organizational support (POS) positively predicted employee AI usage ($\beta = 0.600$, accounting for 45.5% of the total effect), and that the indirect effect of transformational leadership on AI usage by employees was moderated by the competitive climate in the workplace ($\beta = 0.393$, under low competitive climate; $\beta = 0.207$, under high competitive climate). In a series of three surveys of 364 employees at a Chinese travel company, Hu et al. (2025) discovered that adoption of AI was positively related to the employees' knowledge sharing via learning opportunities, and that this indirect effect was significant for paradoxical leadership, which involves making both centralised and decentralised decisions.

In this three-wave field study (n = 237) and 2 x 2 experiment (n = 150), Fousiani et al. (2024) revealed that the link between competitive organisational climate and AI acceptance is inverted depending on the organisation leader's perception of power as a responsibility to support employees versus an opportunity for self-interest. In a qualitative synthesis of leadership theory and AI-integration case evidence from across Southeast Asia, Zamir (2025) found that leadership is the "critical success factor" in the outcomes of adopting AI, and that five leadership competencies were identified, which were: vision-setting, change management, governance, capability-building, and human-AI balance. Whether AI adoption boosts or diminishes employee psycho-

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logical safety is an issue that Kim et al. (2025) uncovered in a three-wave study of 381 South Korean workers, who found that ethical leadership may also play a role in moderating and buffering the negative effects of AI adoption on employee psychological safety and depression.

The fifteen studies here are added to extend this corpus, adding five more leadership-inclusive cases, each in a different national or theoretical perspective. Building on the findings of Fousiani et al. (2024) and Kim et al. (2025), Zhang, Wang, and Liao (2026) found that organisational psychological ownership positively predicted AI "crafting" behaviour ($\beta = 0.142$) and employee-AI collaboration ($\beta = 0.188$), and that paternalistic leadership significantly moderated both relationships, with markedly different effect sizes found across the three sub-dimensions of authoritative, benevolent, and virtuous leadership, further reinforcing the earlier findings of Fousiani et al. (2024) and Kim et al. (2025) that the effect of leadership on AI outcomes depends heavily on the specific nature of leadership, and not simply its existence. In Jordan's IT sector, the authors found that entrepreneurial leadership was strongly and positively associated with innovation performance ($\beta = 0.591$), and the use of AI itself was positively related to innovation performance ($r = 0.553$) but not statistically significant to moderate the relationship between entrepreneurial leadership and innovation performance, which suggests that entrepreneurial leadership and AI use are complementary and statistically independent rather than AI is amplifying entrepreneurial leadership's impact. In their study of 383 workers in the automobile manufacturing industry in Delhi/NCR, Dey and Dixit (2025) extended UTAUT to model leadership style as a mediator in the relationship between AI training adoption and performance and effort expectancy, which were found to be the strongest direct factors; they found that leadership cannot be underestimated in its mediating role between these two factors and AI training adoption. Thomas et al. (2025), surveying 315 UAE hospitality SME respondents, found top-management support was among the strongest predictors of AI adoption intention ($\beta = 0.48$), on a par with competitive pressure ($\beta = 0.47$) and ahead of perceived employee capability ($\beta = 0.30$) — one of the few studies in the corpus to embed a leadership-adjacent construct inside a TOE/TAM design rather than a dedicated leadership theory.

The only Pakistan specific study in this corpus that has a leadership construct is by Jawaid and Shoaib (2026), who surveyed 100 faculty members from private universities in Lahore, Pakistan, and found that AI adoption/familiarity significantly predicted faculty instructional leadership practices ($R^2 = .635$), explaining 63.5% of the variance, with academic rank and teaching experience non-significant as controls. The narrow institutional focus and the small sample of documents scanned for this review is the reason why this is the first empirical indicator in the corpus searched for this review to see organizational AI research in Pakistan include the construct of leadership.

When taken together, these twelve studies show that leadership can predict and explain the adoption, use, and performance of innovation in AI, knowledge sharing, and — in two of the cases (Kim et al., 2025; Zhang et al., 2026) — employees' psychological wellbeing—in eight different national contexts: Asia, Africa, Europe and Middle East. However only one of the twelve (Nguyen et al. 2026 discussed in Section 4.4) includes a measure of employee AI literacy and in eleven of those, the connection between leadership and the acquisition of AI literacy is the adoption, use, or sharing of AI knowledge, or the impact of AI on wellbeing, rather than the process of building that literacy.

### Findings of the AI-literacy-inclusive studies

Long and Magerko (2020) offered one of the first formal competency frameworks for AI literacy as the knowledge and skills needed to be critical about AI systems and use them effectively. Carolus et al. (2023) later designed and validated the Multi-Dimensional Meta AI Literacy Scale (MAILS) based on well-known competency and metacognitive models, using German samples. The systematic review paper by Lintner (2024) revealed a total of 22 studies that validated / re-validated 16 different scales, with generally good internal consistency and structural validity, but, most relevant to this research, that only a minority of scales were assessed for content validity, construct validity or responsiveness, that most scales were self-report instrument, and that none of the scales were tested for cross-cultural validity or measurement error. None of the scales mentioned in Lintner's review had been validated on a Pakistani or South Asian sample.

Two of the studies added extend this measurement gap that silence has until now left open, but not for a sample of Pakistanis. The Generative AI Literacy (GAIL) scale was developed and validated on samples of Chinese employees (EFA n = 278; CFA n = 306), encompassing five dimensions of literacy: basic technical competence, prompt optimisation, content evaluation, innovative application and ethical/compliance awareness, with excellent psychometric properties (CFA fit: CFI = .995, RMSEA = .029) and a strong correlation between GAIL and Job Performance ($\beta = 0.680$) even after the creative self-efficacy was introduced as mediator. Having completed a survey of 200 Indonesian employees using a RBV perspective, Kapsah (2025) discovered AI utilisation significantly positively influenced digital literacy, which significantly mediated the relationship between the two and did not require an AI-literacy measure but was clearly relevant to the same mechanism.

The only study in the full corpus that used a joint leadership/AI literacy model was Nguyen et al. (2026), who used a mixed-method study with 699 Viet Nam marketing employees (21 to support interviews), and found a combination of Diffusion of Innovation and Institutional Theory with explicit constructs for leadership vision/top-management commitment, and a four-dimensional AI literacy measure (application, understanding, evaluation, and ethics). The study revealed that, coercive institutional pressures had a significant impact on the intention to adopt AI, leadership vision had a strong influence on adopting AI, organisational flexibility had a strong influence on adopting AI and AI literacy was an enabling factor, whereas AI anxiety was a countervailing factor. Importantly, in this context, leadership and AI literacy are treated as co-predictors within a broader institutional-adoption context, rather than as a formal mediation chain, in which leadership is hypothesized to drive AI literacy, thereby influencing adoption (which the research agenda of this review (Section 6) proposes to test directly). In the corpus, however, Nguyen et al. (2026) is definitely the most convincing proof that these two constructs can be combined on an empirical basis and that it is productive.

### Findings of the technology/organisation-level studies

The seventeen studies in this corpus that do not use a leadership or (with one partial exception) a literacy construct work at the technology/organisation level. The meta-analysis by Pinto et al. (2025) of 12 TOE-based research studies (n = 3,398 participants) revealed that seven of eight TOE factors significantly influence AI adoption with vendor partnership and organisation readiness the most important factors; "management support" is one of the organisation factors but it is not broken down into specific management behaviours and AI literacy is not included in the analysis. In a survey of 427 manufacturing SMEs in Pakistan, Shaikh et al. (2025) revealed that the use of AI significantly contributed to the environmental sustainability of SMEs in Pakistan by increasing the green human resource management and green employee behaviour of the firms, which were in turn moderated by the organisational culture of the firms. Jamil et al. (2025) surveyed 480 managerial staff in five cities of Pakistan that are export-oriented SMEs, and revealed that AI adoption ($\beta = 0.228$) and technological readiness ($\beta = 0.371$) were found to be significant predictors of employee capacity building, which in turn significantly influenced the performance of SMEs.

These two Pakistan-based studies continue the picture of technology levels without involving leadership nor literacy. In a study of 235 university research scholars in Pakistan, Mirza et al. (2025) employed an extended UTAUT and Innovation Resistance Theory design to determine the key factors influencing the adoption and use of AI. The researchers discovered that personal innovativeness, performance expectancy, social influence, and trust were all important factors for the adoption and use of AI among the survey participants. In this review, the authors outline the key conditions for the benefits of AI to be realised: ‘strategic leadership' and ‘digital literacy programs' were identified by Rang et al. (2025) in their survey of 391 banking-sector employees in Karachi, where integration of AI improved organisational efficiency and risk management, though this was not a formally measured construct.

Díaz-Arancibia et al. (2024), who reviewed 256 articles from an initial sample of 1,617 articles, also concluded that SMEs in developing countries are still more interested in basic information systems than in advanced technologies like AI, that the entrepreneurial ecosystem has a greater impact on the adoption of information systems than government policy, and that only 14 of the 256 articles reviewed took cultural behaviour into account at all. Islam (2026) identified using a review protocol based on the PRISMA guidelines, the integration of AI and digital transformation in public-sector literature in Bangladesh showed significant, but uneven, advances across five service domains, citing infrastructure as one of the key areas for slow integration and a lack of capacity building for the workforce. In 2024, Hossain and Nahid surveyed 315 HR professionals in Bangladesh and determined that technological factors (such as cost, simplicity, and perceived benefit), organisational factors (in particular, management endorsement), and environmental factors (vendor support) significantly influenced the intention to adopt AI, but again treated management endorsement as an undifferentiated organisational factor, rather than a specific leadership behaviour.

Four other investigations extend the geographic scope of the corpus without any leadership or literacy construct. To date, Oleribe et al. (2025) have conducted a global survey of healthcare professionals from six continents, including 506 respondents, revealing that 92.3% feel that AI has a place in patient care, 76.5% agree that AI should be adopted within their organisations, 13.1% of the responding organisations have adopted AI, and 30.2% of the healthcare staff have received any formal training in AI; the top executive leadership was identified as the prime driver for adoption, albeit not formally measured. In an extended UTAUT model, Wolfe et al. (2025) surveyed 2257 employees of a multinational professional-services organisation and concluded that organisational seniority was significantly related to adoption (70.4% for directors compared with 50.0% for consultants, $p < .001$) and that performance expectancy was strongly correlated with both attitude and behavioural intention, which, being a preprint, their results should be

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treated with care until peer-reviewed. In the case of Ecuadorian companies, Pérez-Cepeda et al. (2026) confirmed that there was a high relationship between PEU and PU in terms of perceived ease of use (β = 0.734) and perceived usefulness (β = 0.739) respectively, in a survey of 398 managers in Ecuadorian companies using the TAM framework. When exploring the factors influencing behavioural intention to adopt AI in HR functions, Makumbe et al. (2026) surveyed 500 HR managers in the telecommunications sector of South Africa and concluded that facilitating conditions and effort expectancy had the highest prediction power when using UTAUT.

### Cross-tabulating theory and construct coverage

Table 3 cross-tabulates the theoretical lens used in each study against whether it includes a leadership or AI-literacy construct. At fifteen studies, this pattern appeared almost perfectly separated by theoretical family; at thirty studies, the separation remains strong but is no longer absolute.

| Theoretical family | Studies (n) | Leadership-inclusive | Literacy-inclusive |
|---|---|---|---|
| **Technology-organisation / institutional adoption lenses (TOE, TAM, UTAUT, DOI, RBV, DCT, SCT, OC, IRT)** | 14 | 1 of 14 | 1 of 14 |
| **Leadership-focused frameworks (transformational, ethical, paradoxical, digital, servant, adaptive, entrepreneurial, instructional, paternalistic leadership)** | 10 | 10 of 10 | 0 of 10 |
| **AI literacy / metacognition frameworks** | 4 | 0 of 4 | 4 of 4 |
| **Hybrid technology-adoption + leadership + literacy framework** | 1 | 1 of 1 | 1 of 1 |
| **Trust-in-AI** | 1 | 0 of 1 (names gap) | 0 of 1 (names gap) |

The most obvious in this review of a pattern of where the gap highlighted in Section 1 is not incidental, nor is it structural, but is an early sign of erosion. None of ten leadership-theory studies model literacy, 4 of 4 literacy-framework studies model literacy and 13 of 14 technology-organisation-lens studies model neither. Two 2025-2026 studies have started to incorporate a leadership-adjacent/adjacent construct in an otherwise technology/organisation frame (Thomas et al., 2025; Kapsah, 2025), while one study (Nguyen et al., 2026) introduced a leadership construct for the first time in this corpus, together with a technology/institutional adoption construct. Out of the 30 studies, three (10%) are now located outside the near total separation, whereas none were in the 15-study body of texts on which this review began. But it seems that researchers are not yet testing for the same two outcomes – leadership or literacy – and not reporting results; the most recent round of studies indicates that they may be just starting to do so in the same design.

## Discussion

The analysis of the data in Section 4 supports a specific claim that is also falsifiable: there is a meaningful minority of literature that studies the phenomenon of leadership and a meaningful minority of literature that studies the phenomenon of AI literacy, at least in Pakistan's literature and almost never in the same studies; and that in the literature from within Pakistan the meaningful minority of literature studying the phenomenon of leadership is less than in the literature from outside Pakistan. This section examines the theoretical implications of that pattern, the reasons why its relevance for Pakistan is unique and special, the conflicts and challenges among the leadership-inclusive literature that make any easy prescription to "add leadership" to a set of existing patterns problematic, and the implications of the emerging trend of hybrid studies for the future of the field.

**A ceiling in technology-organisation-environment explanations**

Pinto et al.'s (2025) meta-analytic result that seven of 8 TOE factors significantly predict AI adoption was found in the small-scale three of five Pakistani studies reviewed here (Jamil et al., 2025; Mirza et al., 2025; Shaikh et al., 2025), and repeated as far afield as Ecuador (Pérez-Cepeda et al., 2026) and South Africa (Makumbe et al., 2026) indicates that technology- and organisation-level explanations of AI adoption are empirically productive and should not be discarded. Productive is not synonymous with complete. In TOE-family models, the organizational factor of "management support" is generally described as a general construct without specifying which leadership behaviours establish the capabilities of the employees who are likely to be key to the organisation's readiness and/or effective use of AI. Thomas et al.'s (2025) study in UAE represents a partial exception as the "top management support" construct is separated and measured as a specific form of support, not necessarily the way the manager acts or a specific leadership style – it is still measured as generic organizational support. This isn't just a Pakistani tradition but rather a structural issue with the TOE tradition: it's very good at answering the question of when an organisation decides to use AI, but not so good at answering the question of how they use it once they have adopted it.This is not a Pakistani thing, but a problem with the TOE tradition in general: it's very good at answering the question of when organisations use AI, but not so good at answering the question of how they use it once they do (Díaz-Arancibia et al., 2024).

**Why the gap matters more, not less, in Pakistan**

The absence of Pakistani leadership studies does not prove that leadership is not important in Pakistani organisations as compared to other organisations such as the Nigerian, Chinese, Malaysian, South Korean, British, Jordanian, Indian and Vietnamese organisations. Rang et al. (2026) report that Bangladesh's public-sector AI progress is hampered by "insufficient workforce capabilities", Gillespie et al. (2025) report that Pakistan's banking-sector AI gains rely on "strategic leadership" and digital literacy programmes, even though these were not formally measured in their study, and Islam's (2026) findings that trust in AI and a named AI literacy gap are low in Australia — a high-income country with comparatively advanced AI governance infrastructure — together suggest that the capacity constraints around AI literacy and leadership are unlikely to be correspondingly smaller in lower-resource, less AI-governance-mature settings such as Pakistan. If the pattern of leadership-and-literacy research in Pakistan continues as it has, as with the 4/5 studies in this corpus which were almost exclusively about technology and organisational readiness, then Pakistan's 2025 National AI Policy will have the effect of making up ground in terms of adopting organisational AI, but not in terms of the research base for leadership and literacy in terms of what leaders should do, or how prepared employees actually are.

### A complication: leadership is not uniformly good for adoption or for employees

The leadership-inclusive literature reviewed in Section 4.3 doesn't provide an obvious picture of the more leadership the better. Despite the increase of AI use seen in competitive climates, both the findings of Fousiani et al. (2024) and Kim et al. (2025) suggest that leadership behaviour is just as significant as its presence, as competitive climates can lead to greater acceptance of AI when the leaders interpret power as responsibility, and ethical leadership is needed to buffer the negative effects of AI on psychological safety. Even within the Chinese context of paternalistic leadership in service firms, the three sub-dimensions of paternalistic leadership (authoritative, benevolent and virtuous) had distinct moderating effects on the relationship between organisational psychological ownership and employee-AI collaboration, as demonstrated in Zhang et al.'s (2026) study. This has direct implications for the operationalisation of RQ1 and RQ2 (Section 6) in future Pakistani studies, as a study that only identifies the presence or absence of "involvement" in AI adoption—no matter if it is considered "involvement" or "self-interested involvement"—or a study that only considers the presence or absence of "ethical" or "merely directive" leadership would likely under-detect the mechanism this review has identified as missing. The Nigerian evidence here (Idowu & Babalola, 2026) is particularly interesting in that only out of two dimensions of digital-leadership capability, strategic and interpersonal, did the intention to adopt AI differ significantly from the control; and as noted by Al-khatib and Bani Sakher (2026), the impact of entrepreneurial leadership on innovation performance was not significantly influenced by the use of AI, depending on the situation, context, and/or environment.

### Reconciling the technology-level and leadership-level literatures

The pattern that is documented in Section 4 is not so much a competition between the TOE and the leadership and-adoption literatures as the two are, in fact, addressing two different, complementary aspects of the same causal chain: organisational readiness of the form associated with the TOE tradition plausibly affects whether the conditions for adoption are present or not, and leadership behaviour and the AI literacy it induces plausibly affect whether adoption is present if the conditions are, whether it can be effectively, safely, and sustainably used or not. This reading is congruent with the findings of Jamil et al. (2025) who found that technological readiness ($\beta$ = 0.371) has a significant effect on employee capacity building, nearly twice that of the effect of AI adoption ($\beta$ = 0.228); and the only study in the corpus to employ an institutional/technology-adoption framework coupled with the leadership and literacy constructs is that of Nguyen et al. (2026) in Vietnam, which provides the first empirical blueprint for the reconciling model proposed by the research agenda identified by this review, albeit without testing the specific role of literacy as the mediating variable between leadership and adoption.

### A structural gap that is beginning, cautiously, to close

The kind of gap that this review has identified is important to be precise about, as this distinction will inform future research that addresses the gap. This is not so much about studies testing the leadership–literacy–adoption mechanism and finding null or contradictory results: Table 3's cross-tabulation reveals that, apart from one instance spread over thirty studies and eighteen search sessions, this mechanism has been tested in very few studies. That is a different problem, however, than a problem that is truly empirical, where researchers would need to balance two different sets of results; it's just a problem in which they have to figure out how to merge two different sets of constructs that have thus far been largely parallel. This is because the ingredients of methodologies to do this already exist in separate packages: PLS-SEM pipelines are validated on Pakistani and South Asian samples (Dey & Dixit, 2025; Jamil et al., 2025; Mirza et al., 2025; Shaikh et al., 2025); validated AI literacy scales await cross-cultural testing (Carolus et al., 2023; Liu et al., 2025); precedents for mediation models are established in the leadership literature (Wang et al., 2025); and a mixed methods precedent exists for measuring both constructs together (Nguyen et al., 2026), so the research agenda in Section 6 is structured around adaptations and combinations of existing designs rather than new designs being invented from scratch.

## Research agenda

Five research questions follow directly from the gaps identified in Sections 4 and 5, each paired with an indicative design grounded in methods already established within the reviewed corpus.

| Research question | Suggested design | Precedent in reviewed corpus |
|---|---|---|
| **RQ1 — Do the leadership capability dimensions found to predict AI adoption in Nigeria, China, and Jordan hold in Pakistani SME contexts?** | Cross-sectional PLS-SEM survey of Pakistani SME leaders and employees | Idowu & Babalola (2026); Al-khatib & Bani Sakher (2026); Jamil et al. (2025) |
| **RQ2 — Does leadership behaviour predict employee AI literacy specifically, as distinct from predicting adoption or usage outcomes directly?** | Mediation model with AI literacy as the explicit mediating construct | Wang et al. (2025) mediation design; Nguyen et al. (2026) joint measurement, adapted to a formal mediation test |
| **RQ3 — How does Pakistan's 2025 National AI Policy shape organisational leaders' AI-literacy-building practices at the firm level?** | Qualitative interview study with organisational leaders post-policy rollout | Islam (2026); Zamir (2025); Nguyen et al. (2026) interview component |
| **RQ4 — Can an existing validated AI literacy scale be validated for use in a Pakistani or South Asian organisational sample?** | Psychometric validation study (CFA, reliability, measurement invariance) of MAILS, GAIL, or a comparable scale | Carolus et al. (2023); Liu et al. (2025); Lintner (2024) |
| **RQ5 — Does the ethical-leadership and paternalistic-leadership buffering effects on AI-adoption-related employee strain generalise to lower-trust institutional environments such as Pakistan's?** | Replication of a time-lagged design in a Pakistani or South Asian sample | Kim et al. (2025); Zhang et al. (2026); Gillespie et al. (2025) |

### Integrative framework

This paper proposes that Leadership Behaviour and AI Governance in Organisations are both predictors of employee AI Literacy, which in turn predicts AI Adoption and Use Outcomes, with the strength of these relationships moderated by the Quality of Leadership (Ethical or Self-Interested, Benevolent or Authoritative, Supportive or Directive) and Boundary Conditions (Sectors, Firm Size, and National/Institutional Context including AI Policy Environments such as 2025 National AI Policy of Pakistan). Unlike Nguyen et al.'s (2026) study from Vietnam, which is the first empirical work to reveal the linkage between both leadership and literacy as predictors in one design, though not as a tested mediation chain, the study outlined in the present paper examined both variables within one design. This is not an empirically tested model, but rather a synthesis of the separate pieces of literature reviewed together suggesting this framework. Testing it is what the research agenda in Section 6 aims to do.

## Implications

### Theoretical implications

This review moves the discussion of leadership and AI literacy beyond the traditional dichotomy of antecedents of adoption (TOE, TAM, and UTAUT-family models) to a single research problem, and suggests that the continued focus in the organisational AI-adoption literature on the problem of adoption as opposed to effective use may be beginning to hit a ceiling given its empirically successful approach and the examples of the five Pakistani studies evaluated in this paper. The rise of hybrid designs (Kapsah, 2025; Nguyen et al., 2026; Thomas et al., 2025) suggests that the field itself is slowly but inevitably making the step towards reconciliation this paper suggests.

### Practical implications

The analysis implies that for practitioners and policy makers in Pakistan and similar emerging economies, strategies for adopting AI are limited to either the technology procurement or the organisation-readiness component of the mechanism identified by the broader literature, as is dominant in four of the five Pakistani studies examined here. The Nigerian, Chinese, Jordanian and UK evidence shows that neither the mere availability of AI tools, nor leadership involvement in any way, but specifically visible, ethically grounded, strategically focused leadership engagement with AI tools predicts positive employee outcomes, and this is something that Pakistani organisations implementing AI through the new national policy are uniquely positioned to test and act on.

### Policy implications

The results of this review indicate that the technology-access and infrastructure indicators (those most directly comparable with the ones already measured in the reviewed Pakistani studies) may not be enough to monitor the implementation of AI in the country and ensure it is being adopted safely and effectively in organisations. The Bangladesh results from Islam (2026) is consistent with the finding that only 30.2% of the global workforce of health care workers surveyed have been formally trained in AI (Oleribe et al., 2025) and the Australian result, still higher income, from Gillespie et al. (2025) that the ability to do this and to lead practice with these tools, not just access the tools, is the limiting factor once basic infrastructure is in place. Such a monitoring framework for the implementation of Pakistan's policy that involved leadership-practice and employee AI-literacy indicators along with adoption-rate indicators would be a response to a question that the academic literature, as this review documents, has just started to answer — one that is policy development and research development mutually reinforcing opportunities and not sequential ones.

## Limitations

The intention was to conduct a more systematic than exhaustive review based on Google Scholar and the major publisher platforms; this would not have included a full Scopus/Web of Science database export, which may have yielded more leadership-inclusive or literacy-inclusive studies that are not included in this review, especially outside the 15 countries represented. The review is also limited to English-language, peer-reviewed sources, creating a real gap in Urdu-language or non-indexed policy and practitioner literature from around Pakistan, as much of the initial institutional reaction to the 2025 National AI Policy is likely to be published in this domain first in local policy and practitioner outlets. A small number of the sources included (Section 3.5) come from more recent regional journals that are not necessarily included in international bibliographic indexing services; in one instance a preprint that has not been peer reviewed has been included; these are identified individually in the text and readers are advised to take them into account accordingly. The results presented here are not "statistically pooled" across the studies, but are presented as an integrative thematic and content-analytic synthesis and as descriptive of this particular, explicitly bounded and transparently bounded corpus, not as a population-level estimate of the larger body of data. There was no formal risk-of-bias appraisal tool applied (Section 3.5), and coding in Table 1 was done by a single coder, but not cross checked by a second coder as would be done in larger team systematic reviews, but which would be possible within the scope of the present paper; readers wishing to extend this review are encouraged to use this coding as a starting point for independent cross-coding rather than as a final word.

## Conclusion

This review set out to answer a specific question: does the organisational AI-adoption literature treat leadership behaviour and employee AI literacy as a joint mechanism, or as two separately studied antecedents? Across thirty coded studies, spanning fifteen individual countries across four continents plus several multi-country and global-scope studies, and both quantitative and qualitative traditions, the answer is largely unambiguous but not absolute — leadership and AI literacy are each active, moderately sized areas of research, only one study in this corpus treats them jointly, and the theoretical-family cross-tabulation in Table 3 shows this separation to be structural, though beginning, in its newest 10%, to erode. That gap is more, not less, pronounced in Pakistan's own fast-growing AI-adoption literature: five Pakistani studies published between 2025 and 2026 demonstrate that the local research community has both the appetite and the methodological capacity to study AI adoption rigorously, using the same validated PLS-SEM and UTAUT-based techniques as their Nigerian, Chinese, Jordanian, and Indian counterparts, and one (Jawaid & Shoaib, 2026) has now taken the first step toward engaging leadership directly. What remains is to point that capacity at leadership and AI literacy jointly, rather than at either construct in isolation or at technology and organisational readiness alone.

With Pakistan's 2025 National AI Policy raising the practical stakes of this question — and with comparable evidence from Bangladesh, Vietnam, and even higher-income Australia suggesting that workforce capability and leadership practice, not infrastructure alone, are the binding constraint on responsible AI adoption — the research agenda set out here offers a starting point for the empirical work this gap calls for. Each of its five research questions is paired with a design already precedented somewhere in the reviewed corpus, meaning the ingredients for closing this gap exist; what has been missing, until studies are designed to combine them formally, is the study itself. That is the specific contribution this paper's own author intends to make through her doctoral research on leadership, AI literacy, and trust in workplace AI.

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