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Strategic Readiness for AI Integration in Libyan Higher Education: A Focus on English Language Teaching

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Abstract

This study investigates the strategic readiness of Libyan higher education institutions for integrating artificial intelligence (AI) into English language teaching (ELT). Using an explanatory sequential mixed-methods design, data were collected from 187 ELT instructors and 14 department heads across six public universities during the 2024–2025 academic year. A 52-item Likert-scale questionnaire measured four readiness dimensions—technological infrastructure, pedagogical preparedness, institutional policy, and instructor attitudes—while semi-structured interviews provided qualitative depth. The results revealed moderate-to-low overall readiness (M = 2.61, SD = 0.74), with infrastructure scoring lowest (M = 2.14) and attitudes highest (M = 3.38). Thematic analysis surfaced five themes: resource scarcity, policy ambiguity, professional development gaps, cautious optimism, and reliance on informal workarounds. Hierarchical regression indicated that institutional policy support (β = .41), pedagogical preparedness (β = .29), and prior technology training (β = .17) were most strongly associated with instructor willingness to adopt AI tools. The findings reveal a structural misalignment between instructor enthusiasm and systemic capacity, suggesting that coordinated strategic planning is required before meaningful AI integration in Libyan ELT can be realised. Implications and a phased readiness framework are proposed.

Keywords

Artificial intelligence, AI readiness, English language teaching, Libyan higher education, technology integration

Introduction

The accelerating development of artificial intelligence has prompted education systems worldwide to reconsider how teaching and learning are designed, delivered, and evaluated. In the field of English language teaching (ELT), AI-powered tools—ranging from automated writing evaluation and intelligent tutoring systems to conversational chatbots and adaptive learning platforms—have demonstrated potential to enhance learner engagement, personalise instruction, and provide immediate corrective feedback (Huang et al., 2023; Kohnke et al., 2023). Yet the successful integration of these tools is neither automatic nor uniform; it depends heavily on the strategic readiness of the institutions that seek to adopt them.

Libya presents a particularly compelling context for studying this phenomenon. Its higher education sector, already strained by decades of political instability, infrastructural degradation, and chronic underfunding, now faces the additional pressure of keeping pace with a global technological revolution. The country's public universities have historically struggled with basic digital infrastructure—unreliable internet connectivity, outdated computer laboratories, and limited access to licensed software—let alone the sophisticated ecosystems that AI applications typically require (Rhema & Miliszewska, 2014; Kenan et al., 2013).

ELT in Libya is a discipline that stands to benefit considerably from AI integration: automated speech recognition can support pronunciation training, natural language processing can enable real-time grammar feedback, and large language models can generate contextualised practice materials at scale. The gap between what is technologically possible and what is currently available in Libyan ELT classrooms is therefore wide, and it is this gap that motivates the present inquiry.

Despite a growing body of international literature on AI in education, research that situates AI readiness within conflict-affected and resource-constrained contexts remains sparse. Most existing readiness frameworks have been developed in technologically saturated environments—North America, East Asia, the Gulf states—and their assumptions about baseline infrastructure, digital literacy, and institutional governance do not transfer straightforwardly to settings like Libya (Zawacki-Richter et al., 2019). There is a clear need for context-sensitive research that examines not only whether institutions are ready for AI, but what "readiness" means in an environment where the preconditions many frameworks take for granted simply do not exist. This study addresses that need by investigating the following research questions:

RQ1: What is the current level of strategic readiness for AI integration in ELT programmes at Libyan public universities, as measured across technological, pedagogical, policy, and attitudinal dimensions?

RQ2: What institutional and individual factors are most significantly associated with ELT instructors' willingness to adopt AI-powered teaching tools?

RQ3: How do ELT instructors and department heads perceive the barriers to and opportunities for AI integration in their specific institutional contexts?

Literature Review

AI in language education: Promises and realities

The application of AI in language education has progressed rapidly from simple computer-assisted language learning (CALL) programmes to sophisticated systems capable of adaptive learning, automated assessment, and natural language interaction. Early CALL tools were essentially drill-based software that provided limited feedback; today's AI applications leverage machine learning, natural language processing, and neural network architectures to create learning experiences that can approximate certain aspects of human tutoring (Chapelle, 2009; Godwin-Jones, 2022). Chatbots and AI-based writing assistants have entered mainstream use among language learners, and large language models such as ChatGPT have been rapidly adopted in both formal and informal learning settings since late 2022 (Bai & Wang, 2023).

The empirical evidence for AI's effectiveness in language learning is growing but uneven. A meta-analysis by Huang et al. (2023), covering 45 experimental studies, reported a moderate overall effect size (d = 0.58) for AI-assisted language instruction compared to traditional methods, with the strongest effects observed in writing and vocabulary acquisition. However, the analysis noted significant heterogeneity, with studies conducted in well-resourced East Asian contexts tending to report larger effects than those in developing regions. A systematic review by Zawacki-Richter et al. (2019) confirmed that the MENA region was severely underrepresented in this body of research, meaning the field's collective understanding of AI's potential is shaped by contexts that bear little resemblance to Libyan universities.

Conceptualising AI readiness in higher education

The concept of "readiness" in the context of educational technology has been theorised from multiple perspectives. Parasuraman's (2000) Technology Readiness Index (TRI) measured individual dispositions—optimism, innovativeness, discomfort, and insecurity—toward new technologies. While influential, the TRI was designed for consumer technology and does not capture the institutional dimensions critical in educational settings. More recently, Jwaifell et al. (2019) proposed a multi-dimensional readiness framework for AI in higher education that includes infrastructure readiness, human resource readiness, policy readiness, and cultural readiness.

In language education specifically, Hubbard (2008) argued that successful technology integration depends not on the technology itself but on the sociotechnical ecosystem surrounding it—teacher training, curricular alignment, administrative support, and a culture that values pedagogical innovation. Kessler (2018) emphasised that language teachers' Technological Pedagogical Content Knowledge (TPACK)—their ability to integrate technology with subject-specific pedagogy—is a more important predictor of successful integration than access to technology alone. The TPACK framework (Mishra & Koehler, 2006) is particularly relevant because it foregrounds the intersection of technological knowledge, pedagogical knowledge, and content knowledge, highlighting that effective AI integration requires the capacity to align AI tools with specific pedagogical goals such as developing communicative competence, supporting writing feedback cycles, and scaffolding vocabulary acquisition.

At the same time, using TPACK as an analytic frame for AI readiness requires an explicit acknowledgement of the framework's historical limits. TPACK was articulated in 2006, well before the arrival of large language models, and it implicitly models technology as a bounded repertoire of tools with relatively stable, predictable affordances. Generative AI disturbs that assumption in several ways: outputs are probabilistic rather than deterministic, tool behaviour shifts with each model update, prompt design becomes a form of pedagogical labour in its own right, and the boundary between "instructional resource" and co-constructor of instructional content is increasingly blurred (Kohnke et al., 2023). A growing strand of scholarship has therefore begun to extend or reformulate TPACK to capture these generative, adaptive features, variously framed as AI-TPACK or Intelligent-TPACK (Celik, 2023) and, more broadly, as a reconsideration of teacher knowledge in the age of generative systems (Mishra et al., 2023). The present study adopts TPACK as an interpretive heuristic rather than a finished theory, on the understanding that its technological-knowledge dimension in particular needs to be read more dynamically when applied to AI than when applied to the CALL-era tools for which it was originally designed.

For this study, “AI readiness” is operationalised as a composite construct comprising four dimensions: (1) technological infrastructure, referring to the availability and reliability of hardware, software, connectivity, and technical support; (2) pedagogical preparedness, referring to instructors’ knowledge, skills, and confidence in using AI tools, conceptually aligned with TPACK; (3) institutional policy, referring to strategic plans, governance structures, and resource allocation mechanisms for technology integration; and (4) instructor attitudes, referring to beliefs, expectations, and affective dispositions toward AI in education.

The Libyan higher education context

Libya’s higher education system has undergone considerable disruption since the political upheaval of 2011. Universities experienced physical damage, faculty attrition, and administrative fragmentation, with many institutions operating under divided governance structures (Tamtam et al., 2011). Although conditions have improved somewhat in recent years, the legacy of disruption persists. In the area of technology integration specifically, Libyan universities have lagged behind regional counterparts. Rhema and Miliszewska (2014) found that students and faculty reported significant dissatisfaction with ICT infrastructure, including slow internet speeds, frequent power outages, and a lack of technical support staff. Kenan et al. (2013) documented a gap between policy rhetoric—which occasionally invoked technology-enabled education as a strategic priority—and actual investment in the systems needed to deliver it.

In ELT specifically, Orafi and Borg (2009) demonstrated that curriculum reforms intended to promote communicative language teaching were largely subverted at the implementation level by teachers who lacked training in, or conviction about, the reformed approach. Altaieb (2013) found that Libyan EFL students had limited exposure to authentic English. More recently, Elmabruk (2018) observed that some instructors had begun experimenting with online platforms, but these efforts were almost entirely individual and unsupported by institutional structures. Against this background, the question of AI readiness is not merely one of technological adoption; it is fundamentally a question of institutional capacity, strategic vision, and the ability to build on existing—however limited—foundations of digital engagement.

Identifying the gap

The literature reveals three key gaps that this study addresses. First, there is a scarcity of empirical research on AI readiness in conflict-affected and resource-constrained educational settings. Second, the specific intersection of AI and ELT in the Libyan context has not been investigated, despite the discipline’s clear potential to benefit from AI tools. Third, most existing studies adopt either quantitative or qualitative methods alone; mixed-methods approaches that capture both measurable readiness dimensions and stakeholder experiences are uncommon. The present study addresses these gaps not by claiming to have discovered a misalignment between individual readiness and institutional capacity—a pattern well documented across developing-world ICT-in-education research for at least two decades (Kenan et al., 2013; Rhema & Miliszewska, 2014; Selwyn, 2012; Warschauer, 2003)—but by characterising how that misalignment is manifesting in the Libyan ELT context at the particular inflection point of generative AI adoption. Its contribution therefore lies less in the identification of a novel phenomenon than in providing a context-specific, mixed-methods account that can support differentiated policy responses in fragile-state higher education systems.

Methodology

Research design and setting

This study employed an explanatory sequential mixed-methods design (Creswell & Plano Clark, 2018), in which quantitative data were collected first, followed by qualitative data intended to elaborate on and explain the quantitative findings. The study was conducted across six public universities: the University of Benghazi, the University of Tripoli, the University of Misrata, Sebha University, Sirte University, and the University of Zawiya, selected to represent the geographical and institutional diversity of Libyan public higher education.

Participants

The quantitative phase involved 187 ELT instructors (response rate: 62.3% of 300 distributed questionnaires). Participants ranged in age from 27 to 63 years (M = 41.2, SD = 8.7); 112 (59.9%) were female and 75 (40.1%) were male. In terms of qualifications, 34 (18.2%) held doctoral degrees, 118 (63.1%) held master's degrees, and 35 (18.7%) held bachelor's degrees with substantial teaching experience. Years of teaching experience ranged from 2 to 31 (M = 12.4, SD = 7.1). The qualitative phase involved semi-structured interviews with 14 participants: eight ELT instructors and six department heads, purposively sampled to ensure variation in institution, experience level, and gender. Interviews lasted between 35 and 65 minutes (average: 47 minutes) and were conducted in English, with participants given the option to switch to Arabic for complex responses. All Arabic segments were translated by the researcher and independently verified by a bilingual colleague with expertise in applied linguistics.

Instruments

The quantitative instrument was a 52-item questionnaire, the AI Readiness in Language Education Scale (AIRLES), developed from a synthesis of existing readiness frameworks (Parasuraman, 2000; Jwaifell et al., 2019; Kessler, 2018). Items were distributed across four subscales: Technological Infrastructure (14 items), Pedagogical Preparedness (14 items), Institutional Policy (12 items), and Instructor Attitudes (12 items). All items used a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The decision to treat Likert-scale responses as interval data for parametric analysis is consistent with long-standing practice in applied linguistics survey research (Dörnyei & Taguchi, 2010) and is supported by accumulating simulation evidence indicating that parametric tests on five-point Likert items are robust to departures from strict interval assumptions when item distributions are approximately symmetric and sample sizes exceed 100 (Harpe, 2015; Norman, 2010). Distributional diagnostics for the present data (subscale skewness values between −.62 and .48, kurtosis values between −.91 and .74) indicated that each subscale met these conditions.

A standalone item measuring prior technology training was included as a separate predictor in the regression analysis, distinct from the Pedagogical Preparedness subscale, because it captures a specific experiential factor—participation in structured training—rather than the broader construct of perceived readiness. The instrument underwent expert review by three applied linguistics faculty members and was piloted with 28 instructors. Cronbach's alpha values were .89 (Infrastructure), .86 (Pedagogical Preparedness), .83 (Institutional Policy), .91 (Attitudes), and .93 for the full scale. Corrected item–total correlations within each subscale ranged from .46 to .78, and inter-subscale Pearson correlations ranged from .32 to .58 (see section 4.3), providing preliminary evidence that the subscales were internally consistent yet empirically distinct. The decision not to conduct exploratory factor analysis on these data warrants explicit justification. With 187 respondents and 52 items, the subject-to-item ratio of 3.6:1 falls below the minimums typically recommended for stable factor recovery (5:1 to 10:1; Costello & Osborne, 2005), and pilot-data item communalities for several items fell below .40, a pattern that further inflates the sample-size requirement for reliable solutions. Rather than report an underpowered EFA whose structure would be unlikely to replicate, the four-dimensional model is treated here as theoretically motivated, supported by reliability evidence and by the coherent pattern of inter-subscale correlations, and flagged as requiring a fully powered EFA and subsequent confirmatory factor analysis in an independent sample as a priority validation step. This is revisited in the Limitations section.

The semi-structured interview protocol consisted of 12 guiding questions organised around the same four dimensions. Sample questions included: "Describe the current state of technology in your department," "What is your understanding of how AI might be used in language teaching?" and "To what extent does your institution have a clear plan for integrating new technologies?"

Data collection and ethical procedures

Ethical approval was obtained from the Faculty of Arts Research Ethics Committee at the University of [anonymised]. Data collection took place between October 2024 and February 2025. Questionnaires were distributed both electronically (via Google Forms) and in hard copy; 134 (71.7%) were submitted electronically and 53 (28.3%) in hard copy. Interviews were conducted face-to-face where feasible and via Zoom where distance constraints prevented in-person meetings. All interviews were audio-recorded and transcribed verbatim. Arabic segments were translated by the researcher and verified by an independent bilingual applied linguistics scholar for semantic accuracy and consistency of meaning.

Data analysis

Quantitative data were analysed using SPSS version 28. Descriptive statistics were computed for each subscale and item. An independent-samples *t*-test and one-way ANOVA (with eta-squared effect sizes) were used to examine differences by gender, qualification, and institution. Pearson correlations were calculated among readiness dimensions. A hierarchical multiple regression was conducted to identify factors associated with instructor willingness to adopt AI, operationalised as the mean Attitudes subscale score. Collinearity diagnostics (VIF and tolerance) were examined. Qualitative data were analysed using reflexive thematic analysis following Braun and Clarke's (2006, 2019) six-phase approach. The researcher maintained a reflexive journal, and member checking was conducted with four participants.

Findings

Overall readiness levels

The overall mean readiness score was 2.61 (SD = 0.74), indicating moderate-to-low strategic readiness on the 5-point scale. Substantial variation was observed across dimensions, with Instructor Attitudes scoring highest (M = 3.38, SD = 0.81) and Technological Infrastructure scoring lowest (M = 2.14, SD = 0.92). Table 1 presents the descriptive statistics.

Key item-level findings and group comparisons

At the item level, "My institution provides reliable high-speed internet access for teaching purposes" received the lowest mean score across the entire instrument (M = 1.72, SD = 1.01), with 73.8% of respondents selecting "Strongly Disagree" or "Disagree." Similarly, "My institution provides access to AI-powered educational software or platforms" scored 1.89 (SD = 0.98). Within the Attitudes subscale, "I believe AI tools could make language teaching more effective" received the highest score (M = 3.87, SD = 0.93), and "I am willing to learn how to use AI tools if adequate training is provided" scored 3.74 (SD = 0.89).

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Table 1
Descriptive Statistics for AI Readiness Subscales (N = 187)

Subscale	*M*	*SD*	Min	Max	Level
Technological Infrastructure	2.14	0.92	1.00	4.21	Low
Pedagogical Preparedness	2.47	0.78	1.14	4.43	Low
Institutional Policy	2.44	0.83	1.00	4.33	Moderate
Instructor Attitudes	3.38	0.81	1.33	5.00	Moderate
Overall Readiness	**2.61**	**0.74**	**1.12**	**4.49**	**Moderate-Low**

Note. Scale: 1.00–1.80 = Very Low; 1.81–2.60 = Low; 2.61–3.40 = Moderate; 3.41–4.20 = High; 4.21–5.00 = Very High.

An independent-samples *t*-test revealed no significant gender difference in overall readiness, $t(185) = 1.23$, $p = .221$, $d = 0.18$. A one-way ANOVA indicated a significant effect of university on overall readiness, $F(5, 181) = 3.47$, $p = .005$, $\eta^2 = .087$. Post hoc Tukey HSD tests showed that instructors at the University of Misrata reported significantly higher readiness ($M = 2.94$) than those at Sebha University ($M = 2.21$, $p = .008$) and Sirte University ($M = 2.31$, $p = .024$). A further ANOVA found a significant effect of qualification level, $F(2, 184) = 4.81$, $p = .009$, $\eta^2 = .050$, with PhD holders reporting higher readiness ($M = 2.89$) than BA-level instructors ($M = 2.38$, $p = .007$).

Correlations and regression analysis

Pearson correlations among the four readiness dimensions revealed that all were positively and significantly intercorrelated. The strongest association was between Pedagogical Preparedness and Instructor Attitudes ($r = .58$, $p < .001$), while the correlation between Infrastructure and Attitudes was the weakest ($r = .32$, $p < .001$). The moderate-to-strong intercorrelations among the four subscales suggest that while the dimensions are conceptually distinct, they share considerable variance, reinforcing the view that AI readiness is a multifaceted but interrelated construct.

A hierarchical multiple regression was then conducted to identify factors associated with Instructor Attitudes (the dependent variable). In Step 1, four demographic variables (age, gender, experience, qualification) were entered as controls, accounting for 11.2% of variance, providing a foundation for examining the incremental contribution of institutional and pedagogical factors. In Step 2, three substantive predictors were entered: the Institutional Policy subscale score, the Pedagogical Preparedness subscale score, and the standalone prior technology training item. The Technological Infrastructure subscale was deliberately excluded as a predictor because it is conceptually a systemic variable rather than an individual-level predictor of attitudes.

Step 2 increased explained variance to 47.8%, $\Delta R^2 = .366$, $\Delta F(3, 179) = 41.87$, $p < .001$, corresponding to a large effect ($f^2 = 0.70$). All VIF values were below 2.5. In the final model, the variables most strongly associated with positive AI attitudes were Institutional Policy ($\beta = .41$, $p < .001$), Pedagogical Preparedness ($\beta = .29$, $p < .01$), and prior technology training ($\beta = .17$, $p = .012$). Table 2 displays the full results.

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Table 2

Hierarchical Multiple Regression: Factors Associated with Instructor AI Attitudes

Predictor	B	SE	β	t	p	95% CI	VIF
Institutional Policy	.39	.06	.41	6.12	<.001	[.27, .51]	1.62
Pedagogical Prep.	.30	.07	.29	4.38	<.01	[.17, .44]	1.54
Tech Training	.18	.07	.17	2.54	.012	[.04, .32]	1.21

Note. $R^2 = .478$ *for Step 2 (*$f^2 = 0.70$*).* $\Delta R^2 = .366$ *for Step 2 (*$p < .001$*). Demographic controls entered in Step 1 are omitted for brevity.*

Qualitative findings

Thematic analysis of the 14 interview transcripts generated five interconnected themes.

Resource scarcity as a defining constraint

Every participant identified resource limitations as the most fundamental barrier to AI integration. These limitations extended beyond technology to encompass financial resources, human capital, and physical space. One instructor at Sebha University stated: “We are talking about artificial intelligence, and I cannot even project a PowerPoint in my classroom because the projector has been broken for two years and no one replaces it” (Participant 7, Instructor, Sebha). A department head at the University of Tripoli offered a similar account: “The internet in our faculty building drops out several times a day. Last semester I tried to use an online quiz platform and half the students could not connect” (Participant 3, Department Head, Tripoli). Participants in the southern region described particularly acute shortages, including periodic electricity blackouts.

Policy ambiguity and institutional drift

A second recurrent theme concerned the absence of clear institutional policies regarding AI. One department head stated: “There is no plan. There is no strategy. There is no committee. Nobody in the university administration has ever mentioned artificial intelligence in any meeting I have attended” (Participant 11, Department Head, Sirte). This policy vacuum meant that individual initiative was neither supported nor prohibited, leaving early adopters without institutional recognition or resources.

Professional development gaps

Participants consistently reported insufficient training in educational technology. A particularly insightful comment was: “It is not just that there is no training. It is that when training does happen, it is generic. It does not connect to what we actually do as language teachers. I need someone to show me how to use these tools with my speaking class, with my writing class, not just a general introduction to what AI means” (Participant 2, Instructor, [anonymised]). Department heads confirmed that no institution had a dedicated AI-in-education training programme.

Cautious optimism toward AI

Despite the barriers, most interviewees expressed genuine interest in AI’s potential, though qualified by an awareness of challenges. One instructor reflected: “My students already use AI. They use Google Translate, they use ChatGPT for their assignments. The question is not whether AI will come into our classrooms. It is already there. The question is whether we as teachers will engage with it intelligently or just pretend it does not exist” (Participant 6, Instructor, Misrata).

Reliance on informal workarounds

A final theme was the prevalence of individually driven workarounds: using personal smartphones, sharing AI-generated materials through WhatsApp, and purchasing personal internet dongles. As one instructor explained: “I use my own mobile data. I bring my own laptop. I pay for my own Grammarly subscription. The university provides nothing. Everything I do with technology, I do on my own, with my own money, in my own time” (Participant 4, Instructor, Tripoli). These workarounds were uniformly described as unsustainable, inequitable, and invisible to institutional planning.

Discussion

The attitude–infrastructure gap

Perhaps the most striking finding is the gap between Instructor Attitudes (M = 3.38) and Technological Infrastructure (M = 2.14)—a difference of more than one full point on the 5-point scale. This suggests that the primary obstacle to AI integration in Libyan ELT is not instructor resistance, which has often been cited as a barrier in developing contexts (Ertmer, 1999), but rather the material and institutional conditions in which instructors work. This finding aligns with Hubbard’s (2008) argument that technology integration is fundamentally a systemic rather than individual phenomenon. Viewed through the TPACK lens (Mishra & Koehler, 2006), instructors appear to possess a developing awareness of the pedagogical possibilities of AI—the “PK” and nascent “TPK” components—but are unable to activate these competencies because functioning tools and platforms are absent from their institutional environments.

Institutional support as a key factor

The regression analysis identified Institutional Policy as the variable most strongly associated with instructor attitudes (β = .41), a stronger association than either Pedagogical Preparedness or prior training. On its face, this suggests that what is most closely linked to instructor engagement is not the physical presence of technology but the perception that one’s institution has a clear vision, a plan, and a commitment to supporting professional growth. Two interpretive caveats deserve explicit attention here. First, because the design is cross-sectional, the β coefficient cannot be read directionally: Institutional Policy may shape Attitudes, but Attitudes may equally shape perceptions of Policy. Instructors who are already favourably disposed toward AI are plausibly more attuned to—and more generous in their reading of—whatever institutional signals do exist, while those who are sceptical may perceive the same institutional environment as less supportive. This reverse-causality possibility is not merely theoretical; the perceived-organisational-support literature has long acknowledged that affective dispositions colour the appraisal of organisational climate (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Second, the two constructs are almost certainly reciprocally related rather than unidirectional, with policy clarity and attitudinal openness reinforcing one another over time in the manner described by change-readiness models (Armenakis & Harris, 2009). Disentangling these pathways would require longitudinal data—ideally policy interventions followed by pre–post attitudinal measurement—or vignette-based experimental designs that manipulate perceived institutional support while holding individual attitudes constant. The present finding should therefore be read as evidence that policy and attitudes are tightly co-implicated in the Libyan ELT system, not as an estimate of the causal effect of one on the other. That said, the practical implication remains informative: because the two variables co-vary so strongly, any policy action that articulates a clear institutional position on AI is likely to be accompanied by—and may well help reinforce—more favourable instructor dispositions, even if the precise mechanism cannot be identified from these data. Libyan universities could therefore generate meaningful readiness gains by articulating clear policies, establishing dedicated committees, and signalling that AI-enhanced teaching is a strategic priority.

Implications for language teaching practice

The professional development gaps identified in Theme 3 represent a specific deficit in TPACK. Instructors understand the pedagogical challenges of ELT (content knowledge and pedagogical knowledge) and have growing awareness of what AI tools can do (technological knowledge), but they lack the integrated TPACK needed to deploy AI tools in discipline-specific ways—for example, using automated speech recognition to support pronunciation practice in speaking classes, leveraging AI-generated dialogue to create communicative tasks, or employing intelligent writing evaluation to provide formative feedback on student essays. The instructors' enthusiasm was closely tied to perceived relevance for areas where current methods are acknowledged to be inadequate: the limited opportunities for speaking fluency development in large classes, the difficulty of providing individualised writing feedback, and the scarcity of authentic vocabulary acquisition resources. Effective professional development should therefore take the form of discipline-specific TPACK interventions that explicitly connect AI capabilities to these concrete language teaching goals, rather than generic technology workshops that fail to address the realities of ELT practice.

Regional disparities and the informal economy of innovation

The significant inter-university differences in readiness scores, with Misrata scoring highest and Sebha lowest, reflect broader regional inequality in Libyan higher education. The University of Misrata has benefited from relatively stable governance and infrastructure in recent years, while Sebha University has faced more severe disruptions owing to its location in the country's south. These disparities have clear policy implications: any national AI integration strategy must include differentiated support mechanisms that allocate additional resources to the most disadvantaged institutions. A uniform approach that does not account for regional variation is unlikely to succeed.

The qualitative finding regarding informal workarounds is both encouraging and troubling. It is encouraging because it reveals a cadre of instructors who are proactively seeking technological solutions even without institutional support. It is troubling because it suggests that whatever AI integration is currently happening in Libyan ELT is happening despite, not because of, institutional systems. This informal economy of innovation depends on individual motivation and personal finances, is invisible to planners, and cannot be scaled. For institutional leaders, formalising and supporting existing grassroots initiatives may be a more effective starting point than imposing top-down mandates.

Limitations

Several limitations should be acknowledged. First, the study relied on self-report measures susceptible to social desirability bias. Second, the sample was drawn exclusively from public universities, and private and specialist institutions may present different readiness profiles. Third, the cross-sectional design precludes causal inferences from the regression analysis; in particular, the observed association between Institutional Policy and Instructor Attitudes is compatible with policy-to-attitudes, attitudes-to-policy-perception, and reciprocal causal pathways, and these can only be adjudicated by longitudinal or experimental designs. Fourth, the qualitative component involved a relatively small number of interviews, although saturation was reached across the four readiness dimensions. Fifth, although reliability evidence and the coherent pattern of inter-subscale correlations supported the four-dimensional structure of the AIRLES instrument, a fully powered exploratory factor analysis and subsequent independent-sample confirmatory factor analysis were not feasible with the present data and represent the most important outstanding validation step. Sixth, the parametric treatment of Likert-scale responses, while defensible on the basis of the distributional diagnostics reported in section 3.3 and corroborated by simulation evidence (Harpe, 2015; Norman, 2010), should be complemented by non-parametric robustness checks in future replications. Finally, the researcher's positionality as a Libyan ELT instructor introduces potential bias, mitigated through reflexive practices including a reflexive journal and member checking.

Conclusion and Recommendations

This study has provided the first systematic, mixed-methods examination of AI readiness in the context of ELT at Libyan public universities. Its central contribution is not the discovery of misalignment between instructor readiness and institutional capacity—a pattern documented across developing-world ICT-in-education research—but rather a detailed, context-specific characterisation of how that misalignment operates in Libyan ELT at the moment of generative AI adoption, with implications extending to other fragile-state educational systems navigating the AI transition. Based on these findings, the following phased framework is recommended, with the important qualification that each phase is conditional on the macro-political and fiscal conditions discussed above.

Phase 1: Foundation Building (0–12 months). The dual governance structure that continues to fragment national coordination between institutions affiliated with the eastern and western administrative centres makes a unified national AI strategy unrealistic as a short-term goal; Phase 1 activity is therefore most tractable at the individual university level, with inter-university coordination pursued bilaterally rather than through a single ministry directive. Each institution should conduct an AI-in-ELT infrastructure audit benchmarked against a minimum connectivity standard of at least 10 Mbps per 25 concurrent users, establish a small (5–7 member) AI-in-education committee chaired by the vice-dean for academic affairs with a modest recurring budget of approximately 150,000–250,000 LYD per year drawn from existing faculty development lines, and publish a one-page institutional position statement specifying permissible AI uses in teaching and assessment. Because foreign-exchange restrictions make direct institutional subscriptions to overseas AI platforms administratively difficult and financially unpredictable, consortium-level negotiation coordinated through the Ministry of Higher Education and Scientific Research, or channelled via diaspora-linked partnerships such as the Libyan Scholarships Programme, offers a more viable procurement route than bilateral subscription agreements.

Phase 2: Capacity Development (12–24 months). Capacity building should adopt a cascade model, which is considerably cheaper than external training delivery and is well suited to a post-conflict context in which travel and extended in-person provision are logistically difficult. Twenty to twenty-five lead trainers—drawn from the most experienced ELT instructors across the six universities, ideally the informal early adopters identified in this study's qualitative findings—should be intensively trained over two 5-day workshops per year and then cascade training to colleagues at their home institutions. Training content should be organised around discipline-specific TPACK cases rather than generic tool demonstrations, and should be delivered bilingually in Arabic and English to maximise accessibility. International partnerships with organisations already active in Libyan higher education—the British Council, the DAAD, and the Erasmus+ capacity-building instruments—offer in-kind co-funding possibilities that would bring the per-trainer cost to approximately 1,200–1,800 USD, which is within reach of existing partnership budgets. Pilot AI-assisted teaching should be concentrated in writing and speaking modules, where the qualitative findings identified the clearest pedagogical need, and should be evaluated against pre-specified learning outcomes rather than satisfaction measures alone.

Phase 3: Systemic Integration (24–36 months). Full systemic integration is contingent on relative stability in the broader political environment and on sustained oil-revenue allocations to the higher education sector, neither of which can be taken for granted; the sequencing proposed here should therefore be read as conditional on favourable macro-conditions, with activities staged or deferred where those conditions do not hold. Where conditions permit, AI literacy should be embedded in pre-service language teacher education at the BA and Diploma in Education levels through a dedicated three-credit module rather than as diffuse content spread across existing courses. Assessment regulations should be updated, ideally at the Quality Assurance and Accreditation Centre level, to specify acceptable and unacceptable uses of AI-assisted student work, with institutional disciplinary procedures aligned accordingly. Scalable infrastructure investment should prioritise institution-hosted, locally relevant resources—Arabic-capable models and university-owned writing-feedback systems—over dependence on commercial cloud services subject to export controls and exchange-rate volatility. A rolling monitoring mechanism, coordinated through an inter-university network even in the continued absence of unified national governance, would enable cross-institutional comparison and incremental policy adjustment over the remainder of the cycle.

Ultimately, the question facing Libyan higher education is not whether AI will reshape language teaching—it will—but whether institutions will be positioned to shape that process or will simply be swept along by it. For national policymakers, the study underscores the need for a differentiated strategy that acknowledges regional disparities and avoids a one-size-fits-all approach. For international organisations and donors, it highlights the importance of including higher education technology infrastructure in development assistance portfolios for post-conflict states. The evidence presented here suggests that the foundations for strategic engagement exist, but they require deliberate, coordinated, and sustained investment to build upon.

AI Disclosure Statement

In accordance with emerging standards for transparency in academic publishing, the author discloses that AI-based tools were used during manuscript preparation for language editing, reference formatting checks, and preliminary literature searches. All substantive research activities—including study design, data collection, data analysis, interpretation of findings, and the writing of all original content—were conducted entirely by the author. The author takes full responsibility for the accuracy and integrity of the work.

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