



Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya

Dr Ezzden Salem¹ · Dr Hassan Embark Salem² · Dr Hussein Bashir Salem³

¹ Higher Institute of Water Affairs, Ajilat, Libya

² Libyan Academy, Western Coast Branch, Libya

³ Ministry of Higher Education and Scientific Research, Libya

Article type: Critical secondary-empirical evidence synthesis (published data; no original Ajilat respondents)

Corresponding Author's Email: ezzden.embark@gmail.com

Received: 15/8/2026 Revised: 17/8/2026 Accepted: 05/9/2026 Publication: 25/09/2026

Abstract

Generative artificial intelligence (AI) is gaining acceptance in universities, but positive attitudes may coexist with uncertainty about accuracy, responsibility and technical safety. This article critically re-analyses verifiable empirical findings from Libyan higher education and recent UK surveys to develop a theoretically specified case-study framework for the Higher Institute of Water Affairs, Ajilat. It is a secondary-empirical synthesis, not a report of new lecturer interviews at the institute. A Libyan study of 60 EFL instructors reported behavioural intention towards AI-assisted lesson planning at $M = 4.06/5$ and verification behaviour at $M = 4.40/5$, with concern and intention positively associated ($r = .420$, $p < .001$); 68.3% of open-ended responses identified time saving and 48.3% over-reliance as a concern. A separate Benghazi study ($n = 20$) found broadly favourable AI perceptions coupled with self-taught rather than formal adoption. UK Jisc teaching-staff data ($n = 1,765$) reported AI use in teaching at 37% and availability of AI training at 23%. A 2026 UK undergraduate survey ($n = 1,054$) found 95% had used AI and 38% reported institutional provision of AI tools. The synthesis identifies “critical ambivalence”—willingness to use AI alongside scrutiny—as a plausible feature of responsible practice, not a deficiency. However, self-reported verification is not evidence of output correctness, and Libyan EFL findings cannot be generalised to high-stakes water-sector instruction. The paper presents an original evidence matrix, quantitative source diagrams, a task-risk taxonomy and a feasible Ajilat empirical protocol.

Keywords: artificial intelligence; lecturers' attitudes; verification; AI literacy; technical education; adoption and ambivalence; Libya

1. Introduction and scope of the inquiry

AI tools can help lecturers translate or simplify technical reading, produce draft quizzes, generate formative questions and explain unfamiliar terminology. They can also hallucinate references, obscure measurement assumptions, misstate safety thresholds or provide convincing but technically wrong calculations. These risks are emphasised in wider AI education discussions (Kasneci et al., 2023) and are particularly salient in water-related programmes where the meaning of a dosage, laboratory result, pressure value or pump specification cannot be checked by linguistic fluency alone. An educator's “positive attitude” is therefore an incomplete indicator of readiness.

Research often treats adoption as desirable and resistance as a barrier. This framing is too simplistic for professional education. A lecturer who limits AI to low-risk drafting and insists on checking technical claims may be more professionally competent than a frequent adopter who trusts output without verification. Equally, general concern about AI does not establish an inability to use it responsibly. A critical analysis

Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya

should distinguish awareness, experience, trust, risk evaluation, verification practice, policy knowledge and teaching-task consequence.

The Higher Institute of Water Affairs is the intended future case-study site and provides the disciplinary lens for this article. None of the following Libyan or UK survey respondents are represented as Ajilat lecturers. This distinction prevents a formally misleading “case study” claim and allows the article to contribute an analytically useful model before original fieldwork.

2. Theoretical positioning and research questions

Technology Acceptance Model and UTAUT approaches illuminate perceived usefulness, ease, facilitating conditions and behavioural intention (Davis, 1989; Venkatesh et al., 2003). However, an adoption-only framework tends to classify hesitancy as reluctance rather than possible expertise. Hudoud (2026) extends acceptance analysis by measuring creative enhancement, concern and verification; the observed positive association between ethical concern and intention is inconsistent with a simple model in which all concern suppresses adoption. Nevertheless, a cross-sectional correlation cannot determine whether concern causes safe behaviour, and survey self-ratings cannot verify AI-output accuracy.

UNESCO's guidance on generative AI (Miao & Holmes, 2023) and teacher AI competencies (Miao & Cukurova, 2024) support a more demanding construct of responsible integration: human oversight, privacy, pedagogical justification, transparency, verification and fair access. These are not necessarily interchangeable with use frequency. The present analytical model separates low-stakes ideation, medium-stakes formative feedback and high-stakes technical or safety claims, requiring progressively stronger validation.

The research questions are: (1) What do available Libyan studies report about faculty awareness, usefulness, concern and verification? (2) How do UK survey indicators contextualise adoption relative to institutional training and access? (3) Which interpretations are unsupported by the different designs, populations and measures? (4) What Ajilat-specific evidence would be necessary to assess competent, ethical use of AI in technical teaching?

3. Methodology and evidence rules

On 24 October 2026, the authors' critical secondary analysis assembled accessible publisher abstracts and institutional reports with a focus on Libyan lecturer AI research from 2024–2026, two UK survey benchmarks and key international frameworks. Cases were selected purposively for transparent sampling detail or extractable statistics, variation in setting and direct relevance to teacher attitudes, actual AI use or implementation risk. The approach is neither a registered systematic review nor a new institutional survey. No synthetic respondents, transcripts, quotations, regression outputs or AI-generated “Ajilat results” appear in this article.

A structured extraction sheet recorded setting, respondent group, sample size, measurement instrument, quantitative result where reported, analytic design and threats to interpretation. A descriptive comparison is made only within a source: for example, the Hudoud mean of 4.40 for verification behaviour is described as a reported rating, not externally audited accuracy. Source-level samples are never pooled into a fictional “Libyan national” sample and apparent percentage differences across separate questions are not subjected to inferential tests. Reports of correlations are reproduced with their original direction and significance, but not interpreted causally.

Critical appraisal considered cross-sectional timing, convenience recruitment, instrument validity, local disciplinary coverage, nonresponse, social desirability, adoption-definition heterogeneity and the gap between reported intention and enacted verification. For UK comparisons, the analysis foregrounds institutional differences and avoids exporting national rates to Libya. The paper's figures are secondary visualisations of public results, not fresh field measurements.

Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya

Table 1. Extracted empirical AI evidence and inferential boundaries

Source/context	Design / sample	Directly reported evidence	Critical reading
Hudoud (2026), Libya EFL	Questionnaire + open responses; 60 instructors	BI M=4.06; verification item M=4.40; concerns-BI r=.420, p<.001	Attitudes and reported checking; no external correctness audit
Hadaga & Elfalfal (2025), Benghazi	Quantitative questionnaire; 20 teachers	Most respondents favourable; training mainly self-directed	Small, single department; percentage breakdown not extracted
Gratim & Elatrash (2025), Alasmarya	UTAUT questionnaire; 101 faculty	Acceptance associated with UTAUT plus competence and trust constructs	Correlational adoption model, not evidence of learning
Mansour & Abubakar (2025), Sebha	Cross-sectional questionnaire; 240 faculty	Investigated perceived academic-performance contributions	Perception of impact is not objective performance change
Jisc (2025), UK HE	1,765 teaching staff, 22 providers	37% used AI in teaching; 23% offered AI training	Separate survey questions and UK context
Stephenson & Armstrong (2026), UK	1,054 full-time undergraduates	95% AI use; 94% assessed-work support; 38% tools supplied	Student attitudes and self-report, not staff rates

4. Results: acceptance, concern, verification and provision

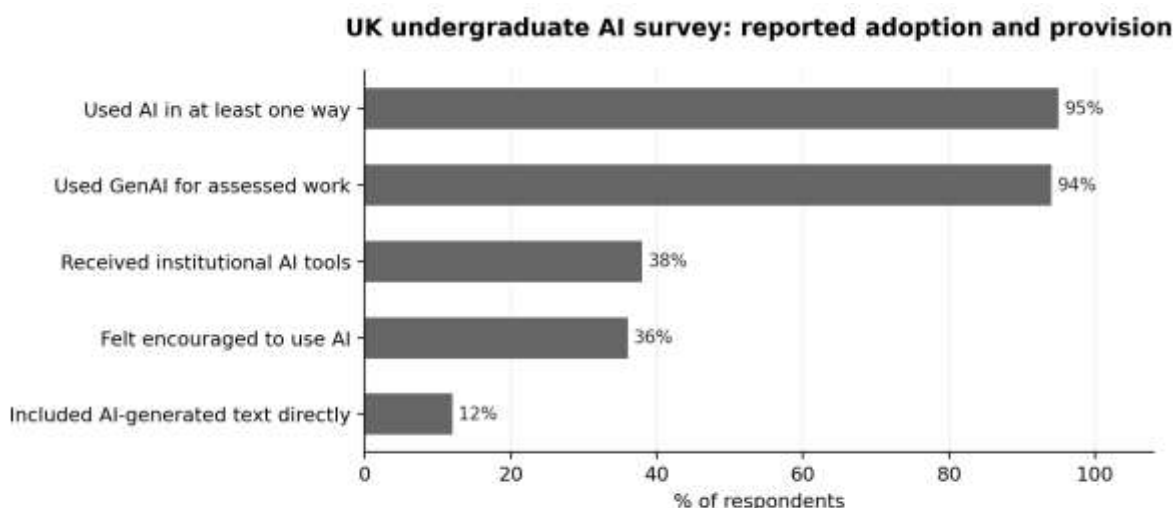
4.1 Critical ambivalence is observable in one Libyan study. Hudoud (2026), analysing 60 Libyan EFL instructors, reported behavioural intention as the highest composite construct ($M = 4.06/5$) and a verification-behaviour item mean of $4.40/5$. A positive association was reported between concerns and intention ($r = .420$, $p < .001$), with time saving identified in 68.3% of open-ended responses and over-reliance in 48.3%. The most defensible interpretation is that readiness to experiment and awareness of risks were not mutually exclusive within that sample. However, this does not show that concern improves safety, that the verification item reflects successful technical fact-checking, or that respondents used AI in the same kinds of tasks. The percentages describe reported coding categories, not the population prevalence of these concerns across Libyan universities.

Hadaga and Elfalfal (2025) surveyed 20 EFL teachers at Benghazi University. Their published abstract described favourable views of AI support for learning and participation while noting reliance on self-directed preparation instead of formal training. Gratim and Elatrash (2025) analysed questionnaires from 101 Alasmarya Islamic University faculty using an extended UTAUT framework that included self-competence, AI trust and AI intelligence; the constructs were associated with adoption-related engagement. Neither finding demonstrates safe, accurate use in engineering or environmental education. Abolkasim and Hasan (2024) separately surveyed more than 1,000 Libyan university students and academic staff about ChatGPT integration, although the aggregate cannot be treated as a lecturer-only result. A 240-person Sebha University faculty survey examined perceptions of academic contribution (Mansour & Abubakar, 2025), but objective productivity or student-performance effects cannot be inferred from questionnaire perceptions alone.

4.2 UK studies reveal a use-support distinction. In Jisc's 2024/25 survey, 37% of 1,765 UK higher-education teaching-staff respondents said they used AI tools in teaching, compared with 24% reported in the prior year's sector survey; 23% reported that AI training was offered (Jisc, 2025b). The 14-percentage-point arithmetic difference between 37% and 23% is a contrast between survey indicators, not a direct count of untrained AI users because question denominators, overlap and responses may differ. HEPI's survey of 1,054 UK undergraduates reported 95% using AI in at least one way, 94% using generative AI to assist assessed work, 38% receiving institutionally provided tools and 12% including AI-generated text directly (Stephenson & Armstrong, 2026). These student rates cannot be compared statistically with the Jisc lecturer rate, because the samples, questions and timeframes differ.

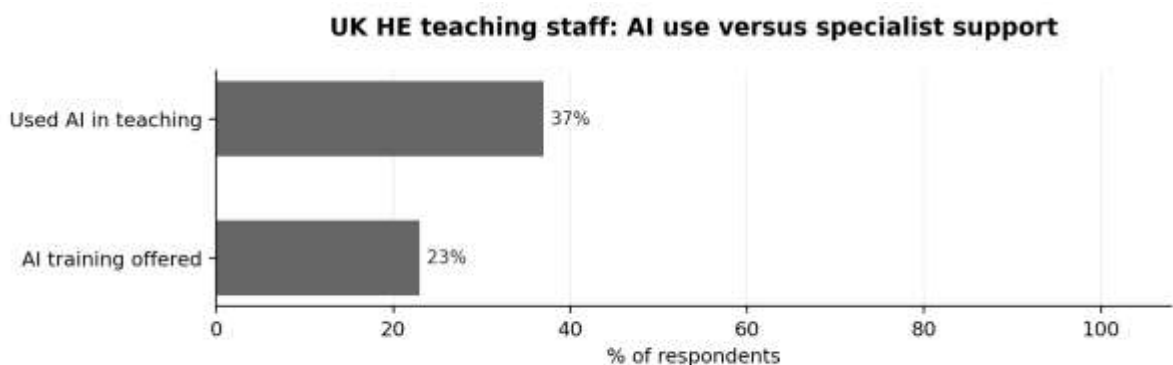
4.3 Adoption metrics omit consequential error. The strongest gap across the studies is between self-reported AI engagement and independently adjudicated output correctness. A claim that AI “improves teaching” requires a defined outcome, such as the proportion of accurate lesson materials, the quality of student reasoning or instructor workload measured consistently. None of the source summaries supplies a water-sector hallucination audit or direct observation of Ajilat lecturer responses to a flawed AI explanation. This is a substantive absence of evidence, not proof that AI is ineffective.

Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya



Source: Stephenson & Armstrong (2026), n=1,054 full-time UK undergraduates; not Libyan lecturer data.

Figure 1. UK undergraduate AI survey outcomes, Stephenson and Armstrong (2026). All values describe UK students, not Libyan lecturers.



Source: Jisc (2025b), n=1,765 UK HE teaching staff; responses are to different questions, not paired-user estimates.

Figure 2. Separate AI teaching-use and training-availability indicators from Jisc (2025).

5. Critical discussion: why acceptance is not competence

A key analytical result is the inadequacy of bipolar “positive/negative attitude” scales as complete readiness measures. AI systems can support the creation of a glossary, but a technical lecturer must still know when “head” means hydraulic potential rather than physical height. An output may be grammatically fluent yet use an incorrect unit, omit a condition or fabricate an applicable standard. Domain expertise is thus an essential moderator of usefulness: the apparent productivity gain becomes a hidden checking cost when material must be verified against manuals, data sheets and professional guidance.

Hudoud's concern—intention correlation is theoretically interesting but particularly susceptible to reverse interpretation. Experienced users may become more conscious of risks through exposure; risk-aware lecturers may use AI only for restricted tasks; or a third variable, such as general professional confidence, may drive both. Self-reported checking can also be routine superficial checking rather than successful detection of incorrect content. Consequently, a well-designed Ajilat study must test behaviour using seeded inaccuracies and compare performance against an independently agreed technical answer key, rather than assuming that questionnaire agreement measures AI literacy.

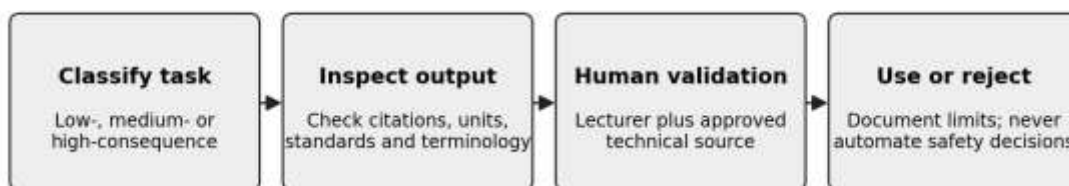
Survey enthusiasm can also conceal unequal governance. If one lecturer accesses a paid institutional system while another enters student records into a consumer chatbot, their apparent use frequency says little about

Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya

privacy practice. Assessment needs to separate legitimate brainstorming, disclosed assisted drafting and submitting generated content as one's own work. A blanket prohibition and unrestricted adoption are both poor substitutes for task-specific policy and enforceable safeguards.

The UK evidence should prompt questions, not supply answers for Libya. A steep uptake among UK undergraduates creates legitimate urgency for staff support, yet differences in procurement, access, language, governance and discipline make simple international benchmarking misleading. Equally, caution should not be framed as cultural resistance. In professional technical education, deliberate non-use of AI for unverified high-consequence decisions may be the appropriate expert response.

Risk-tiered verification of AI materials in technical education



Proposed governance protocol; not a validated Ajilat intervention.

Figure 3. *Proposed risk-tiered AI verification model for the institute; a conceptual workflow requiring empirical evaluation.*

6. Technical-task risk taxonomy and proposed evaluation

For the Ajilat context, an original task taxonomy is proposed. Low-consequence activities include rewriting an administrative notice or generating discussion prompts, subject to privacy and disclosure rules. Medium-consequence activities include translating technical handouts, assembling vocabulary explanations, preparing worked examples and generating formative feedback; these require source and terminology checks by the lecturer. High-consequence activities include water-treatment dosage recommendations, interpreting safety limits, maintenance procedures, engineering calculations or site-operational decisions; AI-generated claims must not be used as standalone authority and require validation against approved technical specifications and competent human review.

A field study, after ethics approval, should collect (a) a lecturer questionnaire on usefulness, ease, confidence, risk and governance, (b) semi-structured interviews seeking concrete examples and non-use decisions, and (c) an opt-in, controlled practical exercise using a balanced set of accurate, ambiguous and deliberately flawed AI-generated water-sector passages. The practical material must be checked and approved by independent water-domain specialists before use. Primary outcomes would be accuracy in detecting and correcting planted errors and appropriate task-specific trust calibration; secondary outcomes would include decision time, explanation quality, disclosure and privacy-rule understanding. No student records or live safety decisions should enter the exercise.

The design should separate self-reported verification frequency from objective performance. Pre-register the rubric and planned group comparisons, and consider discipline, AI experience, prior training and baseline technical experience. Report the denominator for every rate, missing data and uncertainty estimates; avoid complex predictive modelling if the institutional sample is too small. Interview analysis can test the interpretation of “critical ambivalence”, including negative cases where positive intention accompanies poor verification or strong concern accompanies accurate, selective use.

7. Competing explanatory accounts and applied technical scenarios

The strongest interpretation of the available Libyan lecturer studies is conditional acceptance. Yet three competing accounts could explain that pattern. A capability account suggests that higher AI familiarity creates both intention and more accurate risk awareness; a selection account suggests that educators prepared

Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya

to tolerate risk experiment more often; an institution account suggests that guidance and training shape both willingness and critical behaviour. Hudoud's (2026) positive correlation between concern and intention is consistent with several of these accounts but tests none of them causally. Longitudinal designs or a carefully controlled training evaluation would be needed to distinguish them.

The most informative behavioural outcomes would involve real teaching artefacts. An AI-generated description of groundwater recharge might be clear but falsely imply that recharge equals precipitation at every site; a pump-performance explanation might confuse total dynamic head with geometric elevation; a water-quality example might omit sampling conditions or measurement units. These are proposed assessment scenarios rather than observed errors in any named AI system. Evaluators should insert known defects into approved mock materials and ask lecturers to identify, justify and correct them using verified discipline-specific documents. A separate set of accurate items is necessary to determine whether cautious lecturers correctly accept sound information or simply reject everything.

A high overall “critical attitude” score could correspond either to strong technical judgement or undifferentiated mistrust. A well-calibrated respondent should use a tool where its limitations are manageable and withhold reliance where verification is unavailable. Thus the desired metric is not unqualified frequency of use or indiscriminate suspicion; it is appropriate decision quality conditioned on task consequence. Evaluation should include false acceptance of incorrect claims and false rejection of correct claims, alongside explanatory quality and time cost. Pre-specified scoring avoids grading respondents according to whether they favour AI.

The ethical design needs particular care. No real patient, staff or student data, live equipment settings or operational site decisions should be entered in public AI services. Participants should know that exercises concern professional development rather than disciplinary surveillance. Where institutional devices or licensed systems differ, record the tool version and access conditions instead of presenting “AI” as a stable intervention. These design features distinguish responsible empirical AI research from technology boosterism.

Table 2. Prospective scenario-based validation matrix (no Ajilat outcomes reported)

Task tier	Illustrative teaching task	Required validation before instructional use
Low	Draft a discussion question on aquifer types	Lecturer edits language; no personal data; disclose material origin
Moderate	Translate a pump-curve interpretation exercise	Check terms, relationships and units against teaching reference
High	Explain a water-treatment dose or safety threshold	Independent approved source and qualified specialist verification
High	Advise a real operational site action	Do not rely on chatbot output; follow authorised professional procedure

8. Contributions, limitations and conclusions

This paper contributes a risk-sensitive analytic model rather than a numerical institutional estimate. It shows why Libyan lecturer evidence on uptake and ethical ambivalence should be interpreted alongside objective verification and specific educational tasks. The practical recommendation for the Higher Institute of Water Affairs is to develop permitted-use guidance, staged staff training, a verified technical-resource bank, and assessment rules that distinguish disclosed legitimate assistance from unacknowledged substitution. The institution should audit infrastructure and privacy arrangements before mandating any platform.

Methodological limitations include purposive rather than exhaustive selection, unequal report detail, reliance on cross-sectional self-report, lack of independent validation for key constructs and the non-transferability of UK sample percentages to Libya. No Ajilat lecturer survey, interview or test is claimed. The publishable secondary finding is that adoption and concern can coexist, while evidence of genuine technical accuracy, pedagogical improvement and equitable use remains sparse. An original institutional case study will be required to test those claims and produce legitimately site-specific results.

Investigating Lecturers' Perceptions and Attitudes towards the Use of Artificial Intelligence in Teaching and Learning: Critical Empirical Evidence and a Case-Study Framework for the Higher Institute of Water Affairs, Ajilat, Libya

Author declarations for completion before journal submission

Ethics: This document reports analysis of already published, publicly accessible studies and introduces no new human-participant data. Funding, competing interests, correspondence details, author contributions, affiliation approval and final manuscript approval must be completed and verified by the named authors before submission. Data availability: Numerical values used in the figures are transcribed from the cited public reports; no original institutional participant-level dataset exists for this article.

References

- Abolkasim, E., & Hasan, M. (2024). Integrating ChatGPT in education and learning: A case study on Libyan universities. *Journal of Pure & Applied Sciences*, 23(2). <https://doi.org/10.51984/jopas.v23i2.3082>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Gratim, H. M., & Elatrash, E. M. (2025). Examining faculty members' adoption of ChatGPT in Libyan higher education: An extended unified theory of acceptance and use of technology. *Humanities and Natural Sciences Journal*, 6(1), 146–167. <https://doi.org/10.53796/hnsj61/10>
- Hadaga, H. M., & Elfalfal, A. M. (2025). Libyan EFL teachers' perceptions of AI integration in English teaching: A case study at Benghazi University. *Scientific Journal of University of Benghazi*, 38(2), 10–22. <https://doi.org/10.37376/sjuob.v38i2.7446>
- Hudoud, M. A. A. (2026). A TAM-based study of AI-assisted lesson planning among Libyan EFL instructors: Adoption and ambivalence. *Comprehensive Journal of Science*, 10(39), 927–946. <https://doi.org/10.65405/nwx1bd29>
- Jisc. (2025). 2024/25 UK higher education teaching staff digital experience insights survey findings. <https://digitalinsights.jisc.ac.uk/reports-and-briefings/our-reports/2024-25-uk-higher-education-teaching-staff-digital-experience-insights-survey-findings/>
- Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Mansour, J. S. A., & Abubakar, H. (2025). Faculty perceptions of artificial intelligence's role in enhancing academic performance: Field study at Sebha University, Libya. *Sirte University Journal of Humanities*, 15(2), 163–177. <https://doi.org/10.37375/sujh.v15i2.3683>
- Miao, F., & Cukurova, M. (2024). AI competency framework for teachers. UNESCO. <https://doi.org/10.54675/ZJTE2084>
- Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO. <https://www.unesco.org/en/articles/guidance-generative-ai-education-and-research>
- Salem, H. (2019). Libyan lecturers' perceptions of the use of technology in classrooms to support teaching English as a foreign language: A case study in a Libyan university [Doctoral thesis, University of Huddersfield]. <https://eprints.hud.ac.uk/id/eprint/34917/>
- Stephenson, R., & Armstrong, C. (2026). Student generative artificial intelligence survey 2026 (HEPI Report 199). Higher Education Policy Institute. <https://www.hepi.ac.uk/reports/student-generative-ai-survey-2026/>
- UNESCO. (2023). Global education monitoring report 2023: Technology in education—A tool on whose terms? <https://www.unesco.org/gem-report/en/publication/technology>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>