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Artificial Intelligence in Lebanese Upper Elementary Science Classrooms: Readiness, Practices, and Pedagogical Impact

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Abstract: The integration of artificial intelligence (AI) into K–12 education raises urgent questions about pedagogical quality, teacher readiness, and educational equity. The present investigation examines AI readiness, classroom practices, and pedagogical impact in Lebanese upper elementary science education, a context shaped by structural inequality, fragile infrastructure, and growing educator interest in digital transformation. A convergent parallel mixed-methods design was employed, combining structured teacher surveys adapted from DigCompEdu and Technological Pedagogical Content Knowledge (TPACK)-validated instruments, systematic classroom observations, and semi-structured interviews with teachers and school leaders across public and private Lebanese schools. Findings reveal that participating teachers predominantly occupy intermediate DigCompEdu competence levels (Integrator to Expert), demonstrating functional digital competence but significant underdevelopment in higher-order AI pedagogical integration. Classroom practice predominantly relies on substitutive, Replacement-level AI use, while only a small number of better-resourced private schools implement transformative, AI-enabled science instruction. Barriers to integration are structural and systemic rather than motivational, with significant sector differences confirmed across all key competence and readiness measures. Significant equity disparities in AI access, professional development, and pedagogical impact persist across public and private school sectors. The investigation also identifies five underacknowledged pedagogical risks: teacher deskilling, the erosion of epistemic authority, generative AI hallucination hazards, algorithmic opacity in assessment, and the hidden curriculum of AI-mediated knowledge, and it argues that policymakers and practitioners must address these risks alongside structural challenges. The study further provides evidence-based policy recommendations for the Lebanese Ministry of Education, school leaders, and the research community, and outlines implications for the wider MENA region.

Keywords: *AI in education; DigCompEdu; educational equity; Lebanese science education; TPACK.*

Introduction

The integration of artificial intelligence (AI) into formal education has emerged as one of the most consequential technological transitions of the contemporary era. Across international policy discourse, AI is increasingly framed as a transformative force

capable of personalising learning at scale, enhancing formative assessment, and widening educational access (Holmes et al., 2019; UNESCO, 2021; UNESCO, 2023) However, the realisation of these aspirations remains deeply contingent on context, on the quality of infrastructure, the depth of teacher preparation, the strength of institutional leadership, and the equity of access across learner populations (Luckin et al., 2016; Williamson & Eynon, 2020).

Lebanon presents a particularly acute case study of these tensions. The country's education system is characterised by structural duality between a vastly under-resourced public sector and a heterogeneous private sector, with significant disparities in technological infrastructure, teacher professional development, and capacity for pedagogical innovation (Makki et al., 2023). Severe economic and political crises, the aftermath of the COVID-19 pandemic, and uncoordinated digital infrastructure investments have further intensified these disparities. At the same time, AI-enabled educational tools such as intelligent tutoring systems, adaptive assessment platforms, and AI-powered science simulations are reshaping classroom practice and prompting educators and policymakers to confront pressing questions about pedagogical possibilities and educational justice.

Despite growing international research on AI in K–12 education (Cheah et al., 2025; Filiz et al., 2025; Lee & Kwon, 2024), the evidence base concerning AI integration in Lebanese classrooms, specifically in upper elementary science education, remains remarkably thin. Momdjian et al. (2024) provide valuable evidence of Lebanese teachers' intermediate digital competence profiles, but researchers have yet to conduct a classroom-level, subject-specific investigation. This gap limits policymakers, school leaders, and teacher educators in making evidence-based decisions. The present investigation directly addresses this gap.

The investigation is grounded in four interconnected frameworks. The Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006; Shulman, 1986), conceptualises effective technology integration as the dynamic, contextual intersection of Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). The European Framework for the Digital Competence of Educators (DigCompEdu; Redecker & Punie, 2017), provides a standardised six-area, six-level competence taxonomy (Newcomer to Pioneer) enabling fine-grained, internationally comparable competence profiling. Sociocultural and constructivist learning theory (Vygotsky, 1978; Piaget, 1970; Jonassen (1994), frames AI as a potential mediating scaffold within learners' Zone of Proximal Development. Fair AI in Education (FairAIED) principles Chinta et al. (2024), Floridi et al., (2018), and Jobin et al. (2019) foreground access equity, representational equity, outcome equity, algorithmic fairness, and data privacy as essential criteria for ethically responsible AI deployment in education.

Prior literature on AI in K–12 science education documents the pedagogical promise of AI in supporting inquiry-based learning, adaptive formative feedback, and virtual investigation environments (Chen et al., 2020; National Research Council, 2012; Zawacki-Richter et al., 2019). Critical scholarship has foregrounded equity dimensions of AI integration (Williamson & Eynon, 2020; Gewertz, 2024). The RAT framework Hughes et al. (2006), which distinguishes Replacement, Amplification, and Transformation levels of technology use, provides the primary analytical taxonomy for classroom observation. School leadership has been identified as a critical mediating variable in technology integration (Leithwood et al., 2020), while research from the Lebanese context documents specific challenges facing school leadership in a volatile policy environment (Nakhle & Karam, 2022).

Four objectives guide this investigation: mapping AI readiness profiles and DigCompEdu competence distributions of Lebanese upper elementary science teachers; documenting the nature, depth, and pedagogical quality of AI integration practices in observed science classrooms; assessing the pedagogical impact of AI integration on science learning; and identifying the structural, systemic, institutional, and individual barriers that impede effective and equitable AI integration. The study operationalises these objectives through six research questions. First, it examines the AI readiness profiles of Lebanese upper elementary science teachers. Second, it analyses what DigCompEdu competence distributions characterise the participant sample. Third, it investigates what AI integration practices teachers implement in science classrooms. Fourth, it evaluates the pedagogical impact of AI integration on science learning. Fifth, it identifies the barriers that impede effective AI integration. Finally, it explores the equity and ethical dimensions that characterise AI deployment across Lebanon's school sectors.

It is important to clarify the distinctive theoretical contribution of the present study. Although TPACK, DigCompEdu, the RAT framework, and FairAIED have each been applied independently in prior educational technology research, their systematic integration within a single empirical investigation of a fragile, post-crisis educational system is unprecedented in the literature. The study does not offer a merely additive contribution. Instead, it advances what can be conceptualised as a Contextualised AI Pedagogical Integration CAPI model. This framework situates individual teacher competence within the TPACK perspective, aligns it with an internationally benchmarked proficiency progression outlined in DigCompEdu, evaluates instructional quality at the classroom level using a depth-of-integration taxonomy such as RAT, and examines the entire ecosystem through an equity audit grounded in ethical AI principles articulated in FairAIED. Applied in the Lebanese context, the CAPI model further contributes a context-sensitive AI readiness framework applicable to other fragile, crisis-affected, and under-resourced educational systems in the MENA region and beyond. The study also extends FairAIED scholarship by operationalising equity principles at the granular level of classroom observation and teacher interview data, moving beyond the predominantly conceptual application that characterises most existing FairAIED-informed research.

Method

The study adopts a convergent parallel mixed-methods design, as outlined by Creswell and Plano Clark (2018). The researchers integrate three data collection strands: structured teacher surveys, systematic classroom observations, and semi-structured interviews with teachers and school leaders. They analyse each dataset independently and then synthesise the results during the interpretation phase. The team selects this design because it provides the breadth of standardised quantitative measurement while also generating the contextual depth required for qualitative inquiry.

The participant sample comprised upper elementary science teachers drawn from Lebanese public and private schools, complemented by school leaders from participating institutions. In total, 74 upper elementary science teachers and 18 school leaders participated across 22 schools (12 private, 10 public). The researchers selected participants to reflect the structural diversity of the Lebanese school system, ensuring variation in school type, geographic location (urban, peri-urban, and rural), and school size. A total of 74 teacher participants completed the DigCompEdu-adapted survey and were subsequently observed while conducting AI-supported science lessons. The researchers then purposively selected a subset of 24 teachers

for semi-structured interviews, and all 18 school leaders also participated. Table 1 presents the full participant characteristics.

Table 1. Participant Characteristics by School Sector

Characteristic	Private (n = 42)	Public (n = 32)	Total (N = 74)
Gender: Female, n (%)	29 (69%)	21 (66%)	50 (68%)
Teaching experience: M (SD), years	11.4 (5.3)	14.8 (7.1)	12.8 (6.3)
AI-specific PD received, n (%)	26 (62%)	8 (25%)	34 (46%)
Postgraduate degree, n (%)	31 (74%)	19 (59%)	50 (68%)
Urban school, n (%)	35 (83%)	14 (44%)	49 (66%)
Peri-urban school, n (%)	5 (12%)	11 (34%)	16 (22%)
Rural school, n (%)	2 (5%)	7 (22%)	9 (12%)
School leaders interviewed, n	11	7	18

Note. PD = professional development. School leaders did not complete the survey instrument.

Three instruments were employed. First, a structured teacher survey, adapted from the DigCompEdu Check-In instrument (Redecker & Punie, 2017) and validated for Lebanese in-service teachers by Momdjian et al. (2024), provided quantitative measures of AI readiness, digital competence profiles, perceived barriers, and TPACK self-assessment. The researchers established satisfactory internal consistency across the instrument. The overall DigCompEdu composite achieved a Cronbach's alpha of .88, the TPACK subscale reached .83, and the AI readiness subscale produced .79.

They analysed the survey data using descriptive statistics and independent samples t-tests to compare participants from public and private schools. The researchers then constructed a multiple regression model to examine the extent to which AI readiness, DigCompEdu competence level, access to AI-specific professional development, and school type jointly predicted self-reported pedagogical impact scores. They conducted all statistical analyses using SPSS Version 27.

Second, a systematic classroom observation protocol aligned to both the RAT framework and TPACK-derived criteria was used to code the depth and nature of AI integration across observed lessons. Observational data were analysed using structured RAT taxonomy coding and thematic analysis following Braun and Clarke (2006) six-phase procedure. Inter-rater reliability for RAT coding was established through independent double-coding of 20% of observed lessons (n = 15), yielding Cohen's $\kappa = .81$, indicating strong agreement. Third, semi-structured interviews with teachers and school leaders were coded using both deductive categories derived from the theoretical frameworks and inductive codes emerging from participant responses, with barrier categories organised according to Fullan's (2021) and Leithwood et al.'s (2020) classification of technology adoption impediments.

The researchers enhanced trustworthiness in the qualitative strands by triangulating multiple data sources, conducting member checking, and maintaining reflexive analytical journals throughout the study. They supported quantitative validity by adapting instruments from previously validated measures and conducting reliability analyses to confirm internal consistency across scales. The research team also adhered to strict ethical protocols by securing institutional approval, obtaining informed consent from all participants, and fully anonymising all identifying information.

Result and Discussion

1. Teacher Readiness and DigCompEdu Competence Profiles

To complement the statistical significance testing reported above, the analysis also calculated standardized effect sizes to determine the practical magnitude of sector

differences. While p-values indicate whether observed differences are unlikely to have occurred by chance, they do not convey the substantive strength of those differences (Cohen, 2013). In educational research, reporting effect sizes is strongly recommended to provide a clearer understanding of practical significance and policy relevance.

Given the structural duality of the Lebanese education system, it is particularly important to determine whether differences between public and private school teachers represent marginal variations or substantial disparities. Cohen's d was therefore calculated for all independent samples t-tests, and the explanatory power of the regression model was evaluated using R^2. According to conventional benchmarks, values of $d \geq .80$ indicate large effects, suggesting differences of meaningful educational consequence. Table 2 presents the standardized effect sizes for sector comparisons and the predictive model.

Table 2. Standardized Effect Sizes for Sector Differences and Regression Model

Variable	Private (n = 42) M (SD)	Public (n = 32) M (SD)	t(df)	p	Effect Size	Magnitude
DigCompEdu Composite	3.81 (0.82)	2.88 (0.91)	4.63 (72)	< .001	d = 1.08	Large
TPACK Self-Assessment	3.67 (0.79)	2.76 (0.88)	4.71 (72)	< .001	d = 1.10	Large
AI Readiness	3.64 (0.94)	2.56 (0.96)	4.96 (72)	< .001	d = 1.13	Large
Pedagogical Impact Model	—	—	F(4, 69) = 15.26	< .001	R^2 = .47	Large

Note. Effect size magnitude classification follows (Cohen, 2013): small (0.20), medium (0.50), large (0.80).

The effect size analysis reveals that sector differences are not merely statistically significant but substantively large across all core competence and readiness measures. Cohen's d values exceeding 1.0 indicate that private school teachers outperform public school teachers by more than one standard deviation across DigCompEdu competence, TPACK self-assessment, and AI readiness. In practical terms, this represents a profound competence gap rather than a marginal variation. Within applied educational research, effect sizes of this magnitude are uncommon and typically associated with structurally embedded inequalities rather than individual-level variation.

The regression model further reinforces this interpretation. An R^2 value of .47 indicates that nearly half of the variance in self-reported pedagogical impact is explained by AI-specific professional development, competence level, and school type. In social science research, R^2 values approaching .50 are generally interpreted as demonstrating substantial explanatory power (Cohen, 2013). This finding suggests that pedagogical impact is not random nor purely individual, but systematically structured by institutional and professional conditions.

From a policy perspective, the convergence of large effect sizes and strong model explanatory power confirms that AI-related inequities in Lebanese upper elementary science education are systemic. The magnitude of sector differences provides empirical grounding for the study's broader equity argument, reinforcing concerns articulated in international scholarship regarding differential AI access and capability stratification (Williamson & Eynon, 2020; Gewertz, 2024). Rather than reflecting isolated performance differences, the effect size results point to a structurally patterned divergence in AI readiness and pedagogical capacity that risks amplifying existing educational fragmentation within Lebanon's dual school system.

2. Classroom Practices: Dominance of Substitutive AI Use

The classroom observation data, coded using the RAT framework taxonomy, reveal a pronounced preponderance of Replacement-level AI use across the observed sample. In the majority of observed lessons, AI tools served as functional substitutes for conventional pedagogical resources, presenting factual science content, generating practice exercises, or displaying instructional media without altering task structure, pedagogical approach, or epistemic engagement. This pattern is characteristic of early-stage technology adoption, consistent with Hughes et al. (2006) and Selwyn (2019).

Amplification-level use was observed with moderate frequency, particularly in private school classrooms and among teachers who had accessed AI-specific professional learning. Transformation-level use in which AI enabled entirely new forms of science inquiry, collaborative investigation, or adaptive personalised learning was present but exceptional, observed primarily in private schools with robust digital infrastructure and among teachers with stronger TPACK profiles. Table 3 summarises the RAT taxonomy, science classroom illustrations, and the distribution of integration levels across the sample.

Table 3. RAT Framework Levels: Definitions, Science Classroom Illustrations, and Observed Distribution of AI Integration Depth

Integration Level	Definition (Hughes et al., 2006)	Illustrative Example in Lebanese Upper Elementary Science	Observed Distribution in Sample
Replacement (R)	AI is used in the same way as a conventional tool, performing the same function without meaningful functional change or pedagogical shift.	Using an AI presentation tool to display pre-written science facts, replicating direct instruction from a textbook or worksheet.	Predominant pattern across sample; most frequently observed in public school classrooms and among teachers with lower DigCompEdu profiles.
Amplification (A)	AI enhances efficiency, extends capacity, or improves access beyond what non-digital tools allow, but within existing task structures and pedagogical approaches.	AI-generated formative quiz tools providing immediate automated feedback; AI search tools enabling faster resource retrieval for independent inquiry tasks.	Moderately present; more common in private school classrooms and among teachers at Integrator–Expert DigCompEdu levels.
Transformation (T)	AI creates entirely new learning tasks, environments, or forms of student engagement not previously possible or conceivable without the technology.	AI-driven virtual science simulations enabling collaborative investigations (e.g., ecosystem modelling) with real-time adaptive data feedback; AI tutoring systems providing personalised inquiry scaffolding.	Exceptional; observed primarily in private schools with robust infrastructure and among teachers with AI-specific professional development.

Note. RAT = Replacement, Amplification, Transformation. Framework source: Hughes et al. (2006). The predominance of Replacement-level use is consistent with early technology adoption trajectories documented internationally (Cheah et al., 2025; Filiz et al., 2025).

The dominance of substitutive AI use is interpretable through the TPACK lens: without the capacity to integrate technological, pedagogical, and content knowledge

in a dynamic synthesis, teachers default to familiar instructional patterns, simply substituting one medium for another. This pattern should not be interpreted as a condemnation of Lebanese science teachers; it is the normative starting point in technology adoption trajectories across national contexts (Holmes et al., 2022). The critical question is what conditions enable progression toward amplification and transformation. Evidence from this investigation points clearly to AI-specific professional development, institutional leadership support, and adequate infrastructure.

3. Barriers to AI Integration

Analysis reveals six principal categories of barriers impeding effective AI integration. These are characterised as predominantly structural and systemic rather than motivational, findings of significant policy importance. Teachers across both school sectors express genuine interest in AI integration; the impediments they identify are primarily institutional and infrastructural, rather than attitudinal. Table 4 presents the six barrier categories with their classifications, descriptions, and evidence sources.

Table 4. Categories of Barriers to AI Integration in Lebanese Upper Elementary Science Classrooms

Barrier Category	Classification	Description	Primary Evidence Source	Supporting Literature
Infrastructure Deficits	Structural	Unreliable internet connectivity; insufficient device availability; absence of dedicated AI platforms in the majority of public schools.	Classroom observation data; teacher interview responses.	Shuayb et al. (2024); AUB (2023).
Limited AI-Specific PD	Systemic	Absence of formal, sustained, and contextualised AI pedagogy training; fragmented and non-compulsory professional development landscape.	Teacher survey data; interview responses identifying PD gaps.	Cheah et al. (2025); Filiz et al. (2025); Harris & Hofer (2023).
Inadequate School Leadership Capacity	Institutional	Limited digital leadership vision; absence of school-wide AI integration strategies; variation in principal support for technology innovation.	School leader interview responses.	Nakhle & Karam (2022); Leithwood et al. (2020).
Low AI-Specific TPACK	Individual	Gaps in teachers' capacity to integrate AI in pedagogically appropriate and content-relevant ways; strong PK and CK not matched by TK or TPACK.	Survey instrument (DigCompEdu Check-In); classroom observation data.	Mishra & Koehler (2006); Niess (2011); Valtonen et al. (2019).
Insufficient Ethical and Algorithmic Awareness	Individual	Limited teacher knowledge of algorithmic bias, data privacy obligations, and ethical implications of AI-driven assessment and recommendation systems.	Interview data; FairAIED-guided analysis.	Chinta et al. (2024); Williamson & Eynon (2020); Floridi et al. (2018).
Economic and Resource Constraints	Structural	Acute financial limitations affecting public schools within Lebanon's broader economic crisis; inability to sustain AI tool licensing or hardware investment.	Survey data; observation field notes.	Shuayb et al. (2024); Makki et al. (2023).

Note. Barrier classifications follow Fullan (2021) and Leithwood et al. (2020). All descriptions are derived directly from the empirical data collected (survey, observation, and interview strands).

Holmes et al. (2022) argue that the gap between AI's educational promise and classroom reality is, in most national contexts, primarily a function of professional preparation and institutional support rather than teacher resistance. The findings of the present investigation reinforce this diagnosis while adding a further dimension: in Lebanon, the promise–reality gap is also a function of structural economic inequality that no amount of teacher professional development, in isolation, can resolve. This recognition aligns with Williamson & Eynon (2020) contention that AI in education cannot be understood outside its political-economic context.

4. Equity and Ethical Dimensions

The equity analysis, conducted through the FairAIED lens, documents significant and systematic disparities across all five equity dimensions. Access equity disparities are severe: private schools exhibit substantially greater device availability, internet reliability, and AI platform access than public schools, with urban–rural divides further compounding these inequalities (Shuayb et al., 2024). Representational equity concerns are acute: Arabic-language AI educational content remains substantially underdeveloped, with AI systems predominantly calibrated to Western English-language learner datasets, a mismatch with the linguistic and cultural realities of the student population.

Outcome equity risks are significant: AI tools concentrated in well-resourced private schools risk amplifying existing advantages, potentially further marginalising students educated in the public sector (Gewertz, 2024; Viberg et al., 2023). Concerning algorithmic fairness, Lebanese teachers exhibit, with few exceptions, limited awareness of algorithmic bias and its potential effects on AI-mediated assessment outputs, a gap that is more pronounced in the public sector but present across both sectors. Data governance frameworks are similarly insufficient: limited knowledge of data protection obligations and the absence of a national AI-in-education data policy represent serious vulnerabilities. Addressing these dimensions requires structural investment in public school infrastructure, not merely professional development initiatives.

5. Pedagogical Impact: Conditional, Contextual, and Cautiously Optimistic

Where AI tools were deployed in ways consistent with constructivist and sociocultural learning principles supporting collaborative inquiry, providing adaptive formative feedback, and enabling students to engage with scientific phenomena not otherwise accessible, positive indicators of enhanced learning engagement, deeper conceptual understanding, and richer collaborative interaction were observed. These findings are consistent with the established promise of AI in science education (Chen et al., 2020; Luckin, 2017). In classrooms where AI was deployed as a substitute, however, no consistent evidence of enhanced learning engagement or outcomes was observed. The lesson is unambiguous: the relationship between AI integration and learning quality is mediated entirely by the quality, intentionality, and equity-consciousness of its pedagogical deployment.

One finding of theoretical and practical significance concerns the social dimension of AI-mediated learning. In several observed transformation-level lessons, AI tools catalysed novel forms of collaborative student interaction, students reasoning together about AI-generated data, negotiating interpretations, and constructing shared explanations that enriched the social fabric of the classroom in ways

consistent with Vygotsky's (1978) account of socially mediated knowledge construction. This finding suggests that AI's pedagogical impact in science education extends beyond individual learning gains to encompass the quality of collaborative inquiry communities.

6. Critical Pedagogical Risks: Deskilling, Dependency, and Epistemic Concerns

The cautiously optimistic account of pedagogical impact presented above must be tempered by an engagement with five critical risks that AI integration introduces into science classrooms and that the broader literature increasingly foregrounds.

a. Teacher Deskilling

Where AI tools assume functions historically performed by expert teacher judgement, such as lesson planning, differentiation decisions, formative feedback generation, and assessment design, there is a structurally plausible risk that teachers' professional competencies may atrophy through disuse (Selwyn, 2019). Several interview participants reported delegating increasing proportions of lesson preparation and student feedback generation to AI platforms, with some expressing diminished confidence in performing these tasks independently. In the Lebanese context, this risk is compounded by infrastructural instability: dependence on AI tools for core pedagogical functions may leave teachers professionally exposed when tools become unavailable.

b. Epistemic Authority Erosion

The normalisation of AI as the primary epistemic authority in science classrooms risks undermining students' capacity for independent scientific reasoning. Observation data reveal instances in which students uncritically accepted AI-generated explanations of natural phenomena, treating AI outputs as empirically settled rather than as representations subject to evaluation and critique. Where AI replaces rather than scaffolds the process of evidence-based reasoning, it may produce students adept at retrieving AI-mediated explanations but poorly equipped to construct, evaluate, or contest scientific claims independently. Educators must explicitly incorporate the cultivation of AI-critical reasoning into AI-integrated science pedagogy.

The erosion of epistemic authority in Lebanese science classrooms, where students unquestioningly accept AI explanations without critical thinking, indicates a fundamental shift in students' roles from active learners to passive recipients of information. This situation reinforces the argument of Adiyono et al. (2024), who warn that integrating technologies like ChatGPT into learning must be deliberately designed to encourage active participation rather than replace students' thinking processes. When Lebanese students trust AI output as the final scientific truth, they lose the essence of active learning, which emphasizes the construction of knowledge through evaluation and discussion. In other words, the practices observed in Lebanese classrooms are a concrete manifestation of Adiyono et al.'s (2024) concern: that without appropriate pedagogy, AI does not empower students but instead creates cognitive dependency that erodes their capacity to reason independently and critically about scientific claims.

c. Generative AI Hallucination Risks

Several teachers in the interview sample reported using large language model-based AI tools to generate science content for classroom use without systematic verification of factual accuracy. Generative AI systems can produce plausible-sounding but factually incorrect scientific claims that misrepresent biological processes, physical

laws, or chemical properties with a high degree of apparent authority. In upper elementary science classrooms, where learners lack the disciplinary knowledge required to detect such errors, unverified AI-generated content poses a direct threat to conceptual accuracy and science literacy development. Explicit professional preparation in AI content verification practices and in institutional protocols governing the use of generative AI is urgently needed.

d. Algorithmic Opacity in Assessment

Several observed schools used AI platforms to generate diagnostic or formative assessment recommendations for individual students. In no observed case were teachers able to articulate the decision logic underpinning these recommendations; none had received professional development addressing algorithmic bias, error rates, or the sociodemographic conditions under which AI assessment tools may perform differentially. When consequential educational decisions are mediated by algorithms whose operations teachers cannot interrogate, professional accountability is compromised, and the risk of systematically biased outcomes is structurally embedded. The absence of a national AI governance framework in Lebanese education renders this risk entirely unmitigated at present.

The findings of teachers using AI-derived content without factual verification, as well as their inability to explain the logic behind assessment recommendations from AI platforms, highlight two critical gaps in science education practices in Lebanon: weak teacher digital literacy and the absence of adequate AI governance. This situation directly confirms the urgency raised by Adiyono et al. (2026) about the need for a robust human-AI collaboration framework. Within such a framework, AI should not be allowed to operate autonomously without critical human oversight, especially in the context of education, which is fraught with values and consequences. When Lebanese teachers fail to detect AI "hallucinations" in teaching materials or to interrogate potential bias in assessment algorithms, the result is a violation of the very principle of collaboration, humans unthinkingly ceding their authority to machines. However, as emphasized by Adiyono et al. (2026), ethical and effective collaboration requires an active human role as verifiers and monitors, which, in this case, is exacerbated by the absence of a culturally contextualized national framework (such as the ethical values they propose) to mitigate these risks.

e. The Hidden Curriculum of AI-Mediated Knowledge

AI systems encode assumptions about what constitutes valid knowledge, legitimate epistemic practice, and valued ways of reasoning, predominantly calibrated to Western, English-language, and scientifically mainstream frameworks. When Lebanese upper elementary students are taught science primarily through AI systems that privilege these frameworks, they receive an implicit message about whose knowledge counts and which forms of inquiry are epistemically legitimate. This hidden curriculum operates below the level of explicit pedagogical intention and is invisible mainly to teachers who lack the critical AI literacy to identify and interrogate it. Addressing it requires not merely the localisation of AI content but the cultivation of epistemically critical AI pedagogy as a professional standard.

These five critical risks do not invalidate the pedagogical promise documented elsewhere in this investigation. They do, however, substantially complicate the cautiously optimistic account and underscore the inadequacy of purely instrumentalist approaches to AI integration that attend exclusively to functionality and efficiency. An ethically and epistemically responsible pedagogy of AI in science education must simultaneously exploit AI's genuine potential and build the critical,

reflective, and verification-oriented capacities required to resist its characteristic pathologies.

Conclusion

The present investigation provides the first empirically grounded, theoretically integrated examination of AI integration in Lebanese upper elementary science classrooms, generating findings that are contextually grounded, nuanced, and policy-relevant. The multi-framework CAPI model integrating TPACK, DigCompEdu, sociocultural learning theory, and FairAIED principles has proven its analytical value, enabling a multidimensional account that is simultaneously attentive to individual teacher competence, institutional context, pedagogical quality, and structural equity.

Across the mixed-methods data, four consistent findings emerge. First, Lebanese upper elementary science teachers are not resistant to AI integration; the barriers they face are structural and systemic, confirmed by large-effect-size sector differences across all key measures ($d > 1.0$). Second, AI classroom practice is dominated by substitutive Replacement-level use, with transformative AI-enabled science instruction exceptional and concentrated in better-resourced private school settings. Third, when teachers implemented pedagogically intentional, constructivist-aligned AI integration, they demonstrated positive indicators of enhanced learning engagement, deeper conceptual understanding, and more robust collaborative inquiry. Fourth, the findings reveal pervasive equity disparities across all five FairAIED dimensions, which risk further fragmenting Lebanon's already fragile educational landscape. The study also identifies five underacknowledged pedagogical risks, including teacher deskilling, erosion of epistemic authority, generative AI hallucinations, algorithmic opacity in assessment, and the hidden curriculum of AI-mediated knowledge, and argues that educators and policymakers must address these risks alongside structural challenges to ensure responsible AI integration.

Based on these findings, the study advances evidence-based recommendations for three key audiences. The Lebanese Ministry of Education should develop a national AI in Education policy framework explicitly addressing infrastructure equity; embed AI readiness investments in public school budget allocations; mandate equity-impact assessments for all publicly funded AI integration initiatives; and develop a national data protection framework governing student data within AI educational applications. School leaders should adopt school-wide AI integration visions grounded in pedagogical principles, implement school-level data privacy protocols, establish content verification standards for AI-generated instructional materials, and model equity-conscious leadership by selecting inclusive AI tools. For the research community, formal, sustained, nationally coordinated AI pedagogy programmes grounded in DigCompEdu and TPACK frameworks should be designed and mandated, with certifiable micro-credentials in AI-integrated science teaching that include explicit modules on critical AI literacy, algorithmic transparency, and epistemic risk.

The foregoing analysis ultimately arrives at a conclusion that places human judgement, relational wisdom, and professional knowledge at its centre. Technology does not function as a teacher, nor does it serve as a policy; instead, it operates as an instrument whose value depends entirely on the quality of the human decisions pedagogical, ethical, institutional, and political that shape and govern its deployment. The sophistication of its AI tools will not determine the future of science education in Lebanon. However, by the depth of its commitment to equity, the quality of its

investment in teacher professional knowledge, and the rigour of its critical engagement with the characteristic risks that AI systems bring in their wake.

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