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# ARTIFICIAL INTELLIGENCE IN EDUCATION

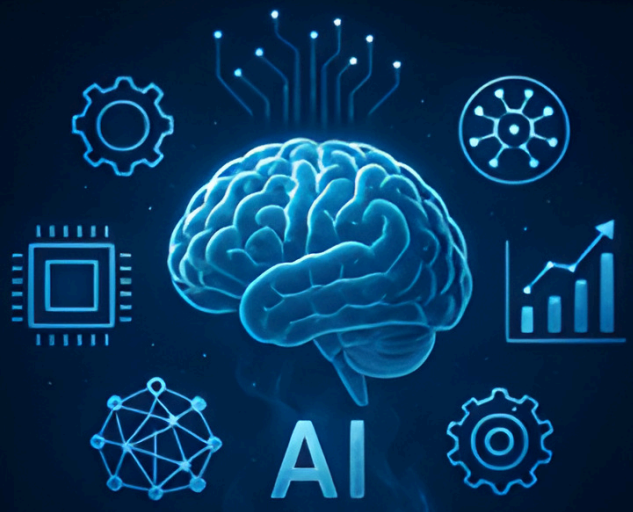
## Guest Editors

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## Editorial

# Artificial Intelligence in Education

*Special Issue, Volume 2, Issue 4, October 2026*

Generative AI reached schools and universities before most institutions had decided what it was for. Teachers met it in student essays and administrators in integrity cases; researchers met it halfway through projects designed for older technologies. This special issue of *Confluence Journal of Multidisciplinary Studies* takes stock of that arrival. It brings together eleven contributions: eight articles, one interview, and two book reviews. They move from theory and policy analysis to a systematic review, classroom studies, and tools that teachers built themselves, and their settings run from corporate learning to a Grade 8 English class in a Moroccan middle school. Read together, they chiefly return one answer: what AI does to learning depends less on the tool than on the conditions in which people use it.

The issue opens with theory. Oumaima Alyassini, Fatima Zahra Touzani, and Rachid Iseksioui reject the instrumental account in which AI simply makes education faster and more personal. In their reading, AI changes the conditions under which knowledge is produced, the way learners are defined, the place of pedagogical authority, and the governance of institutions. Adopted without criticism, it risks hardening technocratic models of schooling, widening algorithmic inequality, and leaving students dependent on machines for what they know. The principles they propose at the end come from critical pedagogy and ethical reflexivity, and they defend education as a space of intellectual and social formation instead of a site of performance optimization.

Videhi Bhamidi, Divya Joseph, and Maathangi Mohan take the question to the workplace, where adults increasingly learn with AI in the flow of their work. Their conceptual paper, written from a scholar-practitioner position, describes a depth-speed tension. AI speeds up access to information and the completion of tasks, yet under some conditions it compresses the productive struggle, reflection, and human relationships through which lasting skills develop. Learner expertise, AI literacy, task complexity, organizational culture, and performance pressure decide which way the balance tips. The authors set out five propositions for empirical testing and close on a principle that schools could borrow as easily as companies: “get the human learning conditions right before reaching for the technology.”

Elhadj Moussa BenMoussa reads ten public documents from six universities in the United Kingdom, continental Europe, and North America to see how they turn academic integrity into rules for writing with generative AI. He finds no uniform march toward automated surveillance. Several of the documents explicitly reject AI detectors, while keeping disclosure requirements, authorship interviews, and instructors’ judgments about writing. His concept of algorithmic

compliance pedagogy names what can go wrong there: suspicion may migrate from a detector score to judgments about style, or about how convincingly a student performs a writing process. BenMoussa presents this as a policy risk, not an observed effect on students, and he asks universities to account for the grounds of their suspicion just as they ask students to account for their work.

Fadoua Er-rakraky and Nafiaa Bouanani turn to the evidence. Their systematic review covers 29 empirical studies, published between 2024 and 2026 and indexed in Scopus, Web of Science, and ERIC, on how AI-powered adaptive tools affect vocabulary acquisition among EFL and ESL university students. Research on the subject is growing quickly, much of it in Asian countries, and ChatGPT is the tool studied most often. The studies report gains through personalized learning, immediate feedback, and contextualized content. The authors' quality appraisal, however, finds methodological weaknesses across the evidence base, and the review concludes that students still need a teacher's guidance to use these tools well.

Salma Habiballah, Khawla Tadist, and Karima Azaimi start from a choice that higher education now faces, between resisting AI-mediated writing and teaching students to use AI responsibly. They choose the second. Drawing on the CALL principle that learning outcomes depend on interaction design, mediation, and learner agency, they treat prompting competence as a communicative skill in its own right. Their Prompting Competence Framework defines six assessable dimensions, from intent and contextual grounding to the verification of output, iteration and repair, and ethical responsibility. A three-phase classroom model (Model, Prompt Studio, Transfer) makes the skill visible enough to teach and assess. They present both as proposals that now need testing across language skills and contexts.

Ibrahim Ben Khajjou, Ibrahim Belmir, and Ahmed Ibrahimi ask whether teachers in resource-constrained institutions can use generative AI to keep course design and assessment aligned. With 150 post-secondary learners in a blended Professional French course for engineering communication, they tested a domain-specialized language model, HorizaEdu, running locally through Ollama with retrieval-augmented generation, and an examination web application that the instructors built on a no-code prototyping platform. The local system reached a mean alignment index of 0.88 against a target of 0.80, with 92 percent faithfulness and 96 percent answer relevance. The examination platform stayed online throughout full-load use and scored 74.5 on the System Usability Scale. As the authors acknowledge, the evidence comes from a single cohort in a single domain. The study still shows that a teacher working with modest means can build constructive alignment into AI-assisted course design as an automated constraint.

Ouidad Infi treats AI as a resource for the teacher. In an eleven-week ESP course for 48 fourth-year civil engineering students, she used it to explore professional situations in the field and to design task-based activities, which the course combined with textbook-based ones. At the end of the course, students rated their behavioral, emotional, and social engagement higher for the AI-supported tasks, while cognitive engagement received similar ratings for both kinds of activity; observations, focus groups, and student work pointed to different forms of cognitive engagement in each. The sustainability results were mixed. Most items were rated higher for the AI-supported tasks, but the largest difference, in perceived professional responsibility for sustainability, was not tied to the activities in the focus-group accounts. Infi does not claim causal effects, and she states that her design cannot isolate what AI contributed. What the study offers is a practical model of teacher-mediated task design for ESP.

Mohamed Chahbi and Imane Bakkali report a quasi-experiment with 60 Grade 8 learners, aged 12 to 16, in two intact classes of a Moroccan middle school. For four weeks one class followed the national curriculum with its textbook, while the other followed the same

curriculum supplemented with augmented-reality materials. AI tools helped only with scripting and preparing content; the teacher reviewed every item, and no AI feedback, grading, or instructional decision entered the classroom. Both classes improved. The experimental class gained more in vocabulary, reading comprehension, and writing, with large effect sizes (Hedges' *g* of 1.67, 1.97, and 1.26). Given the intact classes, the teacher-made tests, the single school, and the short intervention, the authors read these results as associative, and they place the weight on pedagogical design and teacher mediation.

The interview takes the issue beyond the classroom. Imane Derrazi talks with Matthew N. Hannah of the University of Wisconsin–Madison, a digital humanist who studies online conspiracy movements and builds digital scholarship spaces in university libraries. Hannah describes how platforms, conspiracy narratives, and generative AI are changing the ways knowledge is produced, circulated, and trusted. He also discusses access, multilingual scholarship, international collaboration, and the teaching of difficult subjects. His position is clear: computational methods extend humanistic thinking and do not replace it, and the future of the field depends on interdisciplinary community.

Two book reviews close the issue. Khaoula El Khalfi reviews Dana J. Gavin's *Generative AI and the Future of the Humanities: Reading, Writing, Teaching, Labor* (2025). Gavin treats generative AI as the accelerator of a "mass illiteracy event" that has been under way for decades, and she builds her argument around two figures, pollution and the Luddite. El Khalfi credits the book for rejecting AI and classroom surveillance with equal force, and she singles out its most usable proposal, to make students' metacommentary, not the final draft, the main object of assessment. She also finds the theory thin. Gavin argues against the solitary author without engaging Barthes, Foucault, or the composition scholars who challenged that figure decades ago, and she grounds her claim that AI is untrustworthy in a theory of authorial intention that she never defends.

Bouchra Chougrani reviews Sarah Chardonnens's *Intelligence artificielle et apprentissage: Fondements, concepts et applications* (2026), a French-language book for teachers built around the SYNAPSE model. The model divides learning into four phases (reception and activation, adaptation and adjustment, observation and self-regulation, consolidation and storage) with motivation at the center, and the book turns it into classroom routines such as "think first, compare afterward." Chougrani values its decision to begin with the learner's internal trajectory and not with the technology. She is less persuaded by its empirical base, three exploratory studies reported without sample sizes, and she notes that its survey of legal frameworks leaves out Africa.

Some threads run through the whole collection. The empirical studies are careful about what they claim and state their limits plainly, whether a single cohort, intact classes, retrospective ratings, or a short intervention. Er-rakraky and Bouanani find similar weaknesses across a whole body of research, and BenMoussa keeps a policy risk apart from an observed effect. This caution is part of what the issue contributes, and so is its evidence from Morocco. The vocabulary review shows that research on the topic has concentrated in Asian countries; the studies by Infi and by Chahbi and Bakkali add Moroccan engineering and middle-school classrooms that this literature seldom reaches. Across the issue, teacher mediation and human judgment keep returning as the conditions that decide whether AI supports learning or takes its place.

We thank the contributors for their work and for their patience through revision, and the peer reviewers for their detailed and demanding reports. Special thanks go to the guest editors of this issue, Bouchra Chougrani, Nafiaa Bouanani, Fadoua Er-rakraky, and Ibrahim Ben Khajjou, and to the editorial team of *Confluence Journal of Multidisciplinary Studies*. We are grateful, as

always, to the LLCIS research laboratory at Abdelmalek Essaadi University, whose support makes this journal possible.

The tools discussed in these pages will change faster than any journal can publish. The questions their authors ask will last longer: what students actually learn when AI is in the room, and who decides, on what evidence, how it should be used.

**Brahim Barhoun**
*Editor-in-Chief*
*Confluence Journal of Multidisciplinary Studies*
*Abdelmalek Essaadi University*
*October 2026*

## Disclaimer and Conflict of Interest Statement

The views expressed in the articles published in *Confluence Journal of Multidisciplinary Studies* are solely those of the authors and do not necessarily reflect the views of the editorial board or affiliated institutions.

This special issue includes contributions from members of the editorial team and of the LLCIS Research Lab. Three of the guest editors are authors in the issue: Fadoua Er-rakraky and Nafiaa Bouanani co-wrote one article, and Ibrahim Ben Khajjou co-wrote another with the journal's Co-Editor-in-Chief, Ibrahim Belmir, and Ahmed Ibrahimi. A fourth guest editor, Bouchra Chougrani, contributed a book review. All such submissions were subject to the journal's standard double-blind peer-review process and evaluated independently to ensure fairness, objectivity, and the highest standards of scholarly integrity.

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# Reconfiguring Education in the Age of Artificial Intelligence: A Critical Theoretical Inquiry into Pedagogy, Knowledge, and Human Agency

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# Reconfiguring Education in the Age of Artificial Intelligence: A Critical Theoretical Inquiry into Pedagogy, Knowledge, and Human Agency

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## ABSTRACT

The rapid integration of Artificial Intelligence (AI) into educational systems has generated both enthusiasm and unease, often framed through instrumental narratives of efficiency, personalization, and innovation. However, such perspectives risk overlooking the deeper epistemological, pedagogical, and political transformations that AI introduces into the field of education. This article offers a critical theoretical examination of the future of education in the age of AI, arguing that AI is not merely a technological enhancement but a restructuring force that redefines the conditions of knowledge production, learner subjectivity, pedagogical authority, and institutional governance. Drawing on contemporary scholarship in educational theory, critical data studies, and digital sociology, the article interrogates how AI reconfigures key educational concepts such as learning, assessment, literacy, and expertise. It further examines the tensions between personalization and standardization, automation and human agency, and datafication and ethical responsibility. While acknowledging the transformative potential of AI in expanding access and supporting adaptive learning, the article contends that its uncritical adoption risks reinforcing technocratic models of education, algorithmic inequality, and epistemic dependency. The study concludes by articulating a set of human-centered principles for AI integration, grounded in critical pedagogy, ethical reflexivity, and the preservation of education as a space of intellectual and social formation rather than mere performance optimization.

## KEYWORDS

**AI Literacy**

**Artificial Intelligence**

**Critical Pedagogy**

**University Students**

**Datafication**

**Digital Sociology**

**Educational Theory**

## Introduction

The growing presence of Artificial Intelligence (AI) in educational contexts is frequently framed through narratives of innovation, efficiency, and disruption. Across policy reports, institutional strategies, and educational technology discourse, AI is often celebrated as a transformative force capable of modernizing teaching and learning through personalization, automation, and data-driven decision-making. Educational stakeholders are increasingly told that AI can tailor learning experiences to individual needs, automate assessment processes, identify at-risk students, and improve institutional planning with unprecedented speed and precision (Holmes et al. 14; UNESCO). This broader transformation is also becoming visible within the Moroccan educational context, where recent scholarship has called for the integration of AI into secondary-school curricula while emphasizing the need to consider the specific

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conditions and challenges of the Moroccan educational system (El Khayati et al.). Within such narratives, AI tends to be positioned as a largely neutral and beneficial instrument whose principal role is to optimize existing educational systems and make them more effective.
Recent debates surrounding generative AI have further complicated this optimistic narrative by highlighting the pedagogical and epistemic risks associated with large language models in educational settings. While such systems may support accessibility, personalized learning, and rapid feedback, scholars also warn that they may contribute to misinformation, superficial learning practices, overreliance on automated systems, and the erosion of critical engagement if adopted uncritically. In this sense, the educational implications of AI extend beyond efficiency and innovation to broader concerns about knowledge reliability, intellectual autonomy, and the future of human learning itself (Kasneci et al. 2-4).

While these claims are not without substance, they often remain confined to an instrumental understanding of technology, one that treats AI primarily as a set of tools designed to solve practical problems (Zawacki-Richter et al.). Such a framing, however, risks obscuring the deeper significance of AI's integration into education. AI does not merely enhance pre-existing educational practices; it also participates in reshaping the conceptual, epistemological, and social foundations upon which those practices are built. It alters not only how education is delivered, but also how learning is imagined, how knowledge is valued, how students are represented, and how institutional decisions are made. In this sense, AI should not be viewed simply as an innovation applied to education from the outside, but as a transformative force that is increasingly implicated in the internal reorganization of educational life itself.

Recent scholarship increasingly challenges technocratic perspectives by arguing that AI should be understood as a socio-technical phenomenon embedded within broader relations of power, governance, and knowledge production (Williamson and Eynon 225; Selwyn 47). From this perspective, AI does not simply enter education as an external innovation; it reshapes what counts as knowledge, how learning is measured, and how educational subjects are constituted.

This transformation has also intensified ethical concerns regarding surveillance, bias, and inequality within educational environments increasingly shaped by AI infrastructures. Recent research emphasizes that algorithmic systems may reproduce existing social inequalities through biased datasets, uneven access to technological resources, and forms of automated decision-making that disproportionately affect marginalized learners. As Akgün and Greenhow argue, educational AI systems must therefore be examined not only in terms of functionality, but also in relation to questions of fairness, accountability, and social justice (435-36).

What becomes educationally meaningful, measurable, or actionable is increasingly shaped by the computational logics and data structures through which AI systems operate. For this reason, the future of education cannot be reduced to narrow questions of implementation, technical effectiveness, or classroom utility alone. It must also be approached as a contested terrain in which broader struggles over authority, human agency, equity, and the purpose of education itself are being negotiated. To ask what AI will do to education is therefore also to ask what kinds of educational futures are being imagined, whose interests they serve, and what forms of knowledge, pedagogy, and personhood they privilege. The integration of AI raises not only practical concerns about tools and methods, but also deeper philosophical questions about what education is for in a world increasingly shaped by algorithmic systems.

Methodologically, this article employs critical conceptual analysis as its primary mode of inquiry. Rather than presenting empirical data or evaluating the effectiveness of particular AI applications, it examines how the integration of AI into education alters the meanings, assumptions, and relations underlying established educational concepts. The analysis proceeds by bringing key concepts, such as learning, knowledge, pedagogical authority, assessment,

authorship, and learner agency, into critical dialogue with scholarship in educational theory, critical data studies, and digital sociology. AI is therefore approached not simply as a technological object, but as a socio-technical formation whose educational significance becomes visible through the concepts and institutional practices it reorganizes.

The inquiry proceeds through a comparative and interpretive reading of these conceptual transformations. First, it identifies the assumptions embedded in dominant accounts of AI in education, particularly those that frame AI in terms of efficiency, personalization, automation, and optimization. It then examines how these assumptions intersect with broader processes of datafication and algorithmic governance, asking what forms of knowledge, visibility, authority, and learner subjectivity they privilege. The analysis subsequently places these transformations in dialogue with established theoretical perspectives, including constructivism, critical pedagogy, and theories of educational purpose and human agency. This approach makes it possible to identify tensions that may remain obscured within purely instrumental accounts of educational technology, particularly the tensions between personalization and standardization, automation and agency, and epistemic abundance and epistemic responsibility.

The article thus adopts a critical rather than predictive or technologically deterministic orientation. Its purpose is not to establish a single model for the future of AI in education, but to interrogate the conceptual and normative consequences of increasingly AI-mediated educational environments. By examining what becomes newly visible, measurable, authoritative, or actionable through AI systems, the analysis seeks to uncover the assumptions and power relations that accompany technological change. The resulting argument is consequently interpretive and theoretical: it evaluates competing understandings of education in light of AI-driven transformations and uses those tensions to articulate the conditions under which technological integration might remain compatible with human agency, critical judgment, and the broader intellectual and social purposes of education.

## Theoretical Foundations: Education, Datafication, and Algorithmic Governance

### Datafication and the Reconstitution of the Learner

One of the most significant theoretical developments in recent scholarship on Artificial Intelligence in education is the concept of datafication, a term that has become central to critical discussions of digital governance, platformization, and algorithmic power. As van Dijck explains, datafication refers to "the transformation of social action into online quantified data" (198), a process through which behaviors, interactions, and practices become available for tracking, analysis, and predictive intervention[1]. In educational contexts, this process is increasingly visible through the proliferation of learning management systems, adaptive learning platforms, biometric attendance systems, automated feedback software, intelligent tutoring systems, and learning analytics dashboards. Through these tools, learners are no longer engaged solely as students in a pedagogical relationship, but also as data-generating subjects whose every action may be rendered measurable and computationally meaningful.

This process reflects a broader transformation in contemporary digital culture, where human activity is increasingly converted into extractable and economically valuable data. Recent critical scholarship has conceptualized this phenomenon as a form of data colonialism, through which human life itself becomes a resource appropriated by digital infrastructures for economic and computational purposes. Within educational contexts, this raises important concerns regarding ownership, consent, and the commodification of learner behavior (Couldry and Mejias).

The implications of AI-driven educational transformation, however, cannot be understood adequately through experiences of technologically advanced educational systems alone. In many parts of the Global South, and particularly across African educational contexts, the integration of AI takes place within conditions marked by uneven digital infrastructure, linguistic diversity, resource constraints, and persistent inequalities in access to educational technologies. Recent scholarship on AI and personalized learning in African education points to the limited visibility of developing-country contexts within the dominant research literature and highlights the importance of infrastructure, contextual adaptation, digital inequality, and ethical governance when AI systems are introduced into resource-constrained educational environments (Nzama and Nkomo). These conditions complicate universal claims about the transformative potential of AI. What may appear as increased personalization or efficiency in technologically mature systems may, in other contexts, also intensify existing inequalities or reproduce educational models whose assumptions are imported from elsewhere.

The African context also draws attention to a cultural and epistemic dimension of AI that remains insufficiently visible in predominantly Western accounts of educational technology. Recent discussion of AI in African education has raised concerns that educational systems may become dependent on technologies whose linguistic, cultural, and epistemological assumptions are developed elsewhere. Such concerns are particularly significant in educational environments where local languages, indigenous knowledge systems, and culturally situated forms of learning are already underrepresented in digital infrastructures. The question, therefore, is not simply whether African educational systems can gain access to AI, but whose knowledge, languages, values, and conceptions of learning become embedded in the systems through which that access is mediated. A genuinely human-centered approach to AI in education must consequently account for contextual differences and resist treating technological integration as a culturally neutral process.

What is particularly important about this transformation is that it is not limited to the digitization of educational activity; rather, it entails a deeper shift in how learning itself is understood, represented, and governed. Datafication does not merely record educational practices after they occur; it actively shapes the categories through which educational reality is perceived. In this sense, it reorganizes the epistemological foundations of educational judgment. Behaviors such as time spent on a task, frequency of participation, click sequences, hesitation intervals, quiz completion rates, and interaction histories increasingly become proxies for engagement, motivation, comprehension, and even potential. The learner is thus translated into a profile of measurable indicators through which institutional systems seek to make educational processes more visible, manageable, and predictable. As a result, educational subjectivity is increasingly mediated by systems that claim to know the learner through patterns extracted from data rather than through dialogic, contextual, or relational understanding.

This transformation is not merely technical but ontological. As Williamson argues, learners are increasingly constituted through data infrastructures that determine what becomes visible, measurable, and actionable within education (9). Learning is thus interpreted through behavioral traces rather than broader intellectual or social dimensions, producing what may be understood as a calculable learner.

A concrete illustration of this process can be found in Purdue University's Course Signals, an early-warning learning-analytics system designed to identify students who might be experiencing academic difficulty. Rather than relying exclusively on grades, the system drew on multiple categories of data, including students' current academic performance, prior academic history, demographic characteristics, and measures of effort derived from their interactions with the university's learning management system. These data were processed to

generate a traffic-light indicator (green, yellow, or red) communicating different levels of academic risk and enabling instructors to intervene through personalized messages or referrals to academic support (Arnold and Pistilli 267–70).

Course Signals provides a concrete example of what this article conceptualizes as the "calculable learner." The student becomes institutionally legible through selected variables that can be quantified, compared, and translated into a prediction of future performance. The significance of this process lies not in claiming that such indicators are necessarily inaccurate or pedagogically harmful; indeed, early-warning systems may enable timely forms of support. Rather, the case demonstrates that prediction depends on decisions about which aspects of a learner are computationally visible and which remain outside the model. Engagement, for example, becomes partly knowable through recorded interaction with a learning management system, while less quantifiable dimensions of learning (personal circumstances, intellectual curiosity, informal study, changing motivation, or the relational context of the classroom) are more difficult to encode. The "calculable learner" is therefore not the learner in their entirety, but a computational representation constructed from those dimensions of educational life that the system is capable of measuring.

The implications of this are profound. Learning becomes legible less through human interpretation and more through behavioral traces: click patterns, response times, navigation pathways, frequency of logins, assessment performance, and error rates. While such indicators may indeed reveal useful information, they remain partial and often reductive representations of educational experience. They privilege externalized and observable behaviors over the interior, relational, and socially embedded dimensions of learning. In doing so, they contribute to the construction of what may be called the "calculable learner"[2], a student whose educational identity is increasingly defined through metrics, probabilities, and predictive models rather than through lived experience or pedagogical encounter. The learner becomes not simply someone who studies, questions, struggles, and grows, but someone whose educational future can supposedly be anticipated through algorithmic interpretation.

This reconstitution of the learner as a data object must be understood within a broader framework of power. In many ways, it resonates with Michel Foucault's analysis of disciplinary power, particularly his argument that modern institutions operate through techniques of surveillance, normalization, and examination. Schools, like prisons, hospitals, and barracks, historically functioned as disciplinary spaces in which individuals were observed, classified, corrected, and compared. However, the contemporary digital educational environment extends this logic in new and more pervasive ways. Surveillance is no longer limited to the classroom gaze or the institutional report card; it now unfolds continuously and invisibly through platform infrastructures that collect and process learner data in real time. The learner is not only watched but also computationally interpreted, scored, categorized, and nudged (Foucault 170-94, 195-228).

Yet datafication in education goes beyond classical disciplinary power and enters what contemporary scholars describe as algorithmic governance: a form of power that, as Beer notes, is "increasingly embedded in everyday decision-making processes through the use of data and algorithms" (3), operating through automated prediction, behavioral modeling, and anticipatory control. Algorithmic governance differs from older forms of institutional regulation in that it does not simply react to student performance after the fact; rather, it seeks to intervene preemptively by forecasting risk, identifying likely outcomes, and recommending action before events fully unfold. A student may be flagged as "at risk" not because they have failed, but because their digital behavior resembles the patterns of previous students who did. In this way, AI systems do not merely describe educational reality; they increasingly participate in producing it.

This concern resonates with wider critiques of opaque algorithmic systems operating across contemporary institutions. Frank Pasquale warns that many algorithmic processes increasingly function as "black boxes," where important decisions are made through systems whose internal operations remain inaccessible to those affected by them (3). In educational environments, such opacity may limit students' and teachers' ability to understand how algorithmic judgments are formed or challenged.

This predictive logic has serious implications for learner autonomy and educational agency. When students are categorized through predictive models, they may come to be treated not according to who they are or what they might become, but according to what the system has calculated they are likely to do. Such processes risk narrowing educational possibility by replacing openness with probability. A student's future may be quietly shaped by an algorithmic assumption before the student has had the opportunity to exceed, resist, or redefine it. In this sense, datafication can subtly transform education from a space of possibility and formation into a space of anticipatory management. The learner is no longer simply educated; they are increasingly *pre-empted*.

Moreover, the logic of datafication tends to privilege forms of educational value that are easily quantifiable, thereby contributing to a broader managerial rationality within educational institutions. Students become dashboards, risk profiles, and performance indicators. Teachers may be encouraged to respond to metrics rather than to students' lived complexity. Institutional success becomes increasingly tied to retention rates, predictive accuracy, and measurable outcomes. While such developments are often justified in the language of support and efficiency, they also reflect a subtle but significant redefinition of educational purpose. Education risks being reframed less as a process of human development and more as a field of optimization governed by data extraction and algorithmic intervention.

This does not mean that educational data use is inherently harmful. Learning analytics may reveal exclusion patterns and support intervention. The central issue concerns how data are interpreted, who controls them, and what dimensions of learning disappear when data become the dominant lens through which education is understood.

For this reason, datafication must be approached not merely as a technological development but as a political and pedagogical reconfiguration of the learner. It compels us to ask not only what educational systems can know about students through data, but also what they fail to know, what they choose not to value, and what forms of subjectivity they ultimately produce. The future of education in the age of AI will depend, in large part, on whether institutions continue to treat learners primarily as data points to be optimized or whether they preserve an understanding of education as a fundamentally human, relational, and open-ended process of becoming.

## Algorithmic Rationality and the Technocratic Turn in Education

The increasing reliance on Artificial Intelligence in educational settings signals what may be described as a broader technocratic turn in education, a shift in which educational processes, judgments, and priorities are increasingly shaped by computational logics, managerial frameworks, and data-driven systems of control. In this emerging landscape, decision-making processes that were once grounded primarily in professional expertise, pedagogical intuition, institutional culture, and contextual understanding are progressively being mediated by algorithmic models and predictive infrastructures. Whether in the form of early-warning systems, automated assessment tools, performance dashboards, adaptive platforms, or

predictive analytics, AI is increasingly positioned not merely as a support mechanism, but as an authoritative actor in educational governance.

At first glance, this development appears highly desirable. Educational institutions have long struggled with large student populations, uneven learning outcomes, administrative overload, and limited resources. In this context, AI promises efficiency, scalability, and precision. Predictive systems can identify students deemed "at risk," recommend interventions, optimize resource allocation, and support institutional planning with a degree of speed and consistency that human actors alone may not always be able to achieve. Such tools are often presented as objective and evidence-based, offering seemingly neutral forms of insight that can improve educational effectiveness and reduce human error.

Yet the apparent neutrality of such systems must be critically interrogated. What is at stake is not simply the adoption of new technologies, but the emergence of a new form of epistemic authority in education, one in which algorithmic systems increasingly participate in defining what counts as valid knowledge, credible evidence, effective learning, and educational success. In other words, AI does not merely assist educational institutions in making decisions; it also begins to reshape the very grounds upon which those decisions are made. When predictive models identify "risk," when dashboards define performance, or when adaptive systems determine what content a learner should encounter next, they do more than inform practice: they establish particular norms of visibility, value, and intervention.

This development reflects what may be called algorithmic rationality[3], a mode of reasoning grounded in the logic of calculation, prediction, optimization, and procedural efficiency. Algorithmic rationality privileges what can be formalized into data structures, modeled computationally, and rendered actionable through automated systems. It operates according to the assumption that educational processes can be improved by making them more measurable, more predictable, and more controllable. In this framework, complexity is often treated as a problem to be reduced, uncertainty as a variable to be managed, and deviation as a pattern to be corrected.

Such a rationality is not unique to AI, but AI significantly intensifies its reach and legitimacy. Educational institutions have long been shaped by bureaucratic and managerial logics, particularly under neoliberal reforms that emphasize accountability, benchmarking, standardization, and measurable outcomes. However, AI gives these tendencies a new technical infrastructure and a new language of inevitability. It enables educational systems to move from retrospective evaluation to anticipatory governance, in which future outcomes are modeled in advance and institutional action is increasingly guided by probabilities rather than by pedagogical dialogue or ethical deliberation. This is particularly visible in systems that classify students according to predicted dropout risk, future performance, or engagement likelihood. Such systems do not simply observe students; they position them within computational forecasts that may shape how they are treated before their educational trajectories have fully unfolded.

This anticipatory orientation can also be understood through Shoshana Zuboff's analysis of surveillance capitalism, particularly her account of how the extraction and analysis of behavioral data enable digital systems to move from observing conduct toward predicting and shaping future behavior. Although Zuboff develops her argument primarily in relation to digital capitalism rather than education, her analysis offers a useful conceptual lens for understanding datafied educational environments. When learner activity is continuously converted into behavioral data and subsequently used to generate predictions about performance, engagement, or dropout, the educational subject increasingly becomes an object of anticipatory knowledge: a profile whose possible future is modeled before it unfolds. The significance of this process lies not only in surveillance or data collection, but also in the shift from retrospective description

toward predictive intervention. In educational settings, the question is therefore no longer simply what a learner has done, but what the system predicts the learner will do and which institutional responses may follow from that prediction. Zuboff's account thus strengthens the argument that datafication can transform educational governance by making prediction a basis for intervention and by potentially narrowing the space for human judgment within computationally organized futures.

The problem, then, is not only that educational decisions are becoming more automated, but that educational reasoning itself is increasingly being reorganized around the principles of optimization. Algorithmic systems operate according to a logic that seeks to maximize efficiency, reduce variability, and improve outcomes according to predefined indicators. They prioritize those dimensions of education that can be measured, compared, and improved over time. In many cases, this may include attendance, test scores, completion rates, task accuracy, or platform engagement. While such indicators are not inherently irrelevant, they represent only a narrow slice of what education entails. As Selwyn notes, the growing influence of AI reflects a broader shift toward what he describes as "data-driven schooling," in which educational value is increasingly articulated through dashboards, metrics, performance indicators, and forms of computational accountability (47).

This has serious implications for the future of pedagogy. When educational institutions become increasingly dependent on algorithmic systems, they may begin to privilege only those forms of learning that are legible to such systems. This creates a subtle but powerful pressure to redefine educational success in machine-readable terms. Learning becomes valuable insofar as it can be tracked, performance becomes meaningful insofar as it can be visualized, and intervention becomes legitimate insofar as it can be justified through data. As a result, educational priorities may gradually shift away from broader humanistic aims and toward a narrower conception of education as measurable progression through predefined benchmarks.

This narrowing effect is particularly concerning because many of the most important dimensions of education resist easy quantification. Critical reflection, interpretive depth, ethical reasoning, intellectual risk-taking, creativity, ambiguity tolerance, dialogic understanding, and emotional maturation are central to meaningful education, yet they do not lend themselves easily to algorithmic capture. These forms of learning often unfold slowly, unevenly, relationally, and in ways that cannot be fully translated into behavioral metrics or performance dashboards. If educational institutions become too reliant on algorithmic rationality, there is a real danger that such dimensions will be marginalized, not necessarily because they are unimportant, but because they are inconvenient to systems designed around efficiency and measurability.

This concern invites a deeper theoretical reflection on the nature of educational knowledge itself. Education has never been only about the acquisition of information or the optimization of performance. At its richest, it is also about formation: the cultivation of judgment, self-reflection, social responsibility, and the capacity to engage critically with the world. These dimensions are not incidental; they are central to the emancipatory and democratic potential of education. However, when education is increasingly governed through computational systems, there is a risk that it will be reimagined less as a process of formation and more as a process of management. Students become performance profiles, teachers become data interpreters, and institutions become optimization environments.

Moreover, algorithmic rationality tends to privilege a particular model of knowledge, one that values prediction over interpretation, correlation over causation, and operational usefulness over conceptual depth. This has epistemological consequences. Educational systems may begin to trust what algorithms can detect more readily than what teachers can perceive or what

students can articulate. In such a context, professional judgment may be subtly displaced by technical authority, and pedagogical wisdom may be subordinated to computational recommendation. The teacher's interpretive understanding of a student's silence, confusion, or resistance may become less institutionally visible than the data signal generated by platform interaction. This marks not only a shift in tools, but a redistribution of authority within educational space.

For this reason, the future of education depends not simply on whether institutions adopt AI, but on whether they can resist allowing algorithmic rationality to become the dominant grammar of educational value. The central question is not whether AI can make education more efficient, but whether education can remain intellectually, ethically, and socially meaningful under conditions increasingly governed by optimization. If educational value is defined primarily through what can be quantified, predicted, and improved, then education risks losing its capacity to cultivate precisely those forms of thought and being that matter most. The challenge, therefore, is not to reject AI outright, but to ensure that educational institutions do not surrender pedagogy to the seductive but ultimately limited logic of data-driven control.

## Reconfiguring Knowledge and Learning in AI-Mediated Environments

### From Scarcity to Abundance: The Epistemic Shift

Historically, education has been organized around the problem of knowledge scarcity. For much of its institutional history, access to information was limited, unevenly distributed, and often mediated through authoritative structures such as schools, universities, libraries, and scholarly communities. Within this context, educational institutions functioned as central sites of knowledge transmission, where teachers and academic authorities played a crucial role in selecting, organizing, and legitimizing what was worth knowing. Learning, therefore, was largely structured around the acquisition of scarce and institutionally curated knowledge, and educational success was often measured by the extent to which learners could retain and reproduce this information.

The emergence of Artificial Intelligence, particularly generative systems, profoundly disrupts this model by introducing an environment of radical epistemic abundance. Information is no longer limited by access or availability; it can now be produced, reformulated, and expanded on demand.

Recent scholarship on large language models suggests that this shift may fundamentally alter traditional relationships between learners and knowledge production. Gan et al. argue that generative AI systems increasingly function not merely as repositories of information, but as active participants in content creation, explanation, and academic interaction (3). As a result, learners now encounter knowledge in forms that are dynamically generated rather than statically retrieved, thereby transforming how educational authority and expertise are experienced.

Learners are no longer dependent on institutional gatekeepers to encounter knowledge, as AI systems can generate explanations, summaries, arguments, and even entire texts in real time. This shift does not simply increase the quantity of accessible information; it fundamentally alters the conditions under which knowledge is encountered and engaged with.

The implications of this transformation for learning are significant. If knowledge can be instantly generated, then education can no longer define its primary task as the accumulation or retrieval of information. Instead, the emphasis must shift toward the development of epistemic competencies: the ability to evaluate credibility, interpret meaning, identify bias, and situate information within broader intellectual and social contexts. In this sense, learning becomes less about possession of knowledge and more about navigation within complex informational

environments. As Luckin et al. suggest, the role of education in an AI-mediated world increasingly lies in supporting learners to move from passive consumption toward what they describe as "human intelligence working in partnership with artificial intelligence" (14), fostering more active and critical engagement with knowledge systems.

Luckin et al. offer a substantially more affirmative account of AI in education than the critical perspective developed here. Their argument is not simply that AI can automate existing educational practices, but that artificial intelligence can expand access to forms of individualized support that conventional educational systems cannot provide at scale. They envision intelligent tutoring systems, adaptive learning environments, and other AI-supported tools as means of extending personalized guidance, supporting teachers, and enabling learners to develop forms of intelligence suited to an increasingly technological world. From this perspective, AI is not primarily a threat to educational purposes but a resource through which those purposes can be reimagined and extended.

Yet this optimistic account also raises a question that is central to the present analysis: what conception of education is embedded in the process of extending learning through intelligent systems? The promise of individualized support depends on translating aspects of learning into forms that computational systems can detect, model, and respond to. Even when AI is conceived as a partner rather than a replacement for teachers, this partnership remains structured by the categories, data, and forms of intelligibility available to the system. The issue, therefore, is not whether AI can provide useful personalization or expand access to educational support; it is whether the pursuit of these benefits risks privileging those dimensions of learning that can be rendered computationally visible. A human-centered approach must consequently ask not only what AI can do for learners, but also which educational purposes should remain grounded in forms of judgment, dialogue, interpretation, and relational understanding that cannot be reduced to algorithmic optimization.

However, this condition of epistemic abundance is not without its risks. While AI-generated outputs are often fluent, coherent, and rhetorically persuasive, they are not inherently reliable or grounded in verifiable sources. Generative systems produce content based on probabilistic patterns rather than epistemic accountability, which means that inaccuracies, simplifications, or fabricated information may be presented with the same level of confidence as accurate knowledge. This creates a condition of epistemic opacity[4], closely related to the concern with explicability identified by Floridi et al., in which the processes through which knowledge is generated remain largely inaccessible to the user. Unlike traditional sources, where authorship, methodology, and citation can be examined, AI-generated content often lacks transparent grounding, making it more difficult to assess its validity.

In this context, learners require new forms of AI literacy. Contemporary scholarship emphasizes that students must understand not only how to use AI systems, but also their limitations, algorithmic logics, and broader social implications (Stolpe and Hallström 2). Educational institutions therefore face the challenge of cultivating learners capable of critically interrogating rather than merely using AI technologies.

It is no longer sufficient to evaluate sources in conventional terms; learners must also understand how AI systems construct responses, how training data shapes outputs, and how fluency can mask uncertainty or error. This involves a shift from evaluating information as a static product to interrogating it as a dynamic and probabilistic construction. The challenge for education, therefore, is not simply to adapt to an abundance of information, but to cultivate learners who can critically engage with knowledge in environments where the boundaries between accuracy, approximation, and fabrication are increasingly blurred.

## Constructivism Revisited: Learning as Interaction with Intelligent Systems

At first glance, the integration of Artificial Intelligence into education appears to resonate strongly with constructivist theories of learning, which emphasize that knowledge is not passively received but actively constructed through interaction, feedback, and experience. AI-driven environments, particularly adaptive platforms and conversational systems, offer learners opportunities to engage dynamically with content, receive immediate feedback, and follow individualized learning pathways. Such features seem to align with the constructivist emphasis on learner-centeredness, autonomy, and the importance of interaction in shaping understanding. In this sense, AI can be seen as extending earlier pedagogical efforts to move beyond transmission-based models toward more participatory and responsive forms of learning.

However, this apparent alignment requires careful qualification. Constructivism, particularly in its social and socio-cultural variants (e.g., Vygotskian perspectives), does not simply prioritize interaction in a generic sense; it emphasizes meaningful, socially situated interaction, where knowledge emerges through dialogue, negotiation, and shared interpretation within a community of learners. From this perspective, interaction is not merely a technical exchange of input and output, but a relational process grounded in mutual understanding, intentionality, and responsiveness. AI-mediated interaction, by contrast, typically occurs between the learner and a system that can simulate understanding but does not possess consciousness, experience, or genuine interpretive agency. This distinction complicates the assumption that all forms of interaction are pedagogically equivalent (Vygotsky 79-91).

The question, then, is not whether AI enables interaction, but what kind of interaction it enables. When learners engage with AI systems, they encounter responses that are generated through pattern recognition and probabilistic modeling rather than through lived experience or dialogic intention. While such systems can produce contextually appropriate and often highly useful feedback, they do not participate in meaning-making in the same way human interlocutors do. This raises important theoretical questions: Can knowledge be meaningfully co-constructed when one of the participants does not truly "understand"? To what extent does simulated dialogue support, or potentially displace, the social and interpretive dimensions that constructivist theory considers central to learning?

In response to these concerns, some scholars propose reframing AI not as a substitute for teaching, but as a cognitive partner that can augment learning processes without replacing human interaction (Holmes et al.). In this model, AI functions as a supportive tool that assists learners in exploring ideas, testing hypotheses, and receiving formative feedback, while the deeper processes of interpretation, reflection, and social negotiation remain anchored in human relationships. This perspective allows for a more balanced integration of AI within constructivist frameworks, acknowledging its potential benefits without overstating its pedagogical equivalence to human dialogue.

Recent research suggests that learners may attribute excessive epistemic authority to AI-generated responses, especially when fluent outputs mask inaccuracies. This reinforces the need for educators to frame AI as a cognitive support rather than an authoritative source of knowledge (Krupp et al. 6).

However, this balance is not guaranteed. Without careful pedagogical framing, there is a risk that learners may begin to treat AI systems as authoritative sources of knowledge rather than as provisional tools. The fluency, speed, and apparent confidence of AI-generated responses can create an illusion of epistemic reliability, encouraging passive acceptance rather than critical engagement. In such cases, AI may inadvertently reinforce a return to quasi-transmission models of learning, where knowledge is received from a seemingly authoritative source, albeit a machine rather than a teacher.

For this reason, revisiting constructivism in the age of AI requires more than simply integrating new tools into existing frameworks. It calls for a renewed emphasis on critical interaction, where learners are encouraged not only to engage with AI outputs, but to question, interpret, and situate them within broader contexts of knowledge production. The challenge is not to replace human interaction with intelligent systems, but to ensure that AI-mediated learning remains embedded within pedagogical environments that preserve dialogue, reflexivity, and the co-construction of meaning as fundamentally human practices.

## Pedagogical Authority and the Transformation of Teaching

### The Decentering of the Teacher

The rise of Artificial Intelligence in education fundamentally challenges long-standing assumptions about pedagogical authority and the teacher's traditional role within the classroom. For much of modern educational history, the teacher has occupied a central position as a primary source of knowledge, explanation, and intellectual direction. This authority was closely tied to the relative scarcity of information and the institutional role of schools and universities as sites of authorized knowledge transmission. However, in an educational environment increasingly shaped by AI, where explanations, summaries, examples, and even entire lesson structures can be generated on demand, the teacher's role as the principal holder and transmitter of information becomes less central than it once was.

This shift should not be interpreted as evidence that teachers are becoming obsolete. Rather, it signals a reconfiguration of what educational authority means in the first place. In AI-mediated learning environments, the teacher's value lies less in exclusive access to knowledge and more in the ability to interpret, contextualize, and critically mediate it. Teachers increasingly function as guides who help students navigate complex informational ecologies, evaluate the credibility of sources, identify superficial or misleading content, and develop the intellectual habits necessary for independent judgment. The Moroccan context further illustrates the importance of teacher preparation in this transition. Nafidi's study of trainee secondary-school teachers in Morocco found substantial awareness of AI's educational potential but comparatively limited actual use, with the absence of AI training emerging as a significant barrier to effective integration. These findings reinforce the view that the transformation of pedagogical authority depends not only on access to AI tools, but also on teachers' capacity to critically and pedagogically mediate their use. In this sense, pedagogical authority is gradually shifting from the possession of knowledge to the capacity to make sense of knowledge within broader ethical, social, and disciplinary frameworks.

The use of Foucauldian analysis alongside Freirean critical pedagogy in this article requires qualification, since the two traditions do not share an identical conception of the subject, power, or emancipation. Foucault's analysis emphasizes the productive character of power, showing how subjects are constituted through discourses, institutional practices, and regimes of knowledge rather than existing prior to these relations as fully autonomous agents. Freire, by contrast, emphasizes critical consciousness and transformative action through dialogical education, retaining an explicitly emancipatory conception of pedagogy. These positions therefore cannot simply be treated as cumulative stages of a single theory of power and liberation.

This article does not attempt to erase this difference. Instead, the two perspectives perform distinct analytical functions. Foucauldian concepts are used primarily to examine how AI-mediated educational environments produce forms of visibility, classification, normalization,

and subject formation through datafication and algorithmic governance. Freirean critical pedagogy enters at a different level, providing a pedagogical and normative vocabulary for considering dialogue, critical reflection, human agency, and the purposes of education. The movement from Foucault to Freire is therefore not intended to establish theoretical equivalence, but to move from an analysis of how educational subjects are constituted within relations of power toward a consideration of how they might critically engage with and negotiate those relations.

The tension between the two perspectives is consequently retained as analytically productive. The article does not assume that learners can simply step outside relations of power through critical consciousness, nor does it regard subjectivity as so completely determined by power that resistance or transformation becomes impossible. Rather, Foucault helps identify the conditions within which educational subjects are formed, while Freire directs attention toward the possibilities of dialogue, critical reflection, and transformation within those conditions. Used in this deliberately differentiated manner, the two perspectives allow the article to examine both the power relations through which AI-mediated education is organized and the pedagogical possibilities for preserving human agency within those relations.

This transformation resonates strongly with Paulo Freire's critique of what he termed the "banking model" of education, in which "education thus becomes an act of depositing, in which the students are the depositories and the teacher is the depositor" (72). In contrast, Freire advocates a dialogic pedagogy grounded in mutual inquiry, critical consciousness, and the co-construction of meaning. In some respects, AI appears to reinforce the move away from transmission-based teaching by reducing the teacher's monopoly over information. However, it also introduces a new complexity that Freire's model did not have to confront: dialogue is no longer limited to human participants. Students now increasingly interact not only with teachers and peers, but also with intelligent systems that can simulate responsiveness, explanation, and even conversation.

The presence of AI thus complicates the pedagogical relationship in important ways. It raises questions about trust, credibility, and the distribution of authority within the learning environment. If students can receive immediate answers from AI tools, whose explanations are perceived as more trustworthy, the teacher's or the machine's? How is authority negotiated when learners can move between human instruction and algorithmically generated responses? And what happens to the teacher's role when students increasingly encounter knowledge first through AI before bringing it into the classroom? These questions suggest that the future of teaching will not simply involve using AI as an additional resource, but negotiating a transformed educational landscape in which authority is more dispersed, contested, and technologically mediated.

For this reason, the decentering of the teacher should not be understood as a loss of relevance, but as a shift toward a more intellectually and ethically demanding role. Teachers remain indispensable not because they can outproduce AI in terms of information, but because they are uniquely positioned to help students engage with knowledge critically, responsibly, and reflectively. In the age of AI, the teacher may no longer stand at the uncontested center of the classroom, but their role becomes all the more vital in ensuring that learning remains a human, dialogic, and meaning-oriented process.

Rather than eliminating teaching, AI may intensify educators' roles as interpreters and ethical mediators of knowledge. Bayne argues that automated systems often reveal rather than replace the relational dimensions that make teaching distinctively human.

### Teaching as Ethical and Relational Practice

Despite the accelerating integration of Artificial Intelligence into educational environments, teaching remains, at its core, a profoundly relational and ethical practice. Education is not reducible to the transmission of information, the management of performance, or the efficient delivery of content. It is also a process through which individuals are formed in relation to others, to institutions, and to the broader social world. In this regard, teaching cannot be understood solely in cognitive or technical terms. As Gert Biesta argues, education encompasses not only qualification, the acquisition of knowledge, competencies, and skills, but also what he defines as "the ways in which, through education, individuals become part of existing social, cultural and political orders (socialisation) and become subjects of initiative and responsibility (subjectification)" (21). In other words, education is also about introducing learners into social, cultural, and normative worlds, while simultaneously supporting their emergence as ethical, reflective, and responsible subjects. These dimensions of education are foundational, and they resist full automation[5].

This distinction is particularly important in contemporary discussions of AI. While AI systems can increasingly simulate dialogue, generate explanations, and respond to student input in ways that appear pedagogically useful, they do not participate in education as moral or relational beings. They do not carry responsibility for the learner in any meaningful human sense. They do not care, empathize, hesitate ethically, or bear the consequences of pedagogical decisions. Their responsiveness is procedural rather than relational. This distinction is not trivial. It goes to the heart of what education is. Teaching is not simply about helping students arrive at correct answers; it is also about accompanying them through uncertainty, helping them confront complexity, encouraging responsibility, and creating conditions in which they can develop as thinking and socially situated individuals.

Teachers remain indispensable not only because of what they know, but because of the relational conditions they create. They recognize vulnerability, interpret nuance, and foster trust, accountability, and ethical responsiveness in ways automated systems cannot replicate.

In this context, the growing presence of AI may paradoxically intensify, rather than diminish, the importance of human teaching. As education becomes more technologically mediated, the relational and ethical dimensions of pedagogy become more visible and more necessary. The more learners interact with systems that simulate communication without truly inhabiting it, the more vital it becomes to preserve forms of education grounded in empathy, dialogue, and human responsibility. Far from rendering teachers secondary, AI may ultimately clarify why teaching has never been a merely informational task in the first place. It is, and remains, a fundamentally human practice of ethical relation.

Critical analyses increasingly argue that AI systems are embedded within broader structures of power and inequality. Crawford suggests that AI infrastructures reflect forms of extraction and institutional influence that shape their social consequences (8). Educational debates about AI therefore require ethical as well as pedagogical scrutiny.

## AI, Assessment, and the Reconfiguration of Academic Practice

The integration of Artificial Intelligence into educational systems is not only transforming how students learn and how teachers teach; it is also reshaping the very structure of academic practice, particularly in relation to assessment, evaluation, and the production of academic work. Among the most visible and institutionally consequential applications of AI in education is its use in assessment systems, where it is increasingly deployed to grade responses, provide feedback, detect plagiarism, track performance, and support predictive judgments about student

achievement. These developments are often welcomed because they appear to address long-standing challenges within education, including large class sizes, delayed feedback, administrative burden, and the pressure for consistency in evaluation.

Yet assessment is never a purely technical process. It is also a deeply pedagogical and epistemological one. To assess is not merely to measure performance, but to make judgments about what counts as learning, what kinds of knowledge are valued, and what forms of intellectual labor are considered legitimate. For this reason, the growing presence of AI in assessment raises broader questions that go beyond efficiency. It invites a reconsideration of what educational systems choose to recognize, reward, and render visible as evidence of learning. In this sense, AI does not simply change assessment procedures; it contributes to a wider reconfiguration of academic practice itself.

## The Limits of Automated Assessment

AI-driven assessment systems are often presented as highly attractive solutions to some of the most persistent challenges in contemporary education. They promise efficiency, scalability, speed, and consistency, allowing institutions to process large quantities of student work, generate immediate feedback, and reduce the workload associated with repetitive forms of grading. In contexts where educational systems are increasingly pressured to do more with fewer resources, such tools can appear not only useful but necessary. AI can be particularly effective in evaluating structured or rule-based responses, such as multiple-choice questions, short factual answers, grammar exercises, or standardized tasks where correctness can be clearly defined.

Recent studies evaluating large language models in educational assessment suggest promising capacities for grading open-ended responses and generating feedback. Nevertheless, researchers also note substantial limitations regarding consistency, interpretive nuance, and contextual understanding, particularly in disciplines requiring critical reasoning or subjective evaluation (Pinto et al. 4). Such findings reinforce concerns that technical efficiency should not be equated with educational adequacy.

However, the pedagogical usefulness of automated assessment quickly becomes more uncertain when learning moves beyond clearly measurable performance. Not all forms of educational achievement are equally amenable to algorithmic evaluation. While AI may be effective in assessing procedural accuracy or structural conformity, it is far less capable of engaging meaningfully with ambiguity, creativity, interpretive subtlety, or conceptual originality. Forms of student work that rely on layered argumentation, ethical reasoning, contextual sensitivity, or stylistic nuance often exceed the capacities of systems designed primarily to detect patterns and assign scores based on predefined criteria.

This limitation should not be understood merely as a technical shortcoming that will eventually disappear with better software. More fundamentally, it reflects an epistemological tension between what can be measured and what is genuinely educationally meaningful. Automated systems tend to privilege forms of knowledge that can be standardized, formalized, and computationally recognized. In doing so, they risk reinforcing a narrower vision of learning, one in which what counts most is what can be efficiently captured and evaluated by the system. As a result, assessment practices may gradually begin to align with the capacities of the technology rather than with the broader aims of education.

Reliance on AI-driven assessment may gradually reshape curricula themselves, encouraging assignments designed for automation and privileging measurable outputs over interpretive depth. Education risks becoming increasingly oriented toward machine legibility rather than intellectual complexity.

For this reason, the limits of automated assessment must be taken seriously not only as a matter of technological design, but as a question of educational philosophy. The challenge is not simply whether AI can assess more efficiently, but whether education is willing to preserve forms of judgment, interpretation, and intellectual evaluation that cannot, and perhaps should not, be fully automated.

## Generative AI and the Reconfiguration of Authorship

The emergence of generative AI has profoundly unsettled long-standing assumptions about authorship, originality, and academic integrity within educational settings. Tools capable of producing essays, summaries, responses, outlines, and analytical commentary in a matter of seconds have disrupted the traditional relationship between student labor and academic output. In doing so, they have raised urgent questions not only about plagiarism or misuse, but also about the very nature of authorship in contemporary education. If a student can produce a coherent academic text with substantial assistance from AI, then the boundaries between writing, thinking, and authorship become far more complex than earlier academic models assumed.

Emerging scholarship highlights tensions between productivity and intellectual dependency, warning that excessive reliance on generative AI may weaken reflective processes traditionally associated with deeper learning (Yan et al. 5). This raises concerns that efficiency may be privileged over intellectual formation.

This development matters because writing has never functioned solely as a means of displaying knowledge already possessed. In many educational traditions, writing is also understood as a mode of thinking, a process through which ideas are clarified, refined, tested, and transformed. Students often discover what they think through the act of trying to articulate it. Drafting, hesitation, revision, and struggle are not simply obstacles to finished writing; they are often integral to intellectual development itself. When writing is partially or extensively outsourced to AI systems, this formative relationship between writing and thinking may be disrupted. The risk is not only that students submit work that is not fully their own, but that they may bypass the very cognitive and reflective processes through which deeper learning often occurs.

At the same time, the disruption caused by generative AI should not be understood only as a threat. It also presents a significant opportunity to rethink what educational assessment values and how academic work is designed. If AI can generate polished final products with increasing ease, then educational institutions may need to move away from overreliance on static outputs as the primary evidence of learning. Traditional assignment structures that focus mainly on the finished essay or final written response may no longer be sufficient for evaluating intellectual engagement in a meaningful way.

In response, educators may need to place greater emphasis on process, reflexivity, and intellectual positioning. This could involve designing assessments that foreground the development of ideas rather than only their final presentation: annotated drafts, reflective commentaries, oral defenses, revision histories, research logs, peer dialogue, and classroom-based writing processes may all become more important. Such approaches would not simply function as anti-cheating mechanisms; they would also align more closely with the deeper educational purpose of writing as a space of inquiry, self-positioning, and critical formation.

Seen in this light, generative AI does not simply destabilize academic authorship; it compels education to ask more fundamental questions about what it means to produce knowledge, to express understanding, and to claim intellectual ownership in an age of machine-generated language. The challenge is not merely to defend older models of authorship unchanged, but to

develop new pedagogical frameworks in which students remain accountable for thought, judgment, and interpretation even as the tools through which they write continue to evolve.

## Conclusion

The integration of Artificial Intelligence into education is far more than a technical innovation or a passing institutional trend. It represents a profound transformation in the ways knowledge is accessed, produced, organized, and legitimized within contemporary educational systems. As this article has argued, AI is not simply adding new tools to existing pedagogical frameworks; it is actively reshaping the conditions under which learning takes place, the forms of authority that structure educational relationships, and the criteria through which academic value is increasingly recognized. In this sense, AI must be understood not as a neutral enhancement, but as a force that reconfigures education at epistemological, pedagogical, and institutional levels.

At the same time, the significance of AI in education cannot be reduced to either optimism or alarmism. On the one hand, AI offers substantial possibilities: it can support accessibility, personalize aspects of learning, assist with feedback, and expand educational resources in ways that may benefit both learners and institutions. Evidence from Moroccan higher education similarly points to a combination of perceived benefits and persistent concerns, with academics recognizing the potential of AI to enhance educational practices while also identifying challenges related to access, academic integrity, and student–instructor interaction (Mjahad et al. 3, 7). On the other hand, it also introduces serious tensions related to datafication, automation, algorithmic authority, epistemic opacity, and the narrowing of educational value to what can be measured, predicted, and optimized. These challenges cannot be adequately addressed through technical adjustments alone because they are not only technical problems; they are also ethical, political, and philosophical ones.

For this reason, the future of education must be shaped not by technological determinism, but by sustained critical reflection. The central question is not whether AI should be used in education in some absolute sense, but under what conditions, according to which values, and toward what educational ends.

This theoretical inquiry nevertheless has limitations that should be acknowledged. Because the analysis is primarily conceptual and interpretive, it cannot by itself determine how AI-mediated educational practices operate across different institutional, cultural, and socioeconomic contexts, nor can it establish the extent to which the risks identified here materialize in practice. These claims therefore invite empirical investigation through classroom-based studies, interviews with teachers and learners, and research examining how AI systems are actually incorporated into assessment, learning, and institutional decision-making. Comparative research across different educational contexts, particularly between technologically advanced systems and contexts in the Global South, could further test whether the tensions identified in this article take similar or different forms across settings. Such research would complement the theoretical analysis developed here by examining how algorithmic systems are negotiated, resisted, or adapted within concrete educational environments.

Ultimately, education must remain a space where learners develop critical judgment, ethical responsibility, and reflective agency. The future of education depends not only on technological innovation, but also on preserving equity, AI literacy, and profoundly human purposes within increasingly automated environments (Chen et al.).

## Notes

1. The concept of datafication is closely linked to broader processes of platformization and surveillance capitalism (van Dijck et al.).
2. This notion resonates with critiques of quantification in education.
3. Algorithmic rationality extends managerial and bureaucratic logic through computation.
4. Epistemic opacity refers to the difficulty of understanding or accessing the processes through which complex computational systems generate outputs.
5. Biesta's tripartite model (qualification, socialization, subjectification) is central in contemporary theory.

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# Learning in the Age of AI: How AI Is Transforming Adult Learning in Corporate Contexts

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# Learning in the Age of AI: How AI Is Transforming Adult Learning in Corporate Contexts

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## ABSTRACT

This conceptual scholar-practitioner paper examines how generative AI reshapes the conditions under which adults learn at work. As AI enters everyday knowledge work, learning with AI increasingly happens in the flow of work, raising the question of what is being learned and what is merely performed. Synthesizing andragogy and self-directed learning, sociocultural learning theory, and experiential learning, the paper develops a provisional model of the depth-speed tension across four dimensions of workplace learning, namely learner agency and self-direction, learning through practice and experimentation, social and peer learning, and knowledge in the flow of work. It proposes that AI accelerates access to information and task completion but, under certain conditions, can compress the productive struggle, reflection, and human relationships through which durable skills develop. The moderating conditions, including learner expertise, AI literacy, task complexity, organizational culture, and performance pressure, shape whether AI strengthens or weakens learning. The paper identifies the cognitive and relational work that remains hard to delegate to AI, offers five propositions to guide future empirical testing in workplace settings, and outlines implications for learners, managers, learning professionals, and organizations. Its guiding principle is to get the human learning conditions right before reaching for the technology.

## KEYWORDS

**Adult Learning**

**Depth-Speed Tension**

**Generative AI**

**Knowledge Work**

**Self-Directed Learning**

**Workplace Learning**

## Introduction

Since the public release of ChatGPT in late 2022, generative AI tools have come into wide use in knowledge work (Lee et al., sec. 1). Because these tools are largely consumer products that individual workers experiment with on their own, Mohammad Hossein Jarrahi et al. argue that organizations need to invest in training to build workers' AI literacy (18). This raises the question of how learning is supported when technology use develops ahead of deliberate learning design. Adult education scholars note that generative AI is already changing self-directed learning, offering possible benefits such as personalized support and prompt feedback in some contexts while also raising new challenges (Morris et al. 121).

In this paper, "AI" refers primarily to generative AI tools, meaning end-user tools built on deep-learning generative models (Lee et al., sec. 1), used as cognitive assistants in workplace tasks. Examples include conversational chatbots, productivity copilots, and coding or content-generation assistants.

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Related configurations, including retrieval-augmented generation (RAG) systems, adaptive learning platforms, AI tutors, and agentic systems, are identified in the AI Configurations section and discussed where relevant.

The paper focuses on knowledge workers, whom Thomas H. Davenport describes as people with high levels of expertise, education, or experience whose jobs center on creating, distributing, or applying knowledge (10). Knowledge workers are one group of adult learners. We draw in particular on self-directed learning, which Thomas Howard Morris et al. describe as a core pillar of lifelong learning theory in which learners take responsibility for goals relevant to their own context (121).

In workplace settings, adults tend to use generative AI less as a formal learning intervention than as an everyday assistant. In a digital diary and interview study of professionals in academic, IT, healthcare, education, and consulting roles, Jarrahi et al. found that generative AI took on roles such as retriever, originator of first drafts, brainstormer, and reviewer of written text (table 2). Learning in these settings is therefore likely to happen in the flow of work. It is embedded in tasks, prompted by problems, and supported at the moment of need, rather than confined to scheduled programs. Practitioner scholarship has emphasized that employees develop meaningful knowledge and skills through experimentation, contextual application, and peer validation, alongside formal learning initiatives (Spiro and Bhamidi 46). By making retrieval, synthesis, and task support immediately available, AI may change each of these processes.

If AI changes how employees work through tasks, it also raises the question of whether doing a task well with AI means learning from it. Following Nicholas C. Soderstrom and Robert A. Bjork, we treat learning as the relatively permanent changes in knowledge or behavior that support long-term retention and transfer, and performance as the temporary changes that can be observed during or immediately after practice (176). Their review shows that large gains in performance often fail to produce corresponding gains in learning, and that people often mistake their performance during practice for evidence of long-term learning (176). Although this evidence comes from experimental research on motor and verbal learning, it bears directly on AI-assisted work. Generative AI can accelerate access to information, reduce the effort of routine tasks, and provide immediate support, all of which can improve performance. Whether this also produces durable learning may depend on whether AI replaces opportunities for retrieval, reflection, error diagnosis, and peer exchange, or frees time for further inquiry, iteration, feedback, and application. The central question is therefore not whether AI necessarily reduces learning, but under what conditions its use supports, reorganizes, or constrains the development of professional capability.

Existing scholarship addresses parts of this question. In a concept paper, Andreas Rausch examines how AI can support informal workplace learning and describes an "AI ghost learner effect," which can arise when employees adopt AI-generated solutions without the deeper processing and reflection needed to learn from them (sec. 3.3). He also notes that employees may mistake improved performance for improved competence (sec. 3.3), but he does not develop this distinction or specify the conditions under which it arises. In a survey of 319 knowledge workers, Hao-Ping Lee et al. found that higher self-reported confidence in generative AI was associated with less critical thinking (sec. 6.1.1). They also found that generative AI moved workers' effort away from gathering information, solving problems, and executing tasks, and toward verifying information, integrating AI responses, and overseeing the work, a role they call task stewardship (sec. 6.2). Morris et al. describe research on generative AI and self-directed learning as a new field in urgent need of further study (124). Reviewing research on AI and lifelong learning, Ted Palenski et al. find that studies treating AI as part of a wider reconfiguration of people and their contexts are the least represented in the literature

(1216), and they call for deeper engagement with theories of learning and technology (1233). What remains less developed is an integrated account that uses the distinction between performance and learning to specify when everyday generative AI use in knowledge work is likely to strengthen or weaken learning across cognition, tacit knowledge, self-direction, reflection, and social participation.

Responding to that call, this conceptual paper synthesizes andragogy, sociocultural learning theory, and experiential learning, and identifies conditions that moderate the relationship between AI use and workplace learning. The authors' practitioner experience informed the questions guiding the analysis but is not treated as empirical data, and the paper does not claim that the relationships it proposes generalize across organizational settings. Instead, it offers a provisional model and propositions for empirical testing.

## Methodology

This article is a conceptual paper that develops a model for understanding how AI may influence how adults learn in corporate settings. In conceptual papers, arguments are built from previously developed concepts and theories rather than from data in the traditional sense (Jaakkola 19). The paper uses a theory-synthesis design, which integrates several theories to offer a new or enhanced view of a phenomenon (Jaakkola 21). Because it also proposes a model of how AI use, learning mechanisms, and outcomes relate (fig. 1), it combines synthesis with elements of what Elina Jaakkola calls a model design, and she notes that such designs are often combined (21-22). The paper therefore reports no empirical sample and makes no claim of empirical generalization.

The starting point was a problem of practice that the authors encountered in their professional work in adult learning, learning design, and knowledge work. AI-assisted tasks could be completed much faster, yet it was unclear whether durable learning kept pace. The analysis borrows the logic of abduction, in which an unexpected observation is read against several existing theories to produce new explanations (Timmermans and Tavory 167, 169). Stefan Timmermans and Iddo Tavory note that recognizing such a surprise depends on the researcher's position and familiarity with theory (173), which is the role practitioner experience played here, consistent with Donald A. Schön's account of how professionals reflect on puzzling situations in their practice. Practitioner experience shaped the guiding questions but was not treated as empirical data, and no practitioner observations were coded.

Sources were selected for their focus on adults using AI to learn or adults using AI in the workplace, were identified through Google Scholar, and were limited to work published in approximately the last ten years. Foundational works in each theoretical tradition, along with sources that define the AI systems discussed, were added regardless of publication date to anchor the synthesis.

Three theoretical traditions were selected because each foregrounds a different process central to workplace learning. Following Jaakkola's guidance for papers that start from a phenomenon, each tradition was chosen for its fit with that phenomenon and the complementary insight it adds (19). Andragogy explains learner agency and the assumption that adults increasingly take responsibility for directing their own learning (Knowles 43-50). Self-directed learning further explains the processes involved, including the distinction between managing learning activities and monitoring one's understanding (Garrison 21-27). Sociocultural learning theory focuses on participation, relationships, and learning mediated by tools and other people (Vygotsky 25, 30, 54-55, 90-91; Lave and Wenger 29-37). Experiential learning focuses on how experience is transformed through reflection and experimentation (Kolb), a process closely tied to tacit knowledge (Polanyi).

The traditions converge in treating learning as more than acquiring information, but they locate the key mechanism differently. Andragogy and self-directed learning locate it within the individual, in the learner's ability to set goals, manage their learning, and monitor their own understanding. Sociocultural theory locates it between people, in mentoring, feedback, and participation in a community of practice. Experiential learning centers on the individual's reflection, but in this paper's reading it also depends on concrete experiences that are often shared with others. The point of divergence is therefore about whether the individual or the community is the main site of learning. When an employee turns to AI instead of a more experienced colleague, andragogy would see greater independence, since the learner gets answers on demand without relying on others. Sociocultural theory would see a lost opportunity for feedback, mentoring, and participation in the community where professional judgment develops. Experiential learning adds a further concern, since a fast, ready-made answer may shorten the cycle of experience, reflection, and experimentation.

Taken separately, each tradition explains only part of what changes. Andragogy can account for gains in learner control but not for the loss of peer exchange, sociocultural theory can account for changes in participation but less for individual self-monitoring, and experiential learning can account for reduced reflection but not for who provides feedback. Read together, they show that the same gain in speed can affect agency, participation, and reflection at once, sometimes in opposite directions. This combined view underlies what the paper calls the depth-speed tension, developed in the next section. The synthesis organizes the analysis around four theory-derived dimensions. Learner agency and self-direction draw mainly on andragogy, learning through practice and experimentation on experiential learning, and social and peer learning on sociocultural theory. Knowledge in the flow of work draws on situated cognition and tacit knowledge.

Each dimension is examined through a common question, which asks under what conditions AI-assisted work might support, reorganize, or constrain the development of professional capability. The analysis of each dimension draws on those of the eight moderating conditions, set out in the Provisional Model, that bear most directly on it.

## Theoretical Framework

### Self-Directed Learning and Andragogy

Malcolm S. Knowles's andragogy frames adult learning around increasing learner agency, the relevance of learning to practical needs, and readiness to address tasks and responsibilities (43-45). In this view, adults are increasingly inclined to take responsibility for identifying their learning needs, setting goals, and directing their development (Knowles 47-49). Their motivation is often strengthened when learning is relevant to the problems they encounter in practice (Knowles 47-48, 53-54). These are guiding assumptions rather than universal characteristics: self-direction varies across individuals and situations, and also depends on learners' skills and circumstances, including their information literacy (Morris et al. 123). Andragogy therefore explains adults' orientation toward self-direction, but offers less detail on the cognitive and regulatory processes through which it takes place.

D. Randy Garrison extends this picture with a model of self-directed learning built on three overlapping dimensions (21). Self-management concerns task control, meaning the external side of learning, such as carrying out learning goals and managing resources and support (22). Self-monitoring concerns cognitive responsibility. It covers the metacognitive work of tracking one's learning strategies and thinking about one's own thinking, and it is the process through which learners take responsibility for constructing meaning by integrating new ideas with what

they already know (24). Motivation covers both the commitment to a learning goal and the persistence to stay with it (26-27). Garrison treats self-monitoring as central to judging the quality of learning outcomes (24), which makes it the dimension most relevant to the questions this paper asks about AI. Although Garrison developed the model for formal educational settings, this paper applies it to learning at work, where colleagues and managers can play the supporting role he gives to teachers.

AI can considerably extend the self-management dimension. Learners can obtain synthesized, context-specific information on demand, remove practical barriers to inquiry, and pursue their own learning paths without going through formal programs. In a survey of knowledge workers, many participants reported spending less effort finding and organizing information because generative AI gathered it and presented it in a readable form (Lee et al., sec. 5.2.1). Jarrahi et al. likewise found that generative AI helped with breaking down complex concepts and helping professionals see the bigger picture of a topic (table 2; 13).

Self-monitoring poses a different challenge. It concerns the learner's judgment about whether they understand, what remains uncertain, and whether they can apply what they have learned beyond the immediate task. This judgment remains the learner's responsibility, but Garrison notes that self-monitoring depends on both internal and external feedback, and that internal feedback alone may be inaccurate (24-25). Feedback, prompts, assessment, and structured reflection from other people and systems can therefore support it. The concern is not that monitoring cannot be supported from outside, but that fluent, ready-made answers may reduce the learner's own evaluative work. Lee et al. found that knowledge workers who trusted generative AI to handle a task were less likely to reflect critically on its output, and that some accepted that output by default when they doubted their own ability (sec. 4.3.2). When AI is used mainly to produce an acceptable answer, learners may have fewer reasons to retrieve, explain, test, or challenge what they know. When it is used to highlight discrepancies, generate questions, give feedback, or prompt explanation, it can support monitoring instead (Rausch, sec. 3.4).

## Sociocultural Learning Theory: ZPD and Communities of Practice

Where andragogy places the individual at the center of learning, sociocultural theory holds that learning takes place through participation in social relationships and communities of practice. As noted in the Methodology, the two traditions diverge on where learning happens. Self-directed learning describes what the learner does, while sociocultural theory describes the relationships and communities through which that activity becomes meaningful and recognized.

Lev S. Vygotsky's zone of proximal development describes the gap between what a learner can do alone and what they can do with guidance from, or in collaboration with, a more capable person (86). In this paper's reading, the more capable other plays a calibrating role, judging where the learner stands, anticipating what they could do next, and adjusting support as their understanding grows (Vygotsky 86-87). Vygotsky developed the concept in studies of children, so its use here for adult professionals is an extension rather than a direct application. AI systems can provide feedback, scaffolding, and adaptation, but many current systems have less access than a long-standing human mentor to the learner's full cognitive, organizational, and developmental context. Jean Lave and Etienne Wenger extend this relational view from the mentoring pair to the wider communities in which professional learning takes place. Through legitimate peripheral participation, newcomers move from the edges toward the center of a community of practice, gaining not only explicit skills but also the tacit norms, values, and situational judgment that mark competent membership (Lave and Wenger 29). Wenger later

argued that learning in communities of practice is also a process of forming identity, so that learning cannot be separated from belonging.

AI does not remove these relational dimensions of learning. Jarrahi et al. note that knowledge workers largely experiment with generative AI tools on their own, and suggest that communities of practice, where workers share experiences and practical tips, can support collective sensemaking around these tools (18). AI may also augment participation by helping learners find information, prepare for discussions, or rehearse ideas. At the same time, it can replace some interactions. Lee et al. describe workers using generative AI to get feedback on their writing instead of going through rounds of review with colleagues (sec. 5.2.3). Whether this weakens learning depends on whether such interactions still offer feedback, modeling, interpretation, and shared practice. The sociocultural lens therefore points to forms of professional learning that may weaken when AI substitutes for participation, but may strengthen when AI reduces routine effort and frees time for richer human interaction.

### Experiential Learning and the Depth-Speed Tension

The third tradition is David A. Kolb's experiential learning theory, which defines learning as the process through which knowledge is created by transforming experience (38). Kolb describes this as a cycle of four stages, namely concrete experience, reflective observation, abstract conceptualization, and active experimentation. When learners pass through the stages only superficially, especially experience and reflection, they may become familiar with a concept without understanding it well enough to transfer it.

This cycle gives precision to what this paper calls the depth-speed tension. AI helps people complete work faster, but that speed can bypass the slower processes through which skills develop, such as working through a problem from scratch, making and correcting errors, reflecting on the result, and seeking feedback from others. By supplying ready-made conceptualizations in response to a prompt, AI can compress parts of Kolb's cycle, particularly when learners accept an output without working through the underlying problem, reflection, or experimentation themselves. In such cases the learner receives the product of a reasoning process without the experiences through which understanding develops. The same technology can be used differently. Learners may ask AI to explain alternatives, expose assumptions, identify errors, or structure experiments, and use the time saved to deepen their engagement with the cycle rather than replace it.

Soderstrom and Bjork's finding that gains in performance often do not translate into lasting learning (176) helps locate where this risk is greatest in Kolb's cycle. AI is most likely to raise performance without a matching gain in learning when it takes the place of reflective observation and active experimentation, since these are the stages in which learners test and revise their own understanding. It is least likely to do so when learners treat AI output as material for those stages, for example by comparing an AI explanation with their own attempt, or by trying an AI-suggested approach and reflecting on the result.

Survey evidence from knowledge workers points in both directions. Lee et al. found that while generative AI can make work more efficient, it can also reduce critical engagement and may lead to long-term overreliance and weaker independent problem-solving (sec. 7). They note that without regular practice in routine and low-stakes tasks, cognitive abilities can weaken over time (sec. 4.3.2). The same study also found that some workers used generative AI deliberately to build their own skills, for example by working through AI-suggested corrections to improve their writing (sec. 4.3.1). The next section brings these elements together in a provisional model (fig. 1).

## AI Configurations

AI is not treated here as a single technological category. As defined in the Introduction, the analysis centers on generative AI tools used as cognitive assistants in workplace tasks, and terms such as "AI-assisted" and "AI-supported" refer to work involving these tools. Throughout the paper, "AI" refers to these tools unless another configuration is named. Related configurations differ in their levels of autonomy, forms of interaction, and roles in supporting learning, and are discussed where relevant rather than treated as equivalent cases. Within the primary category, coding assistants warrant separate mention because they generate or modify executable artifacts. This creates particular opportunities for iterative experimentation but also for the delegation of technical reasoning. Retrieval-augmented generation (RAG) systems combine a generative model with information retrieved from an external knowledge source (Lewis et al. 9459), which may change the reliability and traceability of workplace information. Adaptive learning platforms and AI tutors can organize task selection, practice, feedback, and assessment more explicitly around learning goals. Agentic systems go beyond generating or recommending content to planning and carrying out multistep actions (Wang et al., sec. 2.1), which increases the extent to which task processes themselves may be delegated. The type of system therefore shapes its learning effects, since what a system does determines which cognitive, social, and experiential processes remain with the learner.

## Provisional Model

Across these configurations, the paper treats the following conditions as moderators of the relationship between AI use and workplace learning. These are (1) learner expertise, (2) task complexity and risk, (3) organizational culture, (4) AI literacy, (5) managerial expectations and performance pressure, (6) system reliability and transparency, (7) the availability and quality of feedback, and (8) whether AI is used mainly for immediate production or for longer-term capability development. These conditions shape whether the speed AI offers represents a productive reallocation of effort or the displacement of learning opportunities.

Building on this synthesis, figure 1 presents a provisional model of how AI use may shape workplace learning. It distinguishes the conditions that shape engagement with AI, forms of use, learning mechanisms, and potential outcomes.

The model runs from left to right. Antecedent conditions shape how a worker engages with an AI system. These include characteristics of the learner, such as expertise, AI literacy, self-regulation, and motivation, features of the task, such as its complexity, stakes, and novelty, and features of the organization, such as its learning culture, managerial expectations, and access to experts. Some of these factors also appear among the moderating conditions, because they shape both how a worker first engages with AI and which pathway that engagement then follows. Engagement is best understood as a spectrum rather than a binary. At one end is substitutive use, where a worker accepts a finished output and delegates much of the underlying thinking. At the other is augmentative use, where the worker asks the system to explain, works through the problem in stages, and stays engaged in the reasoning, reflection, and experimentation the task involves.

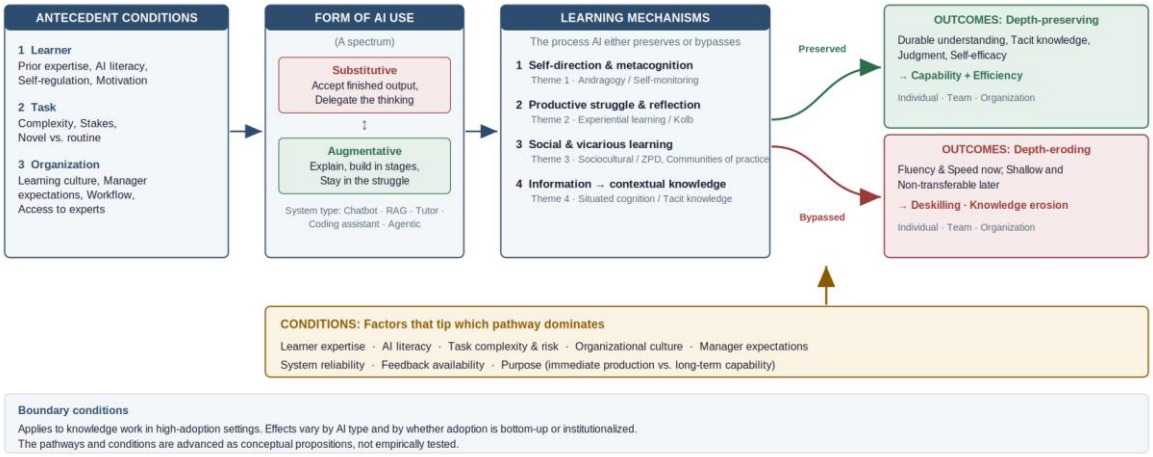



**Fig. 1.** Provisional Model of AI and Workplace Learning: The Depth-Speed Tension

These forms of use may affect four learning mechanisms, which correspond to the paper's four dimensions, namely learner agency and self-direction, learning through practice and experimentation, social and peer learning, and knowledge in the flow of work.

From these mechanisms, the model divides into two potential pathways. On the depth-preserving pathway, the learning mechanisms are maintained or supported, so that AI-assisted work can move faster while also supporting deeper learning. On the depth-eroding pathway, some of these mechanisms are reduced, displaced, or bypassed. This may produce strong immediate performance without equivalent gains in durable or transferable understanding. If sustained, it may contribute to deskilling among individuals and teams and to the erosion of knowledge within organizations.

The model brings together dimensions of learning that are often examined separately and organizes them around the depth-speed tension. It proposes that the same AI system may support, constrain, or reorganize learning depending on the form of use and the conditions around it. The model also has boundary conditions. It applies to knowledge work in settings where AI use is widespread, and its effects are expected to vary by type of AI system and by whether adoption is driven by individual workers or by the organization. The pathways shown in figure 1 are conceptual propositions, not tested findings, and the Conclusion identifies relationships that future research could examine.

## Analysis and Discussion

### Learner Agency and Self-Direction

Self-directed learning is understood as a process in which learners take primary responsibility for identifying their learning needs, setting goals, selecting resources, and evaluating outcomes. AI raises the question of whether greater independence in completing tasks also means greater ownership of learning. At first sight, AI strengthens self-direction by giving learners more control over when, how, and what they learn. In Garrison's terms, this is a gain in self-management. This section asks whether it also supports self-monitoring, the dimension the Theoretical Framework identified as relevant to AI.

Greater control over a task does not necessarily mean deeper self-direction. When learners use AI mainly to automate the thinking needed to reach a performance goal, they can control the task while doing less of the work of building knowledge. Knowles's andragogy assumes

that adults become ready to learn when they need to know how to deal with a task or problem (44). When AI makes it possible to reach the desired outcome without confronting the underlying gap in knowledge, that need may never be felt, and the impulse to inquire and build deeper competence may not arise. Adult learners appear aware of this risk. In an interview study of twenty adult learners, Jinhee Kim et al. found that participants valued AI for tracking their progress but wanted to stay in charge of their own reflection and avoid becoming overly dependent on AI's judgments (1920). They also worried that AI could steer their learning paths and decisions in ways that weaken their agency, and wanted systems that explain their limits and encourage learners to think critically about when to rely on an output (1922, 1924). Although these learners were studied in university online learning rather than at work, their concerns bear directly on employees who use AI in their daily tasks.

Agency in AI-assisted learning is also not simply a matter of being more or less independent. In a mixed-methods study of Chinese undergraduate English learners using generative AI informally, Chun Lai et al. distinguish performance proxy agency, in which learners have the tool complete a task for them, from learning proxy agency, in which they use its output as a resource for learning, for example by comparing an AI translation with their own (8). Both involve delegating to the tool, but only the second turns delegation into learning. Although these participants were language learners rather than employees, the distinction closely parallels the substitutive and augmentative forms of use in figure 1. AI supports agency when learners keep control of their goals, question outputs, compare alternatives, and use the system to extend rather than replace their own reasoning. Several of the moderating conditions set out in the Provisional Model shape which pattern emerges. Learner expertise matters because knowledge workers who are more confident in their own skills tend to evaluate AI output more critically (Lee et al., sec. 6.1.1). Performance pressure matters because workers with little time report having little room to reflect on what AI produces (Lee et al., sec. 4.3.2).

Independence in completing a task and ownership of learning can therefore come apart. A learner who produces the desired output without evaluating its basis, or without considering what they have learned, may gain control over the task without becoming more self-directed. For organizations, this suggests building evaluation, explanation, and reflection into AI-assisted workflows, so that greater self-management is matched by opportunities for self-monitoring.

## Learning through Practice and Experimentation

The speed with which AI produces outputs raises a question about the conditions under which learning occurs. A hypothetical vignette makes this concrete. A business analyst is asked to analyze an unfamiliar dataset and prompts AI to write the code and generate the charts. Within minutes a clean set of results appears, and the task can be delivered. If the analyst accepts the generated code without examining the methods, testing the results, or adapting the analysis, the task may be completed with little development of the underlying capability. In terms of Kolb's cycle, the analyst skips the concrete experience of working through the problem and the reflective observation and active experimentation that would follow it. Matthew Christian Agustin argues that AI can solve problems before learners recognize their knowledge gaps, reducing opportunities for monitoring and reflection and potentially creating a false sense of mastery (sec. 3.5). A finished solution may thus arrive before the analyst has engaged with the problem, reducing opportunities to learn through diagnosis, reflection, and experimentation unless these are taken up elsewhere in the workflow.

Now consider the same analyst approaching the same task differently. Rather than accepting a finished analysis, they ask AI to explain its choice of method, build the code in steps they can follow, and suggest options that they then test against the data themselves. When a result looks

implausible or the code returns an error, the analyst faces a real problem and has to diagnose it. In a concept paper on informal workplace learning, Rausch notes that this kind of reactive learning is typically triggered by deviations from routine, errors, and unfamiliar changes in work tasks, which prompt workers to question what they already know (sec. 2.1). Used this way, the time AI saves on routine work goes into concrete experience, reflection, and experimentation rather than replacing them.

Which path an analyst takes is itself shaped by expertise and prior experience. A novice, with less knowledge to draw on when questioning an output, may be more likely to accept a plausible response without noticing its limits. Lee et al. report that knowledge workers who lacked sufficient domain knowledge found it hard to judge whether AI output was correct (sec. 4.3.2). An experienced analyst is better placed to question methodological choices, spot anomalies, and test alternatives. The same tool may therefore widen or narrow the gap in learning between novices and experts, depending on the learner's prior knowledge, the complexity of the task, and the opportunities available for feedback and experimentation, three of the moderating conditions set out in the Provisional Model.

AI therefore does not in itself deepen or shortcut learning. Whether it speeds up task completion at the expense of understanding, or supports understanding while preserving productive difficulty, depends on how it is used and on the conditions organizations design around that use.

## Social and Peer Learning as an Anchor

Adult learning in organizations is not simply the accumulation of information. It is a relational process through which learners gain access to judgment, practice, and professional identity by interacting with others. In corporate settings, the question is whether AI augments or replaces the human expert, who offers guidance rooted in lived experience and contextual judgment. This section examines three aspects of that role, namely community participation, credible modeling, and tacit knowledge.

AI can take on part of the expert's role. In a single-case study of ten employees at a European infrastructure company, Pedro Oliveira et al. found that AI increasingly handled repetitive and analytical tasks, freeing workers for more strategic and creative work, although participants also reported a perceived loss of human interaction. AI can likewise answer questions, surface resources, and structure information. Its outputs, however, can be wrong or poorly suited to the situation. Knowledge workers in Lee et al.'s survey reported spending effort verifying AI responses that turned out to be inaccurate (sec. 5.2.1), and Morris et al. point to the risk of bias in the information AI systems generate (122). Applying an answer to a specific situation therefore still depends on someone with relevant experience. The question is not whether AI can replace expertise wholesale, but which parts of expert practice AI can support and which still depend on participation in human contexts.

The first aspect is participation in a community of practice. As outlined in the Theoretical Framework, newcomers become competent practitioners by moving gradually toward full participation in a community's practice (Lave and Wenger 29), observing peers, trying things out, and checking their understanding with others. AI-assisted interactions can provide information and even simulated dialogue, but they do not necessarily provide shared participation, mutual accountability, or the situated experience of belonging to a workplace community. Knowledge held in such a community is continually tested against lived practice. This supports not only the task but also the learner's self-monitoring, by prompting reflection, exposing what is not yet understood, and keeping the learner engaged in the effortful work through which understanding becomes durable.

The second aspect is credible modeling. When learners watch an experienced colleague succeed at a task they have been struggling with, they gain confidence that the task is achievable, a model to follow, and someone to identify with professionally. Albert Bandura identifies this kind of vicarious experience, seeing others succeed, as one source of self-efficacy, the belief in one's own ability to perform (197). AI can also influence self-efficacy, since completing a task with AI support or receiving constructive feedback can give learners evidence that a task is manageable. This differs, however, from observing a credible human model, which offers a socially situated example of success and a basis for professional identification.

The third aspect is the nature of expert knowledge. Much of what experts know is tacit, embedded in experience and personal judgment and resistant to being fully put into words (Polanyi 4), though Stephen Gourlay argues that it is better understood as a process of knowing than as a body of knowledge (1). Ikujiro Nonaka and Hirotaka Takeuchi describe knowledge creation as a continuing conversion between tacit and explicit knowledge, through sharing experience directly (socialization), articulating it in explicit form (externalization), combining explicit knowledge (combination), and absorbing it back into practice by doing (internalization) (62-70). Because tacit knowledge passes largely through observation, shared experience, and practice, it may be hard to capture or transfer through AI alone. AI can nevertheless help articulate, organize, and circulate expertise once it has been made explicit, making some knowledge more available to learners, provided they can connect it to their own situated practice. Jarrahi similarly argues that humans retain an advantage over AI in decisions that are uncertain, ambiguous, or dependent on intuition, while AI is stronger in analyzing information and generating options.

Community participation, credible modeling, and tacit knowledge all point to the continuing importance of lived experience and situated judgment in workplace learning, even as AI helps articulate and circulate parts of professional knowledge. Whether AI weakens or strengthens social learning depends partly on organizational culture and the availability of feedback, two of the moderating conditions in the Provisional Model. Learning needs should therefore guide where AI is introduced, including which activities suit AI support and where human participation, feedback, or supervision remains important.

## Knowledge in the Flow of Work

AI-assisted work can provide information, synthesis, explanations, recommendations, and in some applications direct task execution. These outputs do not automatically translate into knowledge or understanding. Their learning value depends on how learners interpret, contextualize, evaluate, and apply them in practice. Russell L. Ackoff's hierarchy of data, information, knowledge, understanding, and wisdom offers a useful conceptual framing for this distinction. Applied to AI-assisted workplace learning, it draws attention to the processes through which information is transformed into usable knowledge, understanding, and ultimately informed judgment (Ackoff 3-4). Alfred North Whitehead similarly warned that ideas which are received but never used or tested remain inert (1). When AI outputs are accepted without examination or application, information may accumulate without becoming durable knowledge. When learners test, contextualize, and apply them in practice, the same capability can support learning in the flow of work. Lee et al. observe this shift among knowledge workers, whose effort moved from gathering information toward verifying and integrating what AI provides (sec. 6.2).

Situated learning theory holds that knowledge acquires meaning through participation in social and practical contexts (Lave and Wenger 29-35). AI can surface information, generate possibilities, and help learners interpret unfamiliar material, but its learning value depends on

whether these outputs are connected to meaningful activity, where learners encounter problems, judge relevance, apply ideas, and learn from consequences. Conrad Gottfredson and Bob Mosher's practitioner framework of five moments of learning helps identify where this connection matters most. The first two moments, learning something new and learning more about it, may suit AI systems that retrieve, synthesize, and explain codified knowledge. The other three, applying knowledge on the job, solving problems when things go wrong, and adapting when conditions change, place greater demands on contextual judgment (Gottfredson and Mosher). AI can still support these moments when it draws on relevant workplace information, gives context-sensitive feedback, or helps learners explore possible responses, provided learners remain responsible for interpreting and applying them.

The need for contextualization also extends to how organizations manage knowledge. Organizational knowledge is often scattered across systems and applications, and it can be siloed, duplicated, or left out of date. In a systematic review, Jitao Yan et al. find that AI can connect fragmented information, integrate knowledge from internal and external sources, and make explicit knowledge more accessible across an organization (528-29). Keeping that knowledge accurate and current, however, still depends on people, and even well-synthesized information becomes knowledge only when learners connect it to their own context.

The same logic applies to individual cognitive engagement. For routine, well-defined, and low-stakes tasks, AI can lower the barrier to starting work and may free attention for more complex thinking, reflecting the role of task complexity and risk among the moderating conditions in the Provisional Model. Where learners delegate reasoning, retrieval, or evaluation without opportunities to practice them elsewhere, however, sustained use may constrain the development of those capabilities. Lee et al. accordingly recommend that training help workers keep foundational skills in information gathering and problem-solving so that they do not become overreliant on AI (sec. 6.2). Organizations can support this by making explicit which tasks are handled by AI, by people, or jointly, while preserving suitable opportunities for human evaluation and learning.

## Implications

For adult learners, AI can help them access, organize, explain, and test information, but a correct output or success on an immediate task does not necessarily show durable understanding. Learners can stay actively involved by explaining their reasoning, retrieving relevant knowledge before turning to AI, applying outputs in context, and reflecting on what they have learned. In Lai et al.'s terms, this means treating AI as a resource for learning rather than only as a way to complete the task (8).

For managers, the main lever is how performance is defined and paced. Where employees are judged only on speed and output, the time AI saves is likely to go into more output rather than into learning, and as the analysis of learner agency showed, time pressure can crowd out reflection. Managers can create space for employees to interpret, challenge, and apply AI outputs, treat errors found in AI-assisted work as opportunities to learn, and keep employees in contact with experienced colleagues who can offer feedback and modeling.

For learning and development professionals, the implication is to design learning into the flow of work rather than only around it. This can include prompts that ask employees to explain or check AI outputs, structured reflection after AI-assisted tasks, and peer review of AI-assisted work. Training in AI literacy should cover not only how to use AI tools but also how to verify, integrate, and question their outputs, while keeping foundational skills in practice (Lee et al., sec. 6.2). Where AI tools are selected or configured, learning professionals can favor systems

that explain their reasoning, signal their limits, and prompt reflection (Kim et al. 1924; Rausch, sec. 3.4).

For organizations, AI deployment should begin with an understanding of the learning processes involved in the work being redesigned. Organizations can identify where reflection, peer exchange, feedback, and experimentation contribute to capability development, and then consider how AI might support these processes or change the opportunities available for them. Decisions about which tasks are suitable for AI-only, human-only, or collaborative execution should reflect longer-term learning objectives as well as operational requirements. Where AI curates and surfaces organizational information at the point of need, it also requires clear ownership of information quality, currency, and relevance, and clear responsibility for evaluating outputs. Because organizational culture is one of the moderating conditions in the Provisional Model, these choices help determine whether AI use tends toward the substitutive or the augmentative end of the spectrum shown in figure 1.

## Limitations

This paper has several limitations. First, it is a conceptual theory synthesis rather than an empirical study. Its four dimensions were derived from the theoretical literature rather than coded from workplace observations, and the framework and propositions have not been tested, so the relationships proposed should be read as provisional. Second, the authors' practitioner backgrounds shaped the questions the paper asks, and different starting points might have brought other theories or concerns into view. Third, the evidence base has limits. Sources were identified through Google Scholar and were mostly published in English in the last ten years, in a field that is changing quickly. Several of the studies cited involve university students, language learners, or small samples in a single organization, and some rely on self-reported data, so their transfer to corporate settings has been argued rather than demonstrated. Fourth, the paper focuses primarily on generative AI used as a cognitive assistant in knowledge work. Other AI configurations, types of work, and organizational and cultural contexts may shape learning differently, and the framework may need refinement when examined across them.

## Conclusion

This paper develops a provisional model of how AI reshapes the conditions under which adults learn at work. Its central contribution is to explain, through the depth-speed tension, how the same gain in speed can either support or constrain durable understanding and professional capability, depending on how AI is used and the conditions around that use. The model shifts attention from AI's capacity to improve immediate performance to the conditions under which AI-assisted work supports or displaces learning.

The analysis suggests that AI-assisted work may weaken learning when it substitutes for opportunities to retrieve knowledge, evaluate outputs, engage in productive struggle, reflect on experience, or participate in shared practice. These risks may be greater where learners have limited expertise or AI literacy, tasks are complex or high-risk, performance pressure rewards speed, feedback is scarce, or AI outputs are unreliable or hard to evaluate. Conversely, AI may strengthen learning when it supports inquiry, explanation, comparison, experimentation, and reflection, when learners keep an active role in evaluating and applying outputs, and when time saved on routine tasks goes into feedback, peer exchange, and capability development. Organizational culture, and whether AI is introduced mainly to raise immediate productivity or to support longer-term learning, also shape which of these outcomes prevails.

As noted in the Limitations, the model is provisional and untested. Its relationships are a basis for investigation rather than established effects, and future research could examine the following propositions.

1. **Substitutive and augmentative use.** AI use that replaces learners' engagement with reasoning, retrieval, and evaluation may be associated with stronger immediate task performance but weaker durable understanding than AI use that scaffolds these processes.
2. **Expertise and AI literacy.** Learners' prior expertise and AI literacy may shape whether AI-assisted work encourages critical evaluation and experimentation or leads to uncritical acceptance of outputs.
3. **Organizational conditions.** Managerial expectations that prioritize rapid task completion, particularly where opportunities for feedback and reflection are limited, may strengthen the association between substitutive AI use and reduced engagement in learning processes.
4. **Social participation.** Where organizational cultures support peer exchange, mentoring, and shared practice, AI may complement workplace learning by freeing time for human interaction. Where it substitutes for these interactions, opportunities for situated and relational learning may be constrained.
5. **Knowledge development.** The effects of AI on organizational knowledge may depend on whether AI-generated information is contextualized, evaluated, shared, and incorporated into collective practice, rather than simply accessed or synthesized for individual task completion.

The Implications section sets out what these propositions mean for learners, managers, learning and development professionals, and organizations. Across all four, the common thread is to treat the time AI saves as a resource that can be invested in learning rather than absorbed entirely by output. The paper's guiding principle follows from this, which is to get the human learning conditions right before reaching for the technology.

Testing these propositions will require longitudinal, workplace-based research, including ethnographic studies of the kind Palenski et al. call for (1233) and assessments of learning over time, across different AI configurations and organizational contexts. Such research can refine the model, clarify the relationship between immediate performance and durable learning, and identify when AI-enabled efficiencies contribute to rather than displace the development of professional capability.

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# Generative AI and the Risk of Algorithmic Compliance in University Academic Integrity Policies

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# Generative AI and the Risk of Algorithmic Compliance in University Academic Integrity Policies

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## ABSTRACT

Generative artificial intelligence has made the relationship between academic integrity and institutional verification more difficult to settle. A declaration, an oral discussion, or a record of drafts can support learning, but it can also become a demand that students continually demonstrate their legitimacy. This article develops the concept of algorithmic compliance pedagogy through a critical reading of ten public documents from six universities in the United Kingdom, continental Europe, and North America, retrieved on 23 October 2026. The analysis combines reflexive thematic reading with attention to policy wording, the allocation of responsibility, and the grounds on which authorship is questioned. The documents do not support a uniform movement toward automated surveillance. Several explicitly reject AI detectors, while preserving disclosure requirements, authorship interviews, and instructor judgments about writing. Five themes examine conditional permission, restrictions on detection, professional discretion, documentary authenticity, and the relationship between compliance and educational purpose. The central concern is that suspicion can migrate from a detector score to judgments about style or the performance of a writing process. This is a policy risk rather than an observed effect on students. The article distinguishes necessary assessment assurance from disproportionate verification through its connection to learning, the burden of documentation, institutional responsibility, and opportunities to contest an inference. It argues that protecting standards requires universities to account for the grounds of suspicion as well as requiring students to account for their work.

## KEYWORDS

**Generative Artificial Intelligence**

**Academic Integrity**

**Higher Education**

**Algorithmic Governance**

**Pedagogical Trust**

**Multilingual Writers**

## Introduction

The arrival of generative artificial intelligence (GenAI) has made familiar questions about authorship harder to answer. A fluent assignment may reflect a student's understanding, extensive external assistance, or some combination of the two. Universities need evidence that their assessments represent the learning they claim to certify. They also need to explain how students can use the tools increasingly available within ordinary writing environments. These responsibilities meet in institutional policies, where the boundary between acceptable assistance and misconduct is translated into instructions about writing, disclosure, and proof.

The difficulty is that verification has an educational cost as well as an institutional purpose. Keeping drafts can help a student understand revision. The same requirement can become a precaution against being accused. An oral discussion can reveal understanding, while an

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unexpected authorship interview can require a student to defend a written performance under different conditions. The question is what makes these practices proportionate to the learning being assessed, and what happens when avoiding suspicion becomes an additional condition of academic participation.

This article introduces algorithmic compliance pedagogy to examine that problem. The term describes a risk within AI governance: educational credibility becomes dependent on satisfying classifications of acceptable assistance or signs of supposedly human authorship, while the relationship between those classifications and the learning outcome receives insufficient scrutiny. It is not a name for every integrity rule or every request for an explanation. The concern arises when a platform judgment, a writing stereotype, or an excessive requirement for process evidence becomes more authoritative than a reasoned appraisal of the student's knowledge.

The distinction matters because current institutional guidance contains substantial resistance to automated suspicion. University College London (UCL) advises against detector use, Vanderbilt and Waterloo explain decisions to disable it, and ETH Zurich questions the reliability of technical recognition. A credible critique must account for these positions. The analysis therefore asks how suspicion and responsibility are organized when institutions restrict automated detection but retain other ways of examining authorship. The documents are identified in Appendix A and examined in the Findings section.

The equity concern remains central. Liang and colleagues' study of early GPT detectors found misclassification affecting non-native English writing. That evidence establishes a problem in the tools and samples tested; it does not establish that every contemporary detector disadvantages every multilingual writer. The wider question is whether a student's language becomes a reason to demand additional proof. Policy advice that treats formulaic wording or a change in style as a signal needs particular care, because the inference from textual appearance to unauthorized assistance is open to alternative explanations (Liang et al. 1-2; "Academic Integrity and Generative AI").

This article does not argue for unrestricted AI use, nor does it dismiss concerns about academic standards. It examines the conditions under which verification supports those standards without making students responsible for resolving every uncertainty about authorship. The contribution is a close account of how declarations, permissions, and evidentiary signals distribute obligations between students and institutions. Its claims concern the language of a bounded documentary corpus and the practices that language recommends. It does not claim to measure institutional implementation or students' experiences.

## Literature Review

### Policy Responses after Generative AI

Research on university AI policy already shows that institutional responses are varied. Jin and colleagues analyze adoption policies and guidance from forty universities across six global regions, identifying attention to academic integrity alongside teaching, training, and equitable access (3-6, 8). Li and colleagues screen 110 universities across three countries and identify 124 policy documents from 64 institutions that had issued guidelines. Their comparison demonstrates differences in policy priorities and governance arrangements (6, 9-11). These studies make a general account of universities responding only through prohibition difficult to sustain. They also establish a basis for examining how broad commitments become specific obligations in assessment.

Dotan, Parker, and Radzilowicz develop a faculty-informed approach to responsible adoption, drawing on collaborative work at the University of Pittsburgh. Their concern with academic freedom and institutional governance supports a discussion of who should decide how AI is used. A participatory process can make the reasons for a rule open to discussion, rather than leaving its educational purpose implicit. This approach directs attention to the authority behind an assessment requirement as well as the student conduct it seeks to regulate (Dotan et al., secs. 2, 5.1-5.2).

The change in students' use also needs careful interpretation. Freeman's 2025 HEPI survey reports extensive use among 1,041 full-time UK undergraduates. Its findings include substantial perceived policy clarity alongside limited institutional training, which complicates the assumption that guidance is uniformly absent or reactive. Stephenson and Armstrong's 2026 report, based on 1,054 UK undergraduates surveyed in December 2025, likewise places widespread use alongside uneven support and differing views about learning. These surveys provide context; they neither verify the practices of the six universities examined here nor show that using AI is equivalent to misconduct (Freeman 1-2; Stephenson and Armstrong 5-6, 9).

International guidance connects governance to educational responsibility. Miao and Holmes's 2023 UNESCO guidance advocates a human-centered approach to generative AI, including protection of agency, inclusion, and linguistic diversity. The 2026 European University Association report by Jørgensen and Phelan places human agency, institutional values, and participatory adoption at the center of its recommendations. These are normative resources for the present argument, rather than additional university cases or evidence that their recommendations have been implemented (Miao and Holmes 24-25; Jørgensen and Phelan 5, 9).

## Detection Performance and Unequal Risk

Detector performance is an empirical question that changes with the tool, model, task, and text. Liang and colleagues compare native and non-native English writing and document a serious fairness problem in early detectors. Weber-Wulff and colleagues test multiple systems and show limitations in distinguishing human writing from generated text, including the effects of translation and obfuscation. These studies justify scrutiny of detection evidence. Their results should not be converted into a timeless error rate for every product (Liang et al. 1-2; Weber-Wulff et al. 26-27).

Perkins and colleagues' 2024 preprint examines how adversarial changes affect detector performance on a constructed test set. It extends the evidence on susceptibility to manipulation, but is identified as a preprint and is not used to estimate the frequency of misconduct in universities. A detector's performance on a constructed test set and the prevalence of prohibited assistance in student work are separate matters. The ethical concern arises when a technical classification is allowed to stand in for the second without adequate evidence (Perkins et al. 6-10, 16-17).

There is important contrary evidence. Van Vlasselaer and colleagues' 2026 study compares four tools on 160 documents with known authorship conditions (7-10). It reports comparatively strong performance by one tool and few false positives, with differences across fully generated, hybrid, and humanized texts. Its additional analysis of 1,163 theses lacks known ground truth and cannot establish a confirmed prevalence of AI use. The study supports attention to differences between tools and conditions; it challenges the assertion that poor performance or linguistic bias must be identical across all generations of detectors (Van Vlasselaer et al. 15-17).

Baker and Hawn's review locates algorithmic bias within the development and deployment of educational systems. Its relevance is broader than text detection: fairness depends on the

conditions in which a classification is used and the consequences attached to it. Even an improving detector does not decide whether the assistance was permitted, whether an accommodation applies, or whether the available evidence supports a misconduct finding. Those decisions require an assessment context and an accountable institutional process (Baker and Hawn 1054-57).

### Trust and the Contribution of Policy Reading

Bearman, Ryan, and Ajjawi's critical review shows why AI should be examined through the discourses that give it educational meaning, rather than treated as a single neutral intervention. Slade and Prinsloo's earlier work on learning analytics similarly questions the assumption that collecting more information about a learner necessarily benefits that learner. These perspectives direct attention to the relationship between visibility, interpretation, and institutional power. They do not establish that every documentation practice is surveillance (Bearman et al. 379-81; Slade and Prinsloo 1510-11).

The edited collection *Higher Education for Good*, by Czerniewicz and Cronin, provides a further resource for thinking about educational purposes and collective responsibility. Its value here lies in sustaining a critical discussion of what universities should enable, alongside what they must regulate. The present article adds a focused question to that discussion: how can an institution make a student's work examinable without treating uncertainty about its production as a presumption against the student? The answer requires attention to the wording of the rule and to the safeguards accompanying it (Czerniewicz and Cronin).

## Theoretical Framework

### Discipline and the Demand for Visibility

Foucault's account of disciplinary power offers a way to examine how expectations of observation organize conduct. Applied to writing assessment, the relevant question is how a requirement to remain explainable might influence a student's preparation before any accusation occurs. The framework directs attention to draft retention, declarations, and the comparison of present work with previous writing. It does not establish what students actually feel or do in response to those requirements. Those effects would need evidence beyond policy documents (Foucault 200-03).

Biesta's account of qualification, socialization, and subjectification helps specify the educational concern. A university legitimately qualifies students, yet education also involves their capacity to exercise judgment and act responsibly. A verification practice can serve qualification while constraining other purposes, or support several purposes at once. An oral explanation, for example, can test understanding and invite reflection. Its value depends on the question asked, the conditions of the discussion and how the answer is interpreted (Biesta 77-79).

Williamson's analysis of datafication adds a question about authority: what changes when a record or classification becomes the means through which a learner is made institutionally knowable? The policy corpus does not demonstrate a complete transfer of judgment to platforms. Instead, it enables examination of how technical outputs, documentary evidence, and professional discretion are brought together. The distinction is necessary because a decision to reject a detector may protect academic judgment while leaving other classificatory assumptions intact (Williamson 12-14).

### Defining Algorithmic Compliance Pedagogy

Algorithmic compliance pedagogy names a particular risk in this arrangement. It arises when satisfying rules or signals associated with machine authorship becomes an educational performance in itself, with insufficient attention to what the student understands. The algorithmic element concerns the influence of computational classification and expectations about generated text. The compliance element concerns the demand to remain institutionally legible. Where a practice is simply ordinary academic attribution, or a clearly justified assessment of competence, the concept should not be applied without further argument.

Three features warrant examination. First, does the institution rely on an inference about authorship that the evidence cannot adequately support? Second, does the requirement to explain a process exceed what is needed to assess the intended learning? Third, can the student question the inference and receive an explanation of the institutional decision? These questions make the concept open to challenge. A clear, limited declaration accompanied by accessible guidance may be evidence against the critique, rather than another instance of it.

The framework also distinguishes a policy invitation from an observed outcome. Instructions can make a form of conduct reasonable, expected, or risky within an assessment. They do not prove that teachers enforce the instruction consistently or that students become compliant performers. The findings therefore analyze the conditions that documents establish for judgment. The discussion considers the educational consequences as possibilities requiring further investigation, while retaining the importance of protecting academic standards.

## Methodology

### Corpus and Selection

The study uses qualitative critical policy document analysis to examine how institutions describe acceptable AI assistance and the evidence through which authorship may be questioned. The corpus consists of ten publicly accessible, English-language documents from six named universities: University College London and the University of Oxford in the United Kingdom; Utrecht University and ETH Zurich in continental Europe; and Vanderbilt University and the University of Waterloo in North America. The country coverage is the United Kingdom, the Netherlands, Switzerland, the United States, and Canada.

The ten documents were retrieved on 23 October 2026 and assigned identifiers P1–P10. They include one university assessment policy, institutional guidelines, student and library advice, a teaching resource, and dated notices explaining detector withdrawal. These genres are distinguished in Appendix A; a recommendation on a teaching webpage is not assumed to have the same status as a formal assessment policy. Dated notices and visible update markers range from August 2023 to July 2026. Several pages are undated, and the latest timestamp on a containing guide does not establish when every section was revised.

Selection was purposive and directed toward documents that made explicit statements about assessment permission, disclosure, detection, professional responsibility, or authorship checks. Searches combined institution names with terms including generative AI, assessment, academic integrity, detection, declaration, and oral interview. Eligible items had to be publicly accessible on an institutional site and relevant to assessment or academic integrity after the public emergence of ChatGPT. The selected set deliberately includes restrictions on detection as well as instructions for verification. It does not claim to represent the distribution of policy positions across universities.

The document, rather than the institution or individual webpage section, is the counting unit. UCL contributes three items, Oxford one, Utrecht one, ETH Zurich two, Vanderbilt two, and Waterloo one. This gives four documents in the United Kingdom group and three in each of the other geographic groups. Multiple pages from one university are analytically related, not independent observations. The sample is weighted toward research-intensive institutions with accessible English-language guidance; no claim of institutional-type diversity or thematic saturation is made.

## Analytical Procedure

The analysis uses a reflexive thematic document reading informed by Braun and Clarke's later account of reflexive thematic analysis (Braun and Clarke). Theory informed the initial questions, but the themes were revised in response to contradictory passages. Close reading attended to modal instructions, the allocation of responsibility, and the circumstances in which a concern could become an authorship inquiry. This makes the interpretation examinable without treating themes as discoveries that exist independently of the reading.

Three questions guided the reading: how is acceptable assistance defined; what evidence can justify questioning authorship; and which obligations fall on students, teachers, and institutions? Initial codes included permission tied to an assignment, disclosure, draft retention, detector restriction, oral verification, judgments about writing style, teacher discretion, procedural safeguards, and pedagogical support. These codes were grouped into five themes concerning permission, detection, professional authority, process evidence, and educational purpose. Restrictions on detection were treated as counterevidence to an account of detection preceding dialogue.

For each document, the record links the source, relevant heading or clause, code, and thematic contribution. A second comparative reading considered whether an interpretation survived the safeguards and qualifications elsewhere in the same document. Table 1 shows the route from codes to themes and identifies every contributing document. Appendix B records the document-to-theme assignments. Counts refer to documents used to develop a theme, including counterevidence; they are not estimates of institutional prevalence, implementation, or the strength of a finding.

**Table 1**
Initial Codes and Contributions to the Five Themes

| Theme | Initial codes grouped in the theme | Contributing documents | Interpretive qualification |
|---|---|---|---|
| **T1 Integrity as suspicion and conditional permission** | Task-specific permission; disclosure; expectations of legitimate authorship | P1, P2, P4, P6, P7, P9 (n = 6) | Permission and clear instructions qualify an interpretation of presumed suspicion. |
| **T2 Detection before dialogue reconsidered** | Detector restriction or withdrawal; privacy; dialogue; negative cases | P1, P2, P4, P7, P8, P9, P10 (n = 7) | These documents mainly challenge detector-led governance; they do not establish implementation. |

| Theme | Initial codes grouped in the theme | Contributing documents | Interpretive qualification |
|---|---|---|---|
| **T3 Teacher authority and the limits of delegation** | Instructor decision rights; style signals; oral inquiry; procedural limits | P1, P4, P5, P6, P7, P8, P9 (n = 7) | Judgment remains with educators, whose inferences still require support and review. |
| **T4 Performative authenticity and process evidence** | Draft retention; authorship interviews; declarations; reflective process accounts | P2, P3, P4, P5, P7, P9 (n = 6) | Process evidence can support learning or verification; its effect is not measured. |
| **T5 Compliance as learning and institutional responsibility** | Learning purpose; institutional duties; access; participation in rules | P1, P4, P5, P6, P7, P8, P9, P10 (n = 8) | The documents establish competing expectations, not observed obedience or learning gains. |

Note. The counts include documents that challenge or qualify a theme. They describe this analysis and are not institutional prevalence estimates.

## Scope and Credibility

Examples of policy becoming recommended practice are drawn from the identified documents. UCL's student guidance describes investigatory vivas; its library guidance recommends retaining drafts. Utrecht's teaching resource distinguishes formative conversation from authorship checking. Vanderbilt's guidance recommends staged assignments and personal reflection while also discussing warning signals. Turnitin's own report guide is used as contextual vendor evidence, outside the ten-document corpus. These sources establish what is recommended or stated publicly; they do not establish how often a practice occurs.

Credibility rests on named sources, visible quotations, locators, and an explicit record of counterexamples. The analysis is interpretive and does not claim independent coding, inter-rater reliability, or validation through student testimony. Generative AI assisted source discovery, organization, and drafting during revision, as declared below. The corpus and coding matrix make the resulting claims available for examination and correction. A reader can disagree with a code assignment or the proposed connection between a clause and an educational risk.

There are limitations. Institutional policy documents often present idealized visions rather than everyday academic practice, and public guidance may conceal internal disagreement or uneven implementation across departments. This study therefore does not claim to capture the lived experience of students or staff. It examines the formal expectations through which integrity is described and authorship is made examinable. Interviews, observations, and analysis of actual decisions would be needed to investigate how these expectations affect trust, workload, or the distribution of suspicion.

The corpus is cross-sectional. A dated withdrawal notice and a current guidance page do not constitute a longitudinal record of institutional change. English-language publication and public accessibility shape what can be examined, and the sample does not represent the Global South or all forms of higher education. A missing statement on a selected page is not evidence that an institution lacks the relevant protection elsewhere. These limits also constrain the conclusions drawn from the five themes.

## Findings

The corpus shows a tension between making work accountable and limiting unjustified suspicion. It does not substantiate a uniform replacement of trust by detection. The five themes below examine that tension through the wording of named documents. Each theme includes protections or qualifications that constrain the interpretation, and the numerical counts describe the documents contributing to it rather than the number of institutions endorsing a single position.

### Integrity as Suspicion and Conditional Permission

UCL's three-category framework distinguishes assessment in which AI is prohibited, assistive, or integral. Its own description, "not a formal policy," matters: the categories support communication, while assessment instructions determine what a student may do. Read alongside the student guidance, this positions authorship as a contextual relationship between assistance, the task, and the student's responsibility. It does not make all assisted work presumptively dishonest ("Three Categories"; "Engaging").

Oxford places obligations on assessment setters as well as students. Staff must define permission, align the task and criteria with it, and specify disclosure. The requirement for "equality of baseline provision of appropriate AI tools" makes the conditions of access part of the institutional responsibility. The analytical point is that an integrity rule can constrain the university's conduct as well as the student's. A demand for transparency is less defensible if the institution has not first made the permitted assistance and available provision clear ("AI Use").

Suspicion remains a possible feature of the same governance arrangement. Vanderbilt's integrity guidance includes the instruction "Review tone" and treats "Inconsistencies between the voice and writing style of prior submissions" as relevant to reporting concerns. These are judgments about appearance and continuity, not direct observations of prohibited assistance. Their inclusion creates a route from a marker's perception of writing to an institutional inquiry. The page also requires alignment with assignment instructions and describes further evidence and testimony, so its language cannot be reduced to automatic conviction on stylistic grounds ("Academic Integrity and Generative AI").

The risk is therefore conditional. A change in writing may reasonably invite an educational question, but it can reflect feedback, revision, language development, or permitted support. For a multilingual writer, being compared with an earlier performance may make improvement itself difficult to explain. That is an interpretation of the possible burden created by the guidance, informed by the detector literature; the corpus contains no student-level evidence that such discrimination occurred. Integrity becomes suspicion when an uncertain signal is treated as a reason the student must disprove, rather than an inference the institution must substantiate.

### Detection before Dialogue Reconsidered

UCL's student guidance states, "UCL does not use GenAI detectors when marking." It then distinguishes a marker's request for information from an automatic accusation. ETH Zurich's integrity guidance states, "Trust in such a method is therefore not appropriate." Its referent is technical recognition of generated output. These passages directly contradict a claim that all institutional integrity advice gives detector scores priority over professional interpretation ("Engaging"; "Academic Integrity").

Waterloo's September 2025 decision notice is similarly explicit: "Time and effort are best spent on education rather than policing misuse of GenAI." The notice identifies reliability, bias,

and costs among its reasons for withdrawing the functionality and points instructors toward redesign and support. The wording does educational work by directing institutional effort away from the tool. It is evidence of a stated alternative to detector-led governance, while remaining a decision notice rather than an evaluation of the effects of that alternative ("Discontinuing").

These restrictions sit within a wider evidentiary problem. Turnitin's own report guide says the output "should not be used as the sole basis" for adverse action. It also distinguishes the AI percentage from a similarity score. The percentage concerns text classified by the model; it is not a finding that a student breached a particular assessment rule. This distinction matters even where a detector performs well under a given test. The institution must connect the evidence to the assistance permitted for the task ("Using").

Detection before dialogue is consequently a proposition the selected documents often resist. The remaining concern is how an institution responds to uncertainty once the score has been withdrawn or restricted. A commitment to dialogue can protect the student, or become an informal investigation without clear limits. The policy question is whether the conversation has an identified purpose, an appropriate evidentiary basis, and a route into the ordinary procedures if a misconduct concern persists. The absence of a detector does not answer those questions.

## Teacher Authority and the Limits of Delegation

ETH Zurich's teaching guidelines state that "Performance assessments must be conducted independently and personally." They also make lecturers responsible for their materials and for deciding the permitted role of AI. UCL's categories leave the final assessment decision with the setter. These provisions preserve professional responsibility rather than documenting its wholesale transfer to a platform. The work of defining what independence means for a particular task remains with educators ("AI in Teaching"; "Three Categories").

Vanderbilt's withdrawal notice instructs staff, "If you have concerns about students misusing AI, talk to them about it." The advice restores a role for the educational relationship, but the accompanying suggestion to compare present writing with earlier work still requires a defensible interpretation. A teacher's familiarity can contribute relevant context. It can also carry assumptions about the style a student is expected to sustain. Replacing a machine score with a human impression therefore changes the form of judgment without settling its fairness ("Guidance").

Utrecht's resource by Koenders and Hsiao offers a further limit: "Having full certainty is therefore not the goal of this meeting." The statement concerns oral inquiry into authorship and understanding. Its significance is that the conversation is not presented as an instrument capable of establishing an entirely pure boundary between human and machine contributions. When concern remains, the resource directs staff toward established examination procedures. Professional judgment is retained, but its purpose and authority require explanation (Koenders and Hsiao).

These provisions distribute substantial discretion to teachers. The risk is that autonomy is paired with responsibility for interpreting uncertain indicators and explaining a decision under pressure. Academic judgment needs support through clear expectations and procedural review; it should not be romanticized as automatically impartial. The proposed concept concerns the conditions of that judgment, including cases where institutional demands make defensibility more salient than educational understanding.

## Performative Authenticity and Process Evidence

UCL's library guidance instructs students to "Retain drafts of your work so you can evidence your process." This is a concrete movement from a finished submission toward an account of its production. A draft can illuminate revision, but the quoted rationale also anticipates a need to substantiate that process. The same artifact can support feedback or a defense of authorship. The wording alone does not show which function dominates in a particular course ("Acknowledging").

Utrecht makes another distinction explicit. Its account of a sampled oral check states that this is "not a grade determining part of the examination." This separates a verification procedure from the original marking judgment, while the resource also requires clarity about its purpose and handling. The separation can protect students from an undeclared change in assessment. It also makes visible an additional institutional task that a student may have to complete after submitting written work (Koenders and Hsiao).

Vanderbilt's recommendations to "Incorporate personal reflections" and "Scaffold assignments" connect process evidence to the prevention of misuse. These forms can create opportunities for learning. Their use as signs of authentic production introduces another possibility: students may learn to narrate a credible process without that narrative establishing the quality of their understanding. Reflection is not self-validating. Its assessment needs to consider the reasons offered and their relationship to the work, rather than its fluency or conformity to an expected personal voice ("Academic Integrity and Generative AI").

Performative authenticity describes that possible separation between an explanation's institutional credibility and its educational substance. It does not imply that declarations or staged submissions are inherently oppressive. A selective explanation tied to the learning outcome can be valuable. A demand for an extensive history that cannot be questioned may impose a different burden, especially where students have unequal confidence in describing their work in the expected language. The corpus establishes the availability of these documentary expectations, not the distribution of their effects.

## Compliance as Learning and Institutional Responsibility

ETH Zurich calls for AI use to be "made transparent at all times," while also allowing course rules to be "jointly developed and subsequently documented." The first formulation extends visibility; the second permits participation in determining the rule. Their coexistence is important. A requirement that appears extensive when isolated may be accompanied by a practice through which students can understand or influence it. The task for analysis is to examine that relationship, rather than classify every demand for transparency as obedience ("Academic Integrity").

UCL's categories quote an institutional protection under which evidence of use without clear direction "will not be penalised." Here the university accepts a consequence for failing to explain its own expectations. That provision places a limit on the idea that students alone must manage uncertainty. Oxford likewise requires assessment setters to define permission and declarations. The relevant form of accountability is reciprocal: students must follow a clear rule, while staff must make the rule educationally and procedurally defensible ("Three Categories"; "AI Use").

The five themes therefore do not show that compliance has replaced learning throughout the selected institutions. They identify a contest over what makes work credible and who must explain a decision. The risk of algorithmic compliance pedagogy becomes sharper where

writing signals or process records are detached from the assessment purpose and treated as proof of a student's legitimacy. The counterexamples show that institutions can also limit this risk through explicit permission, restrictions on detection, dialogue, and duties placed on the assessor.

This interpretation identifies a risk of algorithmic compliance while setting a boundary around the claim. The policies invite particular forms of conduct; they do not demonstrate that students have become obedient or that educational relationships have ceased to matter. Whether students learn primarily to defend themselves, and whether some groups face more frequent demands to do so, remains an empirical question. The documents specify where that question should be investigated and what competing institutional commitments need to be considered.

## Discussion

### What the Concept Explains

The analysis locates the problem in the organization of judgment. Detector withdrawal can coexist with requirements to keep records, narrate a process, and answer questions about changes in style. This combination shows why the debate should extend beyond the accuracy of a particular tool. An institution may restrict automated classification while preserving expectations shaped by the effort to distinguish generated from supposedly authentic writing. The educational issue is how those expectations are connected to an inference about competence or conduct.

Algorithmic compliance pedagogy is useful when it identifies that connection precisely. It would become too broad if every disclosure counted as surveillance, or every request for an explanation counted as mistrust. The corpus contains examples of guidance that seeks to protect students and clarify learning. The concept should therefore distinguish a justified account of work from an unlimited demand to remain above suspicion. The interpretation depends on the task, the evidence sought, and the consequences of failing to provide it.

The strongest contribution of the comparison is the possibility of suspicion migrating across forms of verification. A score can be rejected while a stereotype about generated writing remains influential in human assessment. This does not make the stereotype an algorithm in the technical sense. It shows how expectations associated with machine classification may travel into professional practice. The analytical connection must be established through particular instructions, such as those concerning tone and continuity of style, rather than inferred from the mere presence of an integrity policy.

### The Legitimate Case for Verification

Universities have obligations that trust alone cannot discharge. A qualification communicates a claim about attainment to other students, employers, professional bodies, and the public. Where a student outsources the competence being assessed, awarding credit can misrepresent what has been demonstrated and disadvantage peers who completed the task within its rules. There is therefore a strong educational and institutional case for checking whether an assessment supports the judgment made from it. Vanderbilt's guidance explicitly connects integrity with the credibility of a degree; Utrecht distinguishes the consequences of formative and summative assessment ("Academic Integrity and Generative AI"; Koenders and Hsiao).

That case does not justify every method of checking. A detector classification, an inconsistency in style, and an inability to answer an unexpected question have different evidentiary limits. The institution needs to identify the intended learning, the assistance

permitted, and the reason for concern before deciding what further evidence is proportionate. It also needs to explain how a student can respond. Verification can sustain trust when it makes a defensible judgment possible; it can damage trust when uncertainty is converted into a burden that the student cannot reasonably discharge.

The 2026 detector study makes this argument more demanding. If some systems perform better in specified conditions, criticism cannot rest only on the assertion that detection never works. The relevant institutional question remains whether a tool is suitable for the particular use and whether its output supports the decision under consideration. Evidence of AI-associated text is not, by itself, evidence of unauthorized assistance. Even a more accurate instrument does not settle the educational rule or replace an accountable assessment process (Van Vlasselaer et al. 15-17).

## Proportionate Documentation and Academic Judgment

Four considerations follow from the comparison. The first is the connection to learning. A revision account should show something relevant to the outcome, such as how a student evaluated evidence or changed an argument. If the record adds little information about understanding, its purpose needs examination. The second is proportionality: a limited selection of drafts or decisions may be enough, whereas a complete interaction history can expose unnecessary material and create substantial work for both student and assessor. These are proposals arising from the analysis, not evaluated interventions.

The third consideration is institutional responsibility. Students should not have to infer the acceptable role of AI from conflicting examples or the preferences of an individual marker. The selected guidance contains commitments to clarify permission and support access. Those commitments should be examinable alongside compliance requirements. An institution's use of AI in teaching or feedback also needs explanation. Reciprocal transparency gives students a basis for understanding why assistance is legitimate in one part of an educational relationship and restricted in another.

The fourth is the opportunity to contest an inference. A student should be able to understand why further proof is being requested and offer an account that is considered on its merits. A concern about writing needs to remain open to other explanations, including development, feedback, and permitted support. This does not oblige an assessor to accept every explanation. It requires an institution to state the grounds for its judgment and to connect any consequence to the relevant rule and procedure. Documentation becomes educationally defensible when it contributes to that process.

## Language and the Limits of the Evidence

The concern about multilingual writers must be kept distinct from a claim about all international students. Language background, nationality, and familiarity with an institution are different dimensions. The earlier detector research establishes specific classification problems. The policy passages on tone and style show possible occasions for a burden of explanation. Neither source demonstrates the rate at which particular student groups are investigated across these six universities. Treating the risk as a research question is stronger than repeating an unequal-impact claim without the evidence needed to assess it.

Future research should examine the routes through which concerns are raised, the explanations students provide, and how decisions are reviewed. It should distinguish selection for an interview from a misconduct finding, and both from a learning outcome. Work with

multilingual writers could explore how students explain changes in their writing and whether the requested evidence is accessible. Such research would test whether the formal safeguards identified here operate in practice, as well as whether informal judgments produce burdens the published guidance does not acknowledge.

The same restraint applies to teacher authority. The corpus shows instructions and responsibilities, not staff behavior or workload measured over time. Professional discretion can be supported by the rejection of an unreliable score, yet made difficult by ambiguous expectations about authorship. A critical approach needs to investigate both possibilities. Educational leadership should provide the conditions for defensible judgment instead of assuming that a policy, a platform, or an individual teacher can remove uncertainty altogether.

## Conclusion

This study has examined how ten public documents from six universities make AI assistance permissible, visible, and open to inquiry. The documents do not support a general claim that universities have replaced pedagogy with automated policing. They contain restrictions on detectors, recognition of professional judgment, and commitments to clearer assessment design. At the same time, their instructions about style, draft retention, and oral explanation show how authorship can remain an additional object of institutional verification after automated detection is rejected.

Algorithmic compliance pedagogy identifies a risk within that arrangement. It concerns situations in which conformity to an authorship signal or a documentary expectation becomes more significant than the learning being assessed. The present evidence supports examination of this risk, not a conclusion that the selected universities produce obedient learners. Its effects on students and staff require investigation through experiences and decisions that policy documents alone cannot provide.

The practical implication is that verification should be connected to a stated learning purpose, proportionate evidence, and an accountable institutional judgment. Students have responsibilities for their work, while universities have responsibilities for the clarity of their rules and the grounds on which they question a submission. Protecting academic integrity requires both. A university can ask a student to explain a piece of work while remaining willing to explain, and review, its own reasons for doubt.

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## Appendix A: Corpus Register

A containing guide's timestamp is not treated as a date for every individual section. Full source details, including URLs, appear in Works Cited. Linked documents and external references mentioned by a page are not automatically additional corpus items.

| ID | Institution and country | Document and status | Visible date or update information |
|---|---|---|---|
| **P1** | University College London, United Kingdom | Three Categories of GenAI Use in Assessment<br>Assessment design guidance; explicitly not a formal policy<br>Passages examined: guidance; categories of assessment; notes on academic integrity | Undated live page; announces review during 2026/27 |
| **P2** | University College London, United Kingdom | Engaging with Generative AI in Your Education and Assessment<br>Student assessment and integrity guidance<br>Passages examined: GenAI and academic integrity | Undated live page; announces review during 2026/27 |
| **P3** | University College London, United Kingdom | Acknowledging the Use of Generative AI and Referencing Generative AI<br>Library guidance on acknowledgment and documentation<br>Passages examined: considerations for using generative AI; how to acknowledge use | Section undated; containing guide timestamp 29 July 2026 |
| **P4** | University of Oxford, United Kingdom | AI Use in Summative Assessment<br>University assessment policy<br>Passages examined: staff requirements 1-6; student requirements 7-9; three principles | Page last updated 27 October 2025; displayed review date 2 July 2026 |
| **P5** | Utrecht University, Netherlands | A Follow-up Oral Process Interview: What It Is and What It Should Not Be<br>Teaching and examination guidance by Laura Koenders and Ya-Ping (Amy) Hsiao<br>Passages examined: assessment purposes; random interview before grading; targeted cases; communication | Undated live page; publication date not inferred from acknowledgment |
| **P6** | ETH Zurich, Switzerland | AI in Teaching and Learning<br>Institutional teaching and learning guidelines<br>Passages examined: generative artificial intelligence; responsibility; transparency; fairness | Explicit update notice December 2024 |
| **P7** | ETH Zurich, Switzerland | Academic Integrity<br>Guidance on integrity and originality declarations<br>Passages examined: integrity as an attitude; scientific work; declaration options; technical recognition | Undated live page |
| **P8** | Vanderbilt University, United States | Guidance on AI Detection and Why We're Disabling Turnitin's AI Detector<br>Dated decision notice and teaching guidance<br>Passages examined: decision rationale; advice following withdrawal of detector | 16 August 2023 |
| **P9** | Vanderbilt University, United States | Academic Integrity and Generative AI<br>Institutional teaching and integrity FAQ<br>Passages examined: instructor policy; proactive strategies; detection advice; Honor Council guidance | Undated live page |
| **P10** | University of Waterloo, Canada | Discontinuing Use of AI Detection Functionality in Turnitin: September 2025<br>Decision notice and guidance for instructors<br>Passages examined: rationale for this decision; content redesign and academic integrity | September 2025 (effective date in the title; no publication date shown) |

## Appendix B: Document Contributions to the Five Themes

The matrix records documents used in developing each theme, including protections and counterexamples. A mark indicates a contribution to the interpretation, not endorsement of surveillance or evidence of an observed educational effect. An empty cell means the document was not used for that thematic comparison; it is not a claim that the institution lacks the relevant practice. Each document is counted once within a theme.

| Document | T1 | T2 | T3 | T4 | T5 |
|---|---|---|---|---|---|
| **P1** | 1 | 1 | 1 | | 1 |
| **P2** | 1 | 1 | | 1 | |
| **P3** | | | | 1 | |
| **P4** | 1 | 1 | 1 | 1 | 1 |
| **P5** | | | 1 | 1 | 1 |
| **P6** | 1 | | 1 | | 1 |
| **P7** | 1 | 1 | 1 | 1 | 1 |
| **P8** | | 1 | 1 | | 1 |
| **P9** | 1 | 1 | 1 | 1 | 1 |
| **P10** | | 1 | | | 1 |
| **Total** | 6 | 7 | 7 | 6 | 8 |

T1 = Integrity as suspicion and conditional permission; T2 = Detection before dialogue reconsidered; T3 = Teacher authority and the limits of delegation; T4 = Performative authenticity and process evidence; T5 = Compliance as learning and institutional responsibility.




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# The Effect of AI-Powered Adaptive Tools on Vocabulary Acquisition among University Students: A Systematic Review

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## ABSTRACT

Recently, the use of AI technologies in education has rapidly developed and yielded crucial outcomes in different tasks, and it has become an effective educational approach that provides flexible and personalized learning experiences (Chu et al. 23). In the context of English as a Foreign or Second Language, educational technologies may provide new opportunities for supporting university students' vocabulary acquisition, although their effectiveness varies across learning contexts. This systematic review explores how AI-powered adaptive platforms affect vocabulary acquisition among EFL/ESL university students, uncovering specific tools, AI features, outcomes, and challenges. Following a systematic review protocol, empirical studies indexed in Scopus, Web of Science, and ERIC were screened according to predefined inclusion and exclusion criteria. This review included 29 empirical studies published between 2024 and 2026. The findings show that there is an increase in research on AI-based vocabulary acquisition, especially in Asian countries. ChatGPT emerged as the most frequently used AI tool, and the reviewed studies reported that the use of AI enhances vocabulary acquisition by providing personalized learning, immediate feedback, and contextualized content. However, the quality appraisal identified some methodological limitations across the evidence base, and a number of challenges associated with AI use were also identified, suggesting that teacher guidance remains crucial to ensure the effective use of AI-powered tools in vocabulary acquisition.

## KEYWORDS

**Artificial Intelligence**

**Adaptive Learning**

**Vocabulary Acquisition**

**University Students**

## Introduction

In recent years, the development of educational technologies has led to a growing interest in the application of artificial intelligence in the field of education among the public, policymakers, and academia (Chu et al. 22). AI in education includes a range of technologies, such as machine learning, Natural Language Processing (NLP), and generative AI. These technologies support the development of e-learning platforms that use various adaptive learning techniques, including intelligent tutoring systems, learning analytics, and personalized learning paths. These systems provide contextualized content, immediate feedback, and personalized learning in a flexible way (Gligorea et al.).

Research in the field of second language acquisition has underscored the significance of vocabulary knowledge in overall language proficiency. In fact, it is considered a foundational aspect of language learning and crucial for effective communication and comprehension in a

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second or foreign language context (Nation). However, many students still experience a number of challenges related to vocabulary learning, such as struggling with the meaning of words and their pronunciation (Behforouz et al., "Effect of AI-Based Instruction" 2). After the emergence of AI as an effective educational tool, it has become increasingly used among language learners who aim to improve their vocabulary, grammar, writing, reading and speaking skills (Maghsoudi 53). As a result, a growing number of studies have investigated the effectiveness of AI-powered tools on vocabulary acquisition.

This systematic review is grounded in sociocultural theory and cognitive load theory. The Sociocultural Theory (SCT) views learning as mediated by tools that provide support within the learner's zone of proximal development (Vygotsky), while the Cognitive Load Theory (CLT) explains why such support matters for learning new material (Sweller). Together, these frameworks hold that AI may serve as a scaffold that reduces the extraneous load since it offers help to acquire new information through assistance until it is not needed anymore (Koka et al.; Abdelhalim and Alsehibany). In this review, these theories serve as interpretive lenses for organizing and synthesizing the reported features and learning outcomes. From an SCT perspective, the coding focused on features that reflect interaction, scaffolding and feedback to see how AI-based platforms may facilitate vocabulary learning through mediated interaction. From a CLT perspective, the coding considered features related to the presentation of vocabulary items, personalization and the potential reduction of extraneous cognitive demands.

Although previous systematic reviews focused on the use of AI-based platforms in language learning generally, there are few reviews that addressed their effect on vocabulary learning (Yang; X. Chen). Also, they did not specifically synthesize which adaptive mechanisms affect vocabulary acquisition in higher education. To address this gap, the present review asks:

**RQ1:** What are the demographic and methodological characteristics of research on AI-based vocabulary learning among university students?

**RQ2:** What is the effect of AI-powered tools on L2 vocabulary acquisition among EFL university students compared to traditional learning methods?

**RQ3:** Which AI tools and adaptive features are associated with positive vocabulary acquisition outcomes?

## Literature Review

### Artificial Intelligence (AI) in Education

The field of AI is mainly responsible for using computers to study and mimic human intelligence and the associated thinking abilities. In other words, AI attempts to enable machines to observe and learn from humans and solve problems from the existing problem-solving techniques in addition to developing new solutions through experience (Kaliraj and Devi 5). Artificial Intelligence in Education (AIED) encompasses a number of AI-based tools and technologies that support learning and teaching, including AI-driven, personalized instructional and dialogue systems, learning analytics, game-based learning, chatbots, and AI-powered adaptive learning that enables students to become autonomous learners. Additionally, it includes mobile-assisted learning outside the classroom and real-time feedback (Holmes et al. 82).

The field of AIED is informed by other domains and based on theories from various disciplines, such as AI, cognitive science, and education. Simultaneously, it creates its own research questions that address the nature of knowledge, the way students can learn, and the most effective and suitable teaching practices. In this regard, AIED tools embody particular learning theories, such as Vygotsky's "zone of proximal development." That said, some AIED researchers have questioned the foundations of those theories, using AI and data analysis

techniques to explore the hidden processes of learning (Holmes et al. 82). In essence, AIED successfully combines two primary strands: creating AI-powered tools to improve learning, and leveraging these tools to better grasp learning, and how it actually occurs and to determine which learning methods are more effective in either AI-supported or non-AI-supported classrooms (83).

Adaptive learning is a pedagogical approach that makes use of technology to adjust to each student's specific needs and progress. It offers personalized learning, which is supported by machine learning algorithms, and it adapts the content and the learning pace to the learner's performance and level. Therefore, adaptive learning fosters learning gains and enhances engagement. In the context of e-learning, adaptive learning is understood as addressing students' needs through the use of intelligent systems that personalize the learning experience, such as the content, activities, and assessment. Its main objective is to adapt the learning process in real time according to the learner's progress and level. This goal is achieved by the constant analysis of the learner's data and progress tracking. Consequently, as adaptive learning is becoming a popular option for teachers and educators, they need to be trained to efficiently use AI-powered platforms (Gligorea et al.).

## AI-Based Vocabulary Acquisition

AI plays a significant role in improving the teaching-learning process, helping teachers in creating better teaching strategies, and providing students with an adaptive and improved learning environment. To illustrate, AI can cater to students' different levels and abilities through diagnostic testing and thus create a personalized curriculum. In this way, it is possible to address the drawbacks of the traditional educational models that do not take into account the different educational backgrounds (Kaliraj and Devi 13-14). Similarly, AI is also improving vocabulary instruction by providing personalized, real-time, and context-specific practice opportunities (Maghsoudi 56). Unlike traditional vocabulary teaching methods that rely heavily on memorization, AI tools are based on contextual analysis and scenario-based activities, allowing learners to use vocabulary in practical and authentic environments (Huang et al.).

Another distinction is worth noting: traditional EFL vocabulary acquisition often entails using specific vocabulary exercises, such as fill-in-the-blanks, matching, and sentence creation. Repeated testing and practice are deemed essential tools for evaluating learning outcomes. However, learners differ in their language proficiency, learning abilities and styles, and learning needs. Thus, a unified teaching plan and content would not be suitable and efficient for all students. As a solution, using AI in EFL vocabulary teaching provides educators with an analysis of learners' data, such as performance, accuracy and the time spent on tasks, in order to identify their linguistic strengths and weaknesses, resulting in a comprehensive assessment of their abilities. Based on these data, teachers can design personalized learning materials that meet students' needs. Besides monitoring learners' progress, AI systems can analyze behavioral data to support instruction (Wang et al. 131894).

Yet, limited attention has been given to synthesizing the effect of AI-based technologies on vocabulary learning, especially in the context of higher education. Thus, the present systematic review addresses this gap by examining the use of AI-powered and adaptive tools for EFL/ESL vocabulary learning and synthesizing their reported features, adaptive mechanisms, and effects on vocabulary-related outcomes.

## Methodology

This review is based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al.), using a systematic approach that involves a structured search strategy, study selection, which involved applying inclusion and exclusion criteria, and data synthesis. First, the search string was developed based on the study questions, and three databases were selected to yield a suitable literature search. Second, inclusion and exclusion criteria were also established based on the three study questions, and they guided the selection of appropriate articles and conference papers and the exclusion of irrelevant studies. Finally, the methodological quality of the included studies was appraised, and the results were coded from these studies to answer the research questions and address gaps and limitations. All these stages of the review process were conducted by a single reviewer.

### Search Strategy

To conduct this systematic review, three databases were used: Scopus, Web of Science, and ERIC. These databases were selected based on their frequent use in other systematic reviews in the same research area (Yan et al.; Simonnet et al.). Indeed, Web of Science (WoS) and Scopus are considered the most reliable databases that are widely used as the most comprehensive data sources for academic publications (Pranckutė 1). In the educational field, the Educational Resources Information Center (ERIC) is regarded as the leading subject-specific database (Fitzgerald 30).

In April 2026, the search was executed on the mentioned databases using the following Boolean search string: (“Artificial Intelligence” OR “AI” OR “Adaptive Learning” OR “Machine Learning”) AND (“Vocabulary Acquisition” OR “Vocabulary Learning”). This resulted in 790 records before removing duplicates. All the references from the three databases were exported to Rayyan, which is a web and mobile tool used for screening studies (Ouzzani et al.).

### Study Selection

As shown in Figure 1, in the selection process, 210 duplicates were removed from the 790 studies identified through searches on the mentioned databases. Therefore, 580 studies were screened based on the inclusion and exclusion criteria. In the first screening, 580 papers’ titles and abstracts were screened. After that, the 40 papers included in the first screening were retrieved for full-text screening. Finally, 29 papers that met the inclusion and exclusion criteria were selected for this systematic review.

The PRISMA flowchart (Figure 1) illustrates the whole data extraction process. After retrieving the 40 papers, 11 studies were excluded during eligibility assessment for the following reasons: wrong target population (n=1), focusing on a different intervention type (n=4), absence of empirical data (n=4), and not focusing on vocabulary acquisition as a dependent variable (n=2).

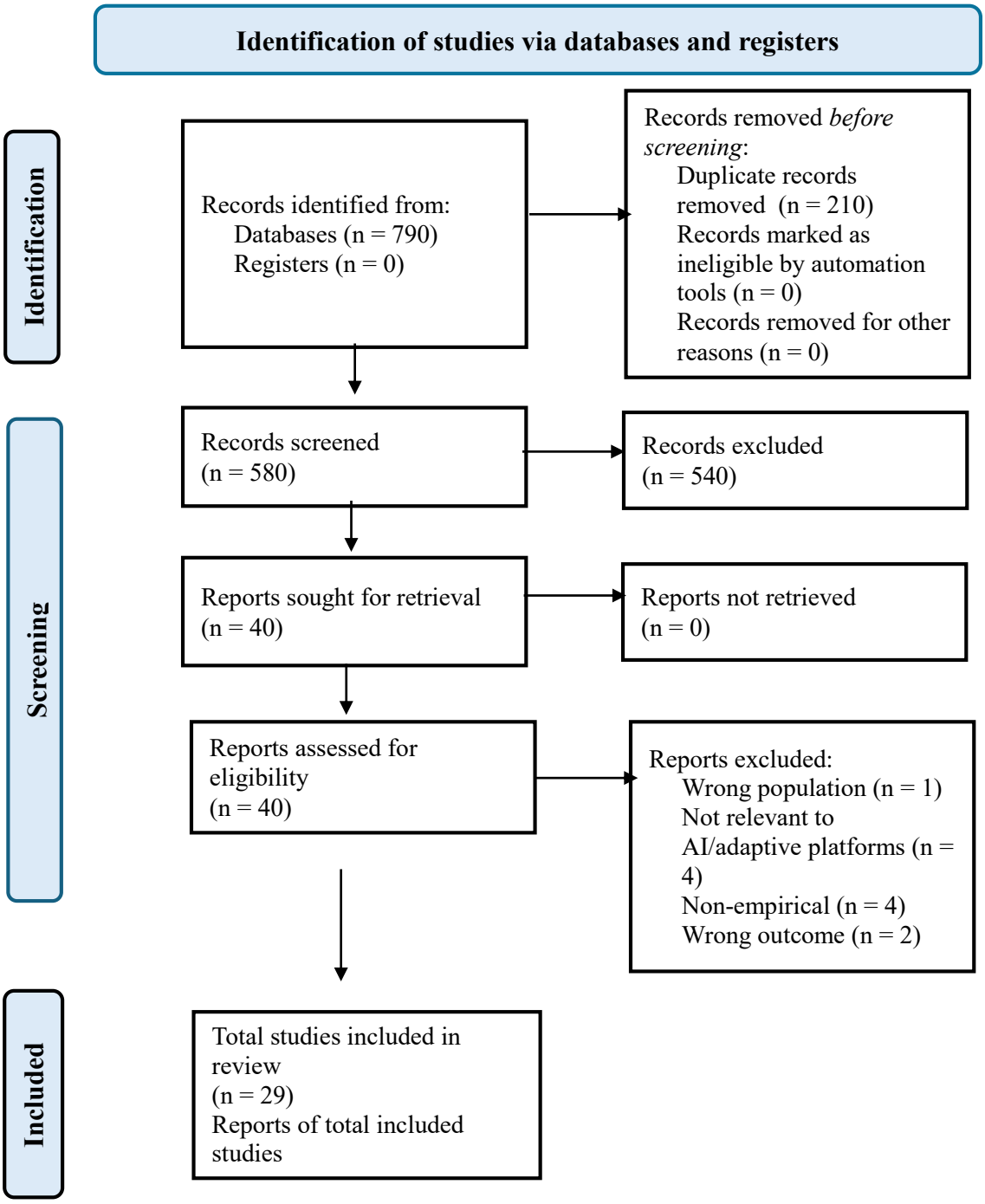



**Fig. 1.** PRISMA Flow Diagram

## Inclusion and Exclusion Criteria

These criteria were defined using the PICOS framework (Figure 2), which includes population, intervention, comparison, outcomes, and study design.

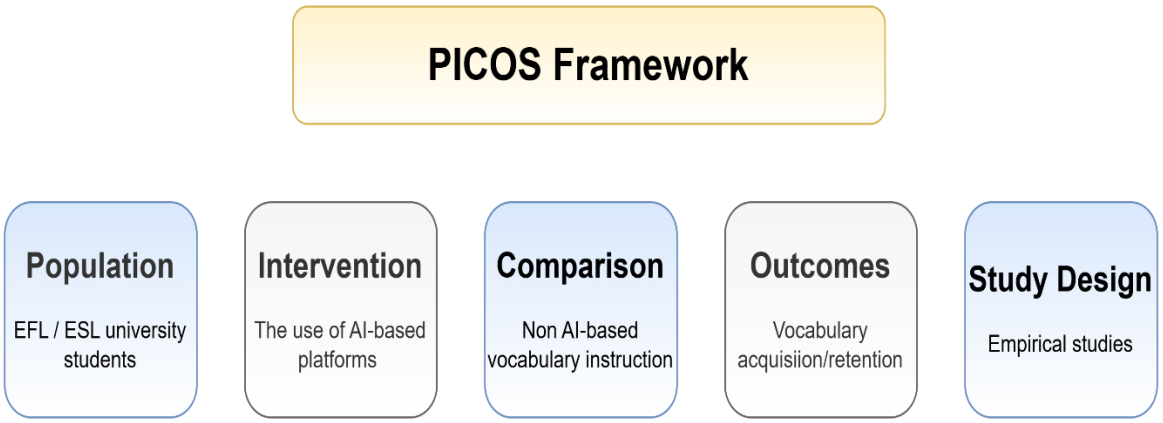



**Fig. 2.** PICOS Framework

## Inclusion Criteria

Journal articles and conference papers which adhere to the following inclusion criteria were included. To begin with, the study must address university students (undergraduate or graduate students) who are learning English as a second or foreign language, must be written in English, and must evaluate specific AI technologies used for vocabulary acquisition. Additionally, the study must measure specific outcomes related to vocabulary acquisition, such as word retention, receptive and productive knowledge, or vocabulary depth and breadth. More importantly, the study must be published in the last five years (between 2022 and 2026).

## Exclusion Criteria

Book chapters, systematic reviews, meta-analyses and non-empirical studies are excluded. Studies must not focus only on traditional Computer-Assisted Language Learning (CALL) or Mobile-Assisted Language Learning tools without AI features. Moreover, they must not target primary or secondary education since this study focuses only on higher education. Finally, studies that measure general language proficiency without providing specific vocabulary outcomes are also excluded.

## Data Extraction and Analysis

A data extraction and coding process was conducted to systematically organize information from the selected studies. Data were extracted using a predefined coding Excel sheet developed by the researcher. Each study was coded according to publication details, number of participants and their characteristics (age and level), country, the AI tools used, research design, study context, treatment period, vocabulary dimension, number of target words, and outcomes. Through the coding process, themes were identified and a thematic analysis was employed to analyze the findings of the selected studies. Reflexive thematic analysis was used to identify, analyze and report the existing themes. As Braun and Clarke (79) stated, this type of analysis aims to organize data and represent it in a detailed way, and find themes that are related to the effect of AI-based platforms on vocabulary acquisition.

### Quality Appraisal

Methodological quality appraisal was done by the first author, using the Mixed Methods Appraisal Tool (MMAT), which is designed for systematic reviews that include qualitative, quantitative and mixed methods studies. The tool includes two initial screening questions, and then the appropriate five MMAT criteria are applied according to each study's research design (qualitative research, randomized controlled trials, non-randomized studies, quantitative descriptive studies, or mixed methods studies). Each criterion was assessed as "Yes", "No", or "Can't Tell". Since it is not advised to calculate an overall quality score, the appraisal findings were used to find methodological strengths and limitations across the included studies (Hong et al. 1).

After using the MMAT, the appraisal revealed that there is variation across the methodological criteria and study designs. Overall, most studies met several of the MMAT criteria. However, there were some recurring methodological limitations, particularly regarding sample representativeness, instrument validity and reliability, and control of confounding variables. To exemplify, most studies drew from a single institution, which limits generalizability. Also, in the non-randomized studies, confounder control is absent, so the vocabulary outcomes might be affected by variables other than the AI tools used. Additionally, some studies do not provide information on the validity and reliability of instruments, such as Cronbach's alpha or the use of standardized instruments. Also, blinding is essentially absent in most experimental studies, with only Shobeiry and Namaziandost reporting blinded instructor delivery status. Detailed data extraction and study-level MMAT appraisal results are provided in the supplementary materials.

## Results

### RQ1: What Are the Demographic and Methodological Characteristics of Research on AI-Based Vocabulary Learning among University Students?

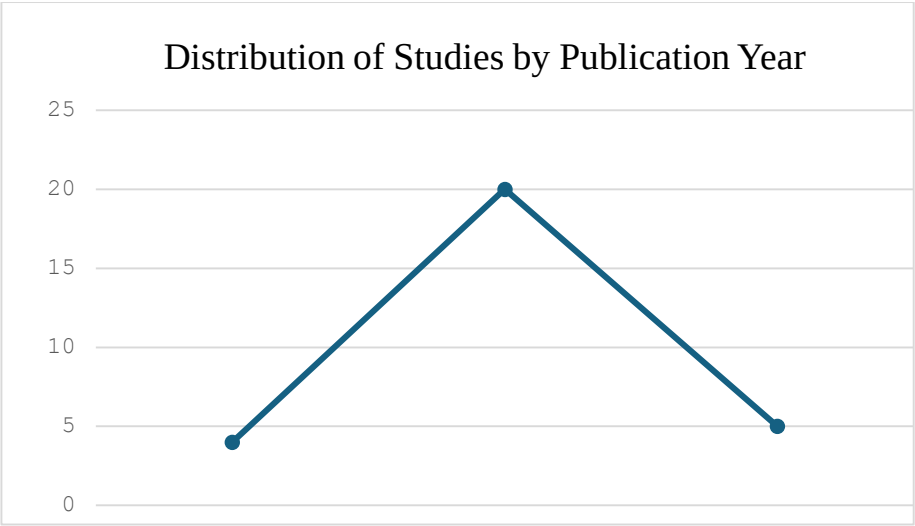



**Fig. 3.** Frequency of Publication Years

Figure 3 illustrates the distribution of included studies by publication year.

As shown above, all of the selected studies were published between 2024 and 2026, and the largest number of studies (n=20) was published in 2025, followed by 2026 (n=5) and 2024 (n=4). This indicates that researchers have become increasingly interested in the use of AI-powered tools for vocabulary acquisition over the last three years.

Figure 4 shows the geographical distribution of the included studies according to the participants' countries.

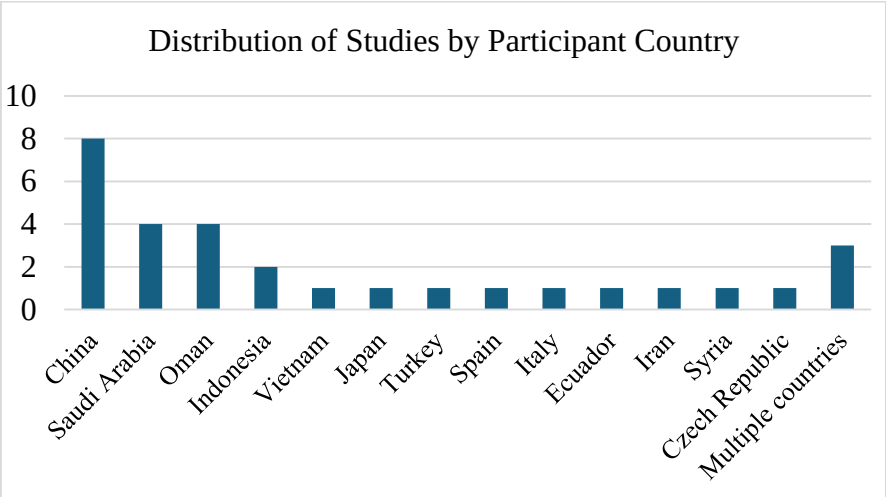



**Fig. 4.** Participants' Countries

Figure 4 illustrates the geographical distribution of the included studies according to participants' countries. The highest number (n=8) of studies was conducted in China, followed by Saudi Arabia (n=4) and Oman (n=4). Other studies were conducted in Vietnam, Japan, Turkey and several additional countries. Overall, this suggests that research on AI-based vocabulary learning is centered in Asian and Middle Eastern educational contexts.

Table 1 summarizes the research methodology employed across the included studies.

**Table 1**
Research Methodology

| Research Methodology | Frequency |
|---|---|
| **Mixed methods** | 17 |
| **Quantitative** | 12 |

The methodological landscape, as shown in Table 1, is dominated by the use of mixed-methods approaches (n=17) and quantitative studies (n=12), which can be divided into surveys, quasi-experimental, and comparative experimental studies. Mixed methods studies were based on

quantitative and qualitative methods, such as quasi-experiments, surveys, observation, learning-platform data and interviews. For instance, Abdelhalim and Alsehibany used a quasi-experimental pre- and post-test design followed by semi-structured interviews, whereas Jácome Paredes et al. combined closed-ended and open-ended questions in an online survey to explore students' experiences. Concerning quantitative studies, Kheder utilized a questionnaire to determine the participants' perspectives towards the use of AI in vocabulary learning while Ng et al. employed a quasi-experimental design to investigate the effect of Copilot AI on vocabulary development.

The included studies involved undergraduate university students whose ages ranged from 18 to 34 years, where reported. Sample sizes ranged from 31 to 600 participants with an average sample size of 121.27. In terms of language proficiency, most participants had a pre-intermediate or intermediate level in English. Still, a few studies included learners at other levels, such as A1 and C1.

### RQ2: What Is the Effect of AI-Powered Tools on L2 Vocabulary Acquisition among EFL University Students?

The number of target vocabulary items ranged from 20 to 100 words with an average of 58.77 words. The treatment period ranged from three to sixteen weeks, with most experiments lasting for four weeks (Behforouz and Al Ghaithi; Namaziandost and Çakmak; Morgana and Poli; Koka et al.; Ng et al.). Among the studies that specified which dimensions of vocabulary knowledge are tackled, receptive and productive vocabulary were the most frequently investigated, while fewer studies focused on vocabulary depth. To exemplify, Abdelhalim and Alsehibany, Y. Chen, and Hao et al. examined the effect of AI-based tools on receptive and productive vocabulary, whereas Morgana and Poli focused on spoken academic collocations as an indicator of vocabulary depth.

Table 2 summarizes the vocabulary, affective, and self-regulation outcomes reported across the included studies. Since individual studies could report multiple outcomes, the outcome categories are not mutually exclusive. Thus, frequencies do not sum to the total number of included studies.

**Table 2**
Reported Outcomes

| Outcome Category | Reported outcome | Frequency |
|---|---|---|
| **Vocabulary Outcomes** | Increased vocabulary acquisition | 11 |
| | Increased productive vocabulary | 6 |
| | Increased receptive vocabulary | 4 |
| | Long-term vocabulary retention | 5 |
| | Short-term vocabulary learning | 2 |
| | Incidental vocabulary learning | 2 |
| | Increased engagement | 7 |

| Outcome Category | Reported outcome | Frequency |
|---|---|---|
| **Affective Outcomes** | Motivation | 2 |
| **Self-regulation Outcomes** | Autonomy | 4 |
| | Metacognitive strategy use | 2 |

Most of the selected studies reported that the use of AI-powered tools yielded positive vocabulary outcomes, particularly in improving productive and receptive vocabulary knowledge (n=10), and increasing long-term vocabulary retention (n=5) while other studies (n=11) did not specify which dimensions are positively affected. Additionally, AI-supported vocabulary learning also led to boosting engagement (n=7) and motivation (n=2) and enhancing self-regulated learning, especially autonomy (n=4) and metacognitive strategy use (n=2). Overall, the findings suggest that the use of AI by university students improves not only vocabulary acquisition but also students' affective factors and self-regulation skills.

### RQ3: Which AI Tools and Adaptive Features Are Associated with Positive Vocabulary Acquisition Outcomes?

Table 3 reports the AI-based tool used in each of the included studies.

**Table 3**
Frequency of the Used AI Tools

| AI Tool | Frequency |
|---|---|
| **ChatGPT** | 11 |
| **Quizlet** | 2 |
| **Duolingo** | 2 |
| **Rosetta Stone** | 1 |
| **Conversational Bot** | 1 |
| **AVAR-RL Model** | 1 |
| **Copilot** | 1 |
| **UNIPUS AIGC Platform** | 1 |
| **Kimi** | 1 |
| **QuillBot** | 1 |

| AI Tool | Frequency |
|---|---|
| **AI Chatbot "Doubao"** | 1 |
| **WhatsApp Bot** | 1 |
| **Kahoot** | 1 |
| **Grok 5** | 1 |
| **ELSA Speak** | 1 |
| **Hedra AI** | 1 |
| **Not reported** | 1 |

Table 3 shows the distribution of the used AI tools among undergraduate students. As illustrated, ChatGPT was the most widely used, reported in 11 studies, followed by Quizlet (n=2) and Duolingo (n=2). The remaining tools, including Rosetta Stone, Copilot, QuillBot, and other Generative AI tools and chatbot systems were each reported in a single study. This shows that ChatGPT dominates vocabulary learning research among university students.

Table 4 presents the adaptive AI features that enhance vocabulary learning. The most commonly reported features involved feedback, personalization and contextualized learning. Feedback was provided through immediate and real-time responses, while personalization enabled students to learn vocabulary according to their individual needs. Other studies, especially the ones using AI chatbots, employed conversational interactions to enable students to engage in dialogues. Additional features included progress tracking, speech recognition, gamification, spaced repetition and content generation.

**Table 4**
Reported AI Features

| AI Feature | Examples from Included Studies |
|---|---|
| **Feedback** | Real-time feedback, adaptive feedback |
| **Personalization** | Personalized content, learning style adaptation |
| **Contextualized learning** | Context-specific input, visual stories, real-life situations |
| **Interactive learning** | Discussion activities, interactive dialogue, conversation support |
| **Monitoring** | Progress tracking |
| **Speech-based features** | Speech detection and recognition |
| **Spaced repetition** | Vocabulary review |

| AI Feature | Examples from Included Studies |
|---|---|
| **Gamification** | Gamified features such as quizzes |
| **Content generation** | Generating example sentences, authentic content |

## Discussion

### The Rapid Growth of AI-Based Vocabulary Learning Research

This review focused on studies published between 2022 and 2026. However, no eligible studies were found for 2022 or 2023. The findings revealed that there is an increase in publications related to AI-based vocabulary learning among university students in 2025, whereas fewer studies were identified in 2026 since the year is still ongoing during this review's data collection process. Thus, the use of AI in vocabulary acquisition is becoming a key area of research within educational technology. This growth might be attributed to the broader and effective integration of AI into higher education (Abdelhalim and Alsehibany 2) and to the fact that a growing number of researchers are leveraging AI tools to tackle language education problems, such as vocabulary acquisition (Zhang and Huang, qtd. in Hao et al. 4). Despite this rapid growth of research, most studies were conducted in Asian countries, particularly in China. This finding aligns with a previous review conducted by Yan et al., which also indicated the strong concentration of publications in Asia, implying that other regions, such as Africa, do not benefit from the needed infrastructure and funding.

### Dominance of ChatGPT

The results indicate that ChatGPT is the most frequently used AI tool. Several researchers, such as Alsagoor et al., Sawaguchi, Jalambo et al., Behforouz and Al Ghaithi, and Poláková and Ivenz, employed ChatGPT in their studies as it has reshaped AIED since its appearance in 2022. This tool allows learners to get real-time feedback, contextualized examples, and personalized content that matches their level. Therefore, it makes learning more flexible and accessible (Poláková and Ivenz 291).

The dominance of ChatGPT may be also explained by the shift from old rule-based chatbots which were only producing pre-programmed answers to large language models, which provide human-like responses. Although there are many AI language learning tools, ChatGPT is distinguished by its flexibility and accessibility (Karataş et al., qtd. in Abdelhalim and Alsehibany 2). These findings align with prior research which demonstrated that ChatGPT was the most used AI chatbot since it helps learners identify and correct errors, provides feedback, and fosters grammatical and semantic accuracy (Kheder 141).

### AI Improves Vocabulary Outcomes

This review's findings highlight the positive impact of AI-powered tools on vocabulary acquisition among EFL university students. All included studies reported that there was a significant improvement in vocabulary gains after the use of AI, either in or outside the classroom, compared to the use of traditional approaches. These positive effects can be attributed to AI features that allow students to learn while having access to immediate feedback, personalized content, and contextualized examples.

Several studies that were published between 2024 and 2026 (Abdelhalim and Alsehibany; Y. Chen; Zhang and Huang; Koka et al.; Behforouz et al.) showed that AI-powered tools improved vocabulary through immediate, corrective and individualized feedback. In other words, they provide direct corrective learning and adaptation of exercise levels in real-time, which helps to close learning gaps and avoiding the fossilization of errors. Also, a number of studies (Zhang and Huang; Namaziandost and Çakmak; Shobeiry and Namaziandost) highlighted how AI-generated examples, storytelling activities and contextualized sentences improved students' vocabulary, unlike relying on learning isolated words.

Other studies focused on how personalized content improves word retention. AI-powered tools' interactive features can decrease the learners' cognitive load, mirroring Sweller's cognitive load theory, and boost their engagement with the tool, hence enhancing memory retention. Among the factors that affect word retention are the relevant contexts in which a word appears and the use of spaced repetition (Y. Chen; Koka et al.). It was also noted that adaptive learning systems' personalized review positively affects long-term retention (Xiang et al. 823).

Some studies (Abdelhalim and Alsehibany; Smith; Morgana and Poli) suggested that structured and guided use of AI-based tools yielded better vocabulary-related outcomes than solitary use. To illustrate, teacher scaffolding, controlled prompts, and peer interaction contribute to creating more memorable vocabulary learning experiences. This aligns with Vygotsky's sociocultural theory which holds that learners can achieve progress when they are exposed to structured external guidance before moving to autonomous mastery.

In sum, the findings indicate that the effectiveness of AI-powered tools in vocabulary acquisition among university students does not stem from only one feature or factor. Rather, it is the result of the combined effects of immediate feedback, personalization, contextualization, and guided teacher support.

### Increased Engagement and Self-Regulation Skills

Beyond vocabulary gains, many studies (Behforouz et al.; Ahmed et al.) showed that AI also increases learner engagement and motivation. For instance, Zhang and Huang found that students in the experimental group demonstrated higher levels of classroom participation, asked more questions, especially targeting productive vocabulary knowledge, and engaged more actively in vocabulary tasks than those in traditional learning groups (11). Therefore, they focused more on communication, meaning construction, and monitoring their output. In the same vein, Koka et al. revealed that interactive and personalized learning promotes affective dimensions, such as increased motivation and autonomy and reduced boredom, leading to more positive effects on vocabulary acquisition (101). Collectively, these findings indicate that AI-powered tools foster a more engaging and learner-centered learning environment.

### Challenges

Despite the reported benefits of AI-assisted vocabulary learning, there are still challenges that face the use of AI-powered tools. Students stated that they are not confident enough to use the acquired words in their everyday conversations, and some students faced difficulties while communicating with AI chatbots, such as increased anxiety levels. Therefore, teachers should concentrate on including interactive activities to retain students' motivation for a longer exposure period (Poláková and Ivenz; Jalambo et al.). Moreover, there are also concerns about the accuracy of answers, over-dependence on the tools, and insufficient training in using AI-

based tools, indicating that teacher guidance and digital literacy are needed for a better use of these tools (Alsagoor et al.; Ahmed et al.).

Additionally, some researchers note that although students exhibit high levels of engagement and motivation, autonomy alone may not guarantee long-term learning benefits. Ng et al. stated that the absence of teacher scaffolding and structured guidance limited long-term vocabulary retention (10). In this respect, Jalambo et al. mentioned that teachers should be aware of the novelty effect of AI-powered tools. Initial motivation disappears over time when the tools are not novel anymore; this is why it is important to deliberately implement chatbots in learning environments to attain better learning outcomes (14).

## Limitations

A key limitation of this review is that study selection, data extraction and quality appraisal were conducted by a single reviewer rather than independently by two or more reviewers. The absence of an independent second assessment due to time constraints may have introduced some subjectivity into the appraisal and prevented the calculation of inter-rater reliability. This risk was partially mitigated by strictly following the MMAT user guide's definitions for each criterion. Still, future reviews would benefit from independent dual appraisal, as recommended in the MMAT guidance (Hong et al. 1).

Another limitation concerns the geographic distribution of the included studies. Most studies were conducted in China, Saudi Arabia, and Oman, with relatively limited representation of other geographical contexts. This concentration may constrain the generalizability of the findings to other EFL contexts, where educational systems and technological infrastructure are different. Hence, the findings should be interpreted with consideration of the contextual characteristics of the included studies' settings, and future research should focus on investigating the underrepresented areas.

## Conclusion

This systematic review investigated the effectiveness of using AI-powered tools in vocabulary acquisition, with a focus on higher education. Its primary goal was to identify the most commonly used AI tools and features and their impact on vocabulary acquisition. After reviewing 29 studies which were published between 2024 and 2026, with no eligible studies identified for 2022 or 2023, the findings emphasize the potential of AI tools to enhance vocabulary acquisition among university students and increase their motivation and engagement while learning. This review also identified ChatGPT as the most frequently used AI tool and highlighted real-time feedback, personalization and contextualized learning as the most commonly associated AI features with positive vocabulary outcomes. However, the strength of this body of literature is limited by the reliance on single-institution samples in most of the included studies, limited confounder control and inadequate reporting of the reliability and validity of the instruments. Therefore, claims about the effect of AI tools on vocabulary learning should be interpreted with caution since these limitations may affect the generalizability of the findings.

Beyond its potential benefits, this review also highlights the challenges that students deal with when using AI while learning, including over-reliance on AI systems, decreased motivation after long-term usage, and lack of digital training. This underlines the importance of structured integration of AI into vocabulary instruction and implies that AI should be viewed as a complementary educational tool rather than a replacement for teachers. Taken together,

the findings of this review have implications for language teachers, higher education institutions, and students by encouraging the integration of AI into higher education through student-centered approaches. Future research should focus on the long-term effects of AI-based tools on vocabulary acquisition since most studies included in this systematic review lasted for four weeks. More importantly, future studies should address the mentioned challenges while integrating AI into vocabulary instruction.

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# Reframing Prompting Competence as a New Direction for CALL in the Age of AI

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## ABSTRACT

Generative AI is changing language learning and academic writing, leading higher education to choose between resisting AI-mediated writing or adapting curricula to help learners use AI responsibly and effectively. Based on established CALL principles that learning outcomes depend on interaction design, mediation, and learner agency, this paper argues that prompting competence should be seen as a key twenty-first-century communicative skill in AI-mediated settings. It introduces a Prompting Competence Framework (PCF) with six assessable dimensions (intent, contextual grounding, linguistic and rhetorical control, output evaluation and verification, iteration and repair, and ethical responsibility) and a three-phase classroom model (Model, Prompt Studio, Transfer) that makes prompting visible, teachable, and assessable. The paper encourages empirical research on the framework and model across different language skills and contexts.

## KEYWORDS

**AI**

**AI Literacy**

**CALL**

**ChatGPT**

**Generative AI**

**Prompt Competence**

**Prompting Literacy**

## Introduction

Large language models (LLMs) have significantly impacted higher education, influencing students' approaches to drafting, revising, translating, summarizing, and brainstorming in language learning. In language education, a central question is whether curricula will prepare students to use these tools effectively and responsibly. UNESCO's global guidance on generative AI highlights pressing concerns, including privacy, validation, and institutional readiness, and advocates for human-centered capacity building and the safeguarding of human agency (UNESCO, *Guidance*).

The pace of change is rapid. Since the public launch of ChatGPT in late 2022, students have increasingly used chatbots for grammar checking, rephrasing, vocabulary lookup, and speaking practice. Initial reports indicate that LLM-based tools are now present in nearly every area of language teaching (Xiao et al. 301). Many students adopted these tools before teachers had determined appropriate responses. Consequently, AI-mediated learning often occurs privately, without teacher input or observable traces.

This gap between what students do and how institutions prepare for AI use is the focus of this article. In EFL/ESL, Jeon (523) notes both opportunities (like more practice time, quick

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feedback, personalization, and less anxiety for some learners) and challenges (such as hallucinated information, uneven feedback, overreliance, and integrity issues).

These issues have led institutions to respond in different ways, from trying to ban AI to allowing it freely. However, research in computer-assisted language learning (CALL) shows that tools alone do not guarantee learning; outcomes depend on task design, mediation, feedback, learner agency, and assessment alignment (Mohamed Ahmed 159).

CALL is well suited to address these issues. For over forty years, CALL researchers have studied how technology changes language learning, showing that a tool's value depends on how it is used (Chapelle 83). Bax (23) described CALL's evolution as moving toward "normalisation," where technology is so integrated that teachers and learners barely notice it. Generative AI is quickly reaching this point. As technology becomes normal, the main question shifts from "Should we allow it?" to "What do learners need to know and do to use it well?"

This study suggests a curriculum response: prompting competence, meaning the ability to create, interpret, evaluate, and refine prompts and outputs, should be taught and assessed as part of communicative competence in AI settings. Prompting is not just about getting better results; it is a language-based practice involving setting goals, adapting to the audience, negotiating meaning, and being careful about truth and accuracy. This paper brings together a theoretical basis for treating prompting as an assessable CALL outcome and proposes a framework and classroom model.

The article is guided by three questions: (1) How can prompting be described as a communicative competence, not just a technical skill? (2) Which parts of this competence can teachers observe and assess in language classrooms? (3) How can a course organize teaching, practice, and assessment to make AI use visible and accountable? The article is conceptual and does not present new data. Instead, it uses research in CALL, applied linguistics, AI in education, and human–computer interaction to build its argument and proposal.

The rest of the article includes a literature review on why prompting belongs in CALL and its links to mediation, communicative competence, prompt literacy, and AI literacy. Later sections introduce the Prompting Competence Framework (PCF), a three-phase classroom model, and an analytic rubric. The article ends with discussions of academic integrity, teaching implications, limitations, and future research directions.

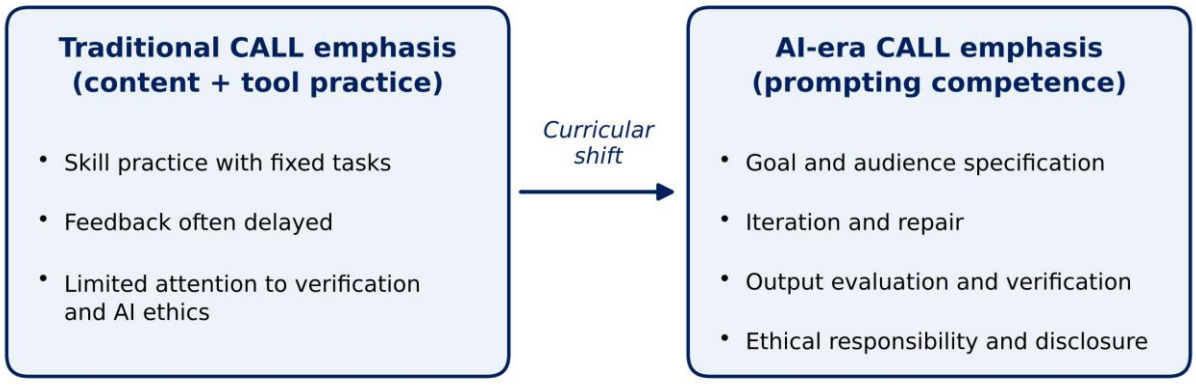



**Fig. 1.** From Teaching Content to Prompting Competence in CALL

## Literature Review

### The Growing Case for Prompting in CALL

CALL has long questioned the idea that technology alone drives learning, instead arguing that learners benefit most when technology-based tasks match teaching goals, encourage real interaction, and include feedback and reflection (Oliver 375). The situation with LLM chat is similar: while interaction increases, so do risks. Outputs can be wrong, sources may be missing or made up, and the interaction may not be practical. This means learners must learn to manage AI as a partner while staying responsible for meaning, evidence, and ethics (Ling and Jan 17).

Moving toward prompting competence is a natural extension of CALL's focus on interaction quality, mediation, learner autonomy, and digital literacy in the AI context (Walter 21). Prompts are not just technical commands; prompting is a communicative act that needs clarity, context, rhetorical choices, and the ability to revise.

Earlier research on chatbots in language learning supports this view. Xiao et al. (303) reviewed studies on conversational agents and found they can give learners extra practice but require careful teaching design. Huang et al. (4) found similar results: chatbots can help language learning, but success depends on design, and some positive results may just be due to the tool's novelty. LLMs are much more flexible than earlier chatbots, able to produce fluent text for almost any request. This flexibility is a strength, but it also means that the quality of interaction depends even more on what and how the user asks.

Another reason to include prompting in CALL is the need for learner training. Hubbard (166) argued that learners often do not know how to use technology for language learning, even if they use it daily. Being a regular user of a device or app does not mean being skilled at using it for learning. This is especially true for AI chat. Many students are used to messaging and social media, but may not know how to prompt an LLM with enough context, ask for evidence, or critically evaluate an answer that appears confident. Prompting competence thus emerges as a necessary and timely form of learner training.

### Evidence on Generative AI in Language Learning

Recent studies describe both promise and concern. Kohnke et al. (537) argued that ChatGPT can help language teaching through personalized practice, model texts, and creating materials, but it must be used carefully due to issues with accuracy, bias, and overreliance. Barrot (3) looked at ChatGPT in second language writing and found benefits like idea generation, feedback, and translation help, but also problems such as inaccurate content, limited critical thinking, and risks to academic integrity. Hockly (445) gave a balanced view of AI in English language teaching, stressing that teachers need to understand both the strengths and limits of these tools.

Other researchers have asked how learners should use such tools. Godwin-Jones ("Partnering" 5) found that learners need guidance to use AI to improve their own language, not just to get a better text. Tseng and Warschauer (258) argued that since AI writing tools are here to stay, teachers should help learners use them thoughtfully, not just try to ban them, while being aware that overreliance may limit language growth.

Overall, this research suggests two things. First, the benefits of AI for language learners depend on how they use it. Second, the main risks, like overreliance, uncritical acceptance, and misuse, also depend on learner behavior. If both benefits and risks depend on how learners interact with the tool, then teaching them how to do so becomes a clear priority. This is the gap the PCF aims to fill.

## Prompting as Mediation and Meaning-Making

The CEFR Companion Volume expands an action-oriented view of language competence through mediation. It emphasizes the learner's role in reprocessing, reformulating, and negotiating meaning for particular audiences and purposes (Council of Europe; Piccardo 288). Prompting can be seen as a form of contemporary mediation: the learner takes the task goal and translates it into constraints for the AI system, evaluates the output for appropriateness and truthfulness, and iteratively works to resolve any misunderstandings. Prompting is therefore linguistic (pragmatics, register, cohesion), rhetorical (purpose, audience, genre), and epistemic (verification and accountability).

Sociocultural theory provides further underpinning for this. Vygotsky argued that human thinking and learning are mediated by tools and signs and that language is the most important of these. Subsequent work in CALL has used this to explore how digital tools can shape what learners are able to do (Thorne 39). From this perspective, the LLM is a new kind of cultural tool and the prompt is the means by which the learner acts upon it. The concept of scaffolding (Wood et al. 89) is also relevant in that an AI system can scaffold language learning by enabling the learner to do what they otherwise could not do on their own. Examples, explanations, and feedback are all possible, but only if the learner is asking for the right kind of support. A learner who types "correct my text" is going to get a very different kind of support from a learner who types "underline the grammar errors in my text, state the rule for each one and don't rewrite the sentences." Godwin-Jones ("Distributed Agency" 7) calls this distributed agency (control over the learning process is shared between the learner, the teacher, and the AI). Prompting competence is the skill that enables the learner to maintain a reasonable degree of that agency.

## Prompting and Communicative Competence

The notion that language ability is more than just grammar has been around for a long time. Hymes (280) postulated that speakers need to know not just what is grammatically correct but also what is appropriate and feasible, and what people in fact do in a given situation. Canale and Swain (28) took that concept and developed a model which had grammatical, sociolinguistic, and strategic components, with Canale (11) later adding discourse competence. These models go some way to explaining why prompting is a language skill. A good prompt has to be grammatical (grammatical competence), appropriate to the purpose and audience (sociolinguistic competence), well structured so that the instructions and context make sense (discourse competence) and be capable of repairing a breakdown if the system has misunderstood (strategic competence). When a learner writes "Rewrite this paragraph for a first-year student who is completely new to the topic, keep the technical terms and explain each one in one sentence," the learner is making decisions about register, audience, and purpose. Those are precisely the decisions that communicative language teaching has always sought to develop.

Research into interaction provides a second pillar. The interaction hypothesis (Long 453) states that learners benefit from communication breaking down and having to negotiate meaning through clarification requests, confirmation checks, and rephrasing. The output hypothesis (Swain 101) adds that the act of producing language itself will lead the learner to become aware of gaps in their knowledge. Prompting incorporates both of these processes. If the output of the system is not what the learner wanted then the learner has to work out what has gone wrong, rephrase the prompt, and try again. An LLM, however, does not show the same level of confusion as a human and will often produce a perfectly fluent response even when it

has completely misunderstood the request. For this reason, negotiation of meaning in prompting is in part the learner's responsibility (the learner has to notice the mismatch as the system will not always signal it). This is also why Wagner et al. (3) are so cautious about assuming that ChatGPT has any real grasp of pragmatics, commonsense, or cultural knowledge.

## From Prompt Literacy to Prompting Competence

### Prompt Literacy as an Emergent Literacy

Prompt literacy is defined as the ability to write effective prompts, understand the outputs, and then iterate on the prompts to get the desired result. In the context of language education, it can be seen as a progression from random experimentation to a more strategic and accountable form of engagement with an AI tool (Hwang et al. 7). Guided prompting projects provide a clear way of demonstrating how the framing of a task, the imposition of constraints, and the specification of audience all impact the language that is produced and the learning value for EFL learners.

The technical literature on prompts is replete with the notion that the wording of the prompt is important. Brown et al. (1888) demonstrated that large language models can be induced to perform new tasks simply by being given a few examples in the prompt, with no further training required. Reynolds and McDonell (3) characterized prompt design as a form of programming in natural language, where minor changes in wording can significantly influence model behavior. Liu et al. (5) surveyed this rapidly expanding field and highlighted the diversity of prompting techniques developed to date. While these computer science studies focus on optimizing model performance, language educators pursue different goals. The objective is not to identify a single optimal prompt, but to enable learners to understand why certain prompts are more effective than others and to cultivate adaptable thinking strategies for evolving tools.

Research on actual users indicates that prompting is a complex skill. Zamfirescu-Pereira et al. (13) found that novice users designing chatbot prompts often worked inconsistently, drew strong conclusions from isolated successes or failures, and struggled to predict the effects of small changes. The title of their paper, "Why Johnny can't prompt," underscores the challenges faced by untrained users. This evidence supports the need for explicit instruction. In language learning contexts, Hwang et al. (9) examined how learners develop prompt literacy as a new skill when engaging with generative AI. Their findings suggest that prompt literacy can be fostered through structured activities rather than relying solely on trial and error.

For clarity, in this article, prompt literacy refers to the knowledge and awareness necessary to compose and interpret prompts. Prompting competence is a broader construct, encompassing prompt literacy as well as the ability to apply prompts in authentic tasks, assess outputs, address issues, and act responsibly in observable and evaluable ways. This distinction aligns with established language education principles differentiating between knowledge about language and the ability to use it (Council of Europe). Competence, in this context, is defined as competence in action.

### AI Literacy as a Supporting Competency Layer

Prompting competence is very much a subset of what we might call AI literacy, which would encompass an understanding of the affordances and limitations of AI, an awareness of the risks and biases that exist, and the ability to act ethically (Kasneci et al. 5). Students need to have a basic mental model of what LLMs can and can't do and a practical routine for assessing claims (Bender et al. 617; Ji et al. 21). In the context of language education, AI literacy would also

include the ability to know when AI feedback should be treated as suggestions rather than as corrections (Kohnke et al. 546).

Long and Magerko (3) define AI literacy as a set of competencies that allow people to assess AI critically, to communicate and collaborate with AI, and to use AI as a tool at home, at work, and online. Ng et al. (4) in their literature review identify four aspects of AI literacy: knowing and understanding AI, using and applying AI, evaluating and creating AI, and AI ethics. Both of these definitions include the ability to communicate with AI and an element of ethical awareness which are, of course, at the heart of prompting. In the PCF, AI literacy is treated as background knowledge and prompting competence as the visible, task-based application of that knowledge.

## Why Verification Matters

Verification is absolutely core to AI literacy as LLMs are designed to generate plausible text rather than necessarily true text. Bender et al. (616) described such systems as "stochastic parrots" that just take patterns from their training data and put them together without any actual understanding of what the text means. Ji et al. (4) looked at hallucination in NLP and found it occurs in a wide variety of tasks and models. Floridi and Chiriatti (686) pointed out that systems like GPT-3 can generate text that appears to be meaningful without any actual basis in truth. For language learners this has real world implications in that an invented citation, a wrong grammar rule, or a culturally inappropriate phrase can all be generated in what will be perfectly grammatical and coherent English. Heersmink et al. (12) note the opacity of LLMs makes it very difficult for users to assess whether or not they can be trusted and they call for a very conscious approach to trustworthiness. Sperber et al. (363) use the term "epistemic vigilance" to describe the mechanisms we use to protect ourselves against being misled by others. In the context of AI-mediated learning, epistemic vigilance has to be taught and learned. Prompting is a good place to do this as learners can incorporate verification into the prompt itself (e.g., asking the system to separate out the claims that would require checking from those that are less problematic). The answer to such a prompt will of course still need to be checked, but the habit of asking is a useful first step.

## Teacher and Student Competency Frameworks

International guidance is increasingly positioning AI engagement as a competency rather than a tool skill. UNESCO's teacher and student competency frameworks both take a human-centered, ethical, and inclusive approach and include progression levels which can be used to inform curriculum design (UNESCO, *Framework for Students*; UNESCO, *Framework for Teachers*). This is consistent with the view that prompting competence should be a teachable and assessable practice, with a clear focus on agency, privacy, and integrity (Kasneci et al. 5).

More recent UNESCO documents are also pertinent. The UNESCO student AI competency framework (UNESCO, *Framework for Students*) covers a human-centered mindset, the ethics of AI, AI techniques and applications, and AI system design with progression from understanding to applying to creating. The accompanying teacher AI competency framework (UNESCO, *Framework for Teachers*) includes a focus on AI pedagogy and teacher professional development. Neither of these documents refers to prompting competence specifically, but the emphasis on human agency, ethical use, and progression over time is very much in line with the PCF. Language educators can therefore present prompting competence as part of a wider

international endeavor to define what people should know and be able to do in an AI-enabled society rather than as some isolated classroom concept.

## The Prompting Competence Framework (PCF)

To make prompting teachable and assessable in language education, this study proposes the Prompting Competence Framework (PCF) with six dimensions. The PCF is designed as a practical rubric in itself: each of the dimensions can be observed in the prompt logs, the revisions, the verification notes, and the reflective rationales (Council of Europe).

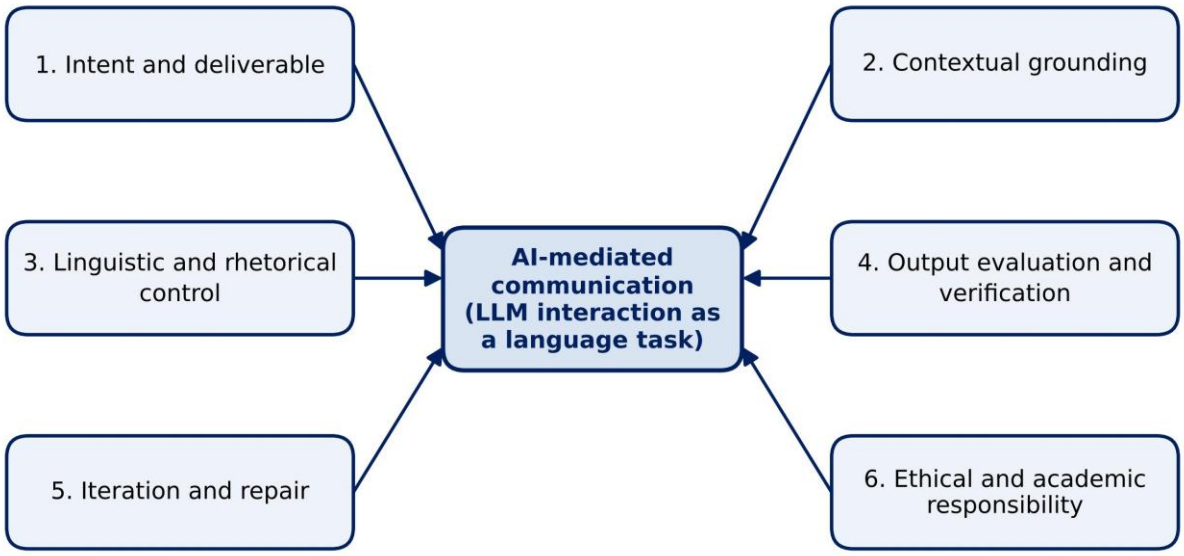



**Fig. 2.** Prompting Competence Framework (PCF): Six Assessable Dimensions

Figure 2 provides a conceptual overview of the six dimensions and how they relate to one another around a common core of AI-mediated communication. Table 1 then takes that framework and turns it into a practical rubric, with a definition and observable indicators for each dimension so that it can be identified in the prompt logs, the revisions, and the reflective rationales.

**Table 1**
Prompting Competence Framework (PCF)

| Dimension | Definition | Observable indicators (examples) |
|---|---|---|
| **Intent and deliverable** | Clarifies communicative goal and task type | Purpose; genre; audience; success criteria; required format |
| **Contextual grounding** | Supplies relevant background and constraints | Topic scope; stance; source text; length; proficiency level |
| **Linguistic and rhetorical control** | Controls register, structure, and discourse moves | Tone/register; cohesion; rhetorical moves; hedging; modality |

| Dimension | Definition | Observable indicators (examples) |
|---|---|---|
| **Output evaluation and verification** | Judges accuracy, relevance, and appropriateness | Flags hallucinations; requests evidence; checks logic; revises claims |
| **Iteration and repair** | Improves prompts based on output | Versioning; targeted constraint edits; rationale for changes; repair strategies |
| **Ethical and academic responsibility** | Uses AI transparently and safely | Disclosure (if required); privacy protection; avoids plagiarism; attribution practices |

## The Six Dimensions in More Detail

The six dimensions are explained below. They are not in any fixed order. In actual practice learners will move between them and a single revision of a prompt may well involve more than one of the dimensions.

### *Intent and Deliverable*

The first dimension is the learner's ability to state what they want to say and why. This is about the purpose of the text, the genre, the audience, and the criteria for success. In language learning terms, this is task analysis. Research into task-based language teaching has shown that tasks which have a clear communicative outcome lead learners to focus their language use on meaning (Ellis 27). A learner who writes the prompt "Write about climate change" has not specified an audience or a purpose and as a result the piece will tend to be rather general and unengaging. A learner who writes "Write a 200-word introduction to a persuasive essay for first-year university students arguing that cities should reduce car use" has made a number of decisions which can be discussed, critiqued, and improved.

### *Contextual Grounding*

The second dimension is the ability to give the system the information it needs. The LLM doesn't have any knowledge of the learner's course, level, or source material unless it is explicitly told. Grounding involves the topic scope, the learner's position, the level of proficiency, length constraints, and, where appropriate, some snippets from the source text. Good grounding requires selection. Too little context leads to rather generic responses; too much irrelevant detail can be a distraction for both the system and the learner. Making the decision as to what is relevant is a form of academic judgment and it's directly related to the skills of summarization and selection that are part of the language course. The learner will also need to consider privacy when providing the context which is of course a connection to the sixth dimension.

### *Linguistic and Rhetorical Control*

The third dimension is the language specificity of prompting. The learner has to be able to control register, tone, and structure in both their prompt and in the output they're asking for.

They might be asking for careful hedging in an academic text, a polite but unambiguous email, or a summary that follows a problem/solution pattern. Genre knowledge is key here. Genre in applied linguistics is the way in which texts are used to achieve a social purpose through the use of identifiable stages and language (Hyland 149). A learner who can identify these features can ask for them and can also check that the output has them. Prompting is thus a way of putting metalinguistic knowledge into practice.

### *Output Evaluation and Verification*

The fourth dimension is probably the most important one for both learning and for integrity. That's the dimension of judging whether the output is accurate, relevant, and appropriate and checking the claims against some external source. A learner might check the facts against a reputable reference, test a grammatical explanation against a dictionary or a corpus, ask a peer or a teacher, or compare the answers they get from different prompts. Triangulation (using more than one source) is a useful principle. Evaluation should also be about language quality. The output might be perfectly grammatical and yet be completely wrong in tone, too general for the task, or simply not something that a learner could actually say. This links in with the research into feedback literacy which argues that the learner has to be able to assess the feedback and decide how to use it (Carless and Boud 1322).

### *Iteration and Repair*

The fifth dimension is the one that acknowledges that good outcomes are very rarely the result of the very first prompt. The learner has to look at the output, work out what's wrong, and then decide what aspect of the prompt to alter. It's about effective iteration. Rather than re-prompting from scratch, the learner will change one constraint, add an example, or ask for a different structure. The process of keeping the various versions (v1, v2, v3, etc.) is part of the process. This is very much in the spirit of strategic competence as defined by Canale and Swain (30) (their notion of strategies for dealing with breakdowns in communication) and is also very much in keeping with the concept of self-regulated learning (Zimmerman 67) where the learner plans, monitors, and reflects on their own learning.

### *Ethical and Academic Responsibility*

The sixth dimension is about transparent, safe, and fair use. This involves adhering to the relevant course and institutional rules regarding AI use, disclosing when AI assistance has been used (where required), not entering any private or sensitive data and giving due credit. It also includes an awareness of bias as LLMs will reflect the social and cultural patterns present in their training data (Bender et al. 614). Ethical responsibility is embedded within the framework as a dimension to be assessed rather than just as a caveat. It is something that students need to be given practice in doing and in explaining their decisions about. An example of this would be the decision as to whether a suggested paragraph could legitimately be described as their own.

The dimensions together describe a cycle rather than a checklist. The learner defines the task, grounds it, shapes the language, evaluates the outcome, repairs the prompt, and takes responsibility for the final piece. The PCF does not purport to be complete or definitive. It is offered as a starting point for teachers and researchers to test, adapt, and extend.

## Pedagogical Integration Model

A major curricular issue is making prompting competence visible as learning rather than allowing AI use to become a private, invisible shortcut. The model proposed here is a three-stage model (Model→Prompt Studio→Transfer) which links instruction, practice, and assessment evidence. The model explicitly addresses mediation, verification, iteration, and ethical responsibility (Council of Europe).

The three stages follow a very familiar pedagogical pattern. The teacher models in stage one, the students practice with support in stage two and then work more independently in stage three. This is of course the "gradual release of responsibility" (Pearson and Gallagher 334) and the "scaffolding" concept (Wood et al. 89) in action. The model also adheres to the principle of constructive alignment (Biggs 348) in that the intended learning outcome, the teaching activities, and the assessment all relate to the same skill. If a course says it wants students to use AI responsibly but only assesses the final product, then the assessment is misaligned with the intended outcome. The model avoids this misalignment by assessing both the process and the product.

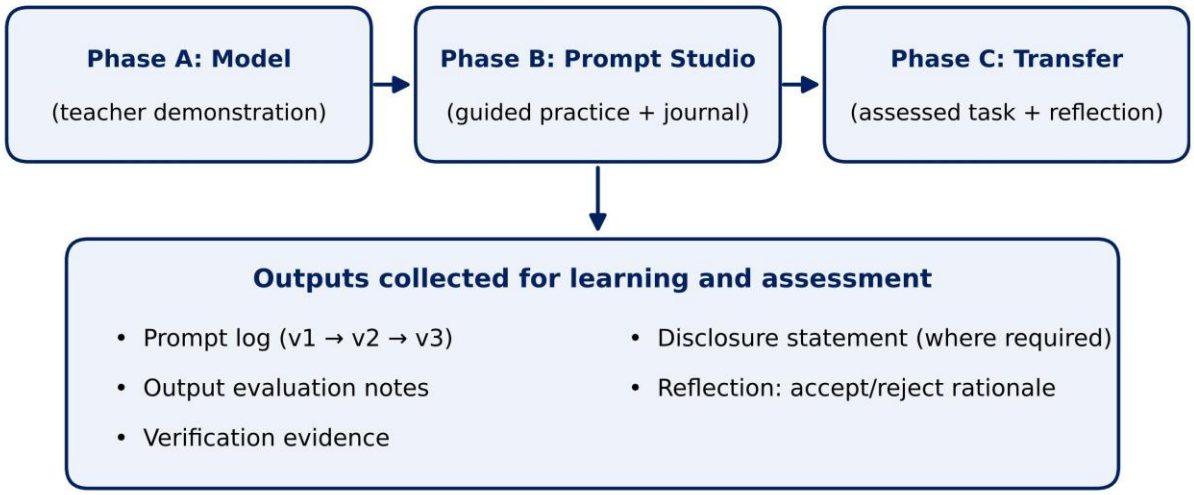



**Fig. 3.** Classroom Integration Model: Model, Prompt Studio, Transfer

### Phase A: Model (Teacher Demonstration)

In Phase A, the teacher demonstrates the effect of changes to prompt structure on both output quality and epistemic risk. A practical approach would be to work through the anatomy of the prompt (instruction, context, constraints, format, verification request) and compare outputs from a poorly specified prompt to a well-specified one. The intention is not to teach a set of rules, but to establish cause and effect.

The teacher might simply project two prompts for the same task. One might read "Write about my internship." The other might read "Write a 150-word paragraph in a formal register for a university application letter about my internship at a software company. Mention teamwork and problem solving. Use first person. Avoid clichés." The students would then look at the two outputs and discuss what had changed and why. The teacher could then point out that even the second output may contain invented content or a tone that is not appropriate to the student, and model how to interrogate it (e.g., "Which of the sentences describe things I didn't

tell you?"). The point is that the quality of the prompt has an effect on the quality of the output, but a good prompt does not in any way eliminate the need for checking.

### Phase B: Prompt Studio (Guided Practice and Journals)

Phase B sees students working in pairs using a prompt journal which records the various prompt versions (v1/v2/v3). They record what changes they have made and why, their evaluation of the output, and the verification steps they have taken. This phase is all about building awareness of how the various language choices in the prompt (tone, audience, stance, constraints) affect the interaction.

The pair work in this phase has a very specific purpose. By having to explain their choices to a partner they are forced to articulate their reasoning, which in turn promotes metacognition (Flavell 906) and provides the teacher with material for feedback. The prompt journal is the record of that thinking. The teacher could ask the pairs to swap journals and suggest one improvement or simply have a short whole class discussion about a couple of interesting cases (e.g., a prompt that has failed in a useful way). The prompt studio sessions should be low stakes so that students are able to try, fail, and report honestly. If every journal entry is going to be marked harshly, then students may be inclined to hide their mistakes or simply invent neat stories of their process. Formative feedback (which tells the learner where they are and how to improve) is the more appropriate type of feedback at this stage.

### Phase C: Transfer (Assessed Task)

Phase C sees students complete an assessed writing or ESP task using a set of marking criteria which include process evidence (prompt log, verification notes, and a brief reflection). This in turn reduces the incentive to produce untraceable AI submissions and ensures the assessment is in line with the competence we are trying to develop.

The task can be tailored to suit the particular course. In an academic writing course, it could be a problem/solution paragraph based on three sources. In an ESP course, it could be a short technical report or a client email. In a mediation course it could be a summary of a policy text for a particular audience (see Appendix C). The key thing is that the task requires the student to make their decisions visible in the process, i.e. which AI suggestions they have used, which they have rejected, and what they have checked. Where the teacher wants further assurance that the work is actually the student's own, it is possible to add a short oral follow-up or some in-class drafting. Students can also be asked to reflect on what they have learned about audience and tone which brings the task back to the language learning objectives of the course.

## Assessment: PCF Analytic Rubric

To support classroom implementation, the present study provides an abbreviated 4-level analytic rubric. In practice, the rubric is applied to the prompt log and a brief reflective memo which records the evaluation and verification steps.

It is important to use the rubric appropriately. First, it should be applied to evidence of process (the prompt log, the verification notes, and the reflections) as well as to the final product as the final product alone will not reveal how the learner has worked. Second, the criteria should be made available to students in advance and ideally discussed with the students, with examples, as students do improve when they understand the criteria by which their work will be assessed. Third, teachers should expect that students will not make progress at the same rate across all of the criteria. A student may be quite advanced in terms of task specification and still be at an early stage in terms of verification. Such profiles are of course very useful for feedback and that

is one of the reasons why the rubric is analytic rather than holistic. Finally, descriptors such as "systematic" or "strategic" need to be interpreted in the context of the course. Teachers can improve reliability and fairness by double marking a sample of the journals and discussing any discrepancies.

**Table 2**
PCF Analytic Rubric (Abridged)

| Criterion | Emerging | Developing | Proficient | Advanced |
|---|---|---|---|---|
| **Task specification** | Vague goal | Goal stated | Goal + deliverable clear | Goal + audience + success criteria |
| **Context and constraints** | Minimal context | Some constraints | Adequate grounding | Optimized constraints + relevance |
| **Evaluation and verification** | Accepts output | Spots surface issues | Checks logic + key facts | Systematic verification + triangulation |
| **Iteration quality** | Few revisions | Minor tweaks | Targeted improvement | Strategic experimentation + repair |
| **Ethical responsibility** | Unclear boundaries | Partial transparency | Follows course policy | Models best-practice privacy/disclosure |

## Academic Integrity by Design

Academic integrity in the GenAI era is increasingly a governance and assessment design issue rather than a detection issue (Kasneci et al. 5). When AI is a common drafting partner, an "AI vs. no AI" policy is not really viable. The way forward is integrity by design with assessment design that (a) makes the process visible, (b) values justification and verification, and (c) promotes student agency.

Integrity by design would involve grading both the process evidence (prompt logs and verification notes) and the final product, the use of secure checkpoints (in-class outlines, oral defenses, supervised drafting), requiring disclosure in line with institutional policy and teaching privacy hygiene (e.g., not including any sensitive data in prompts) (UNESCO, *Guidance*).

Early institutional responses point in this direction. Moorhouse et al. looked at the policies of the top universities and found that the majority of their guidance was about academic integrity and advice to staff on assessment design. Cotton et al. (234) looked at how institutions could respond to ChatGPT and recommended clear policies, education for students on academic integrity and assessment design that is difficult to complete using AI alone. Rudolph et al. (355) similarly argued that the arrival of ChatGPT should lead to a rethinking of assessment rather than simply to better detection.

Detection tools on their own are a poor solution. Liang et al. (2) found that several of the most widely used AI detectors actually misclassified writing by non-native English speakers as AI-generated more often than writing by native speakers. For EFL learners this means a detection-based approach is not only unreliable but could be potentially unfair. Integrity by design also requires an honest discussion about what constitutes legitimate help. Students already use dictionaries, spell checkers, and their peers. The question is where to draw the line and that will be different for different tasks. For a grammar exercise whose purpose is to practice

a particular form, AI correction would be entirely inappropriate. For a task on audience adaptation however, AI drafting might be acceptable if the student is able to evaluate and revise the output and can explain how it was used. Course teams should state these boundaries for each task and explain the rationale for them.

## Discussion

This study views the use of generative AI in language education as a way to build competence, not just to add new tools. By making prompting competence a main goal in computer-assisted language learning (CALL), educators can better match classroom practices to the needs of AI-based academic and professional communication. The Prompting Competence Framework (PCF) shows that using AI well means more than producing fluent text; it requires clear goals, audience awareness, rhetorical control, and careful evaluation and checking.

The classroom model supports academic integrity by making the learning process open and assessable. When assessment values process evidence and reflection, AI becomes a support rather than a hidden shortcut. The model also changes the teacher's role to that of a designer and guide, responsible for creating tasks, setting ethical standards, teaching how to check AI outputs, and building a classroom culture that values agency and responsibility.

The framework has important implications for teacher development. Teaching prompting competence means teachers need to understand how large language models (LLMs) work, design tasks that make AI use visible, and give feedback on process evidence. Many teachers are not yet trained in these areas. Kohnke et al. (545) noted that both teachers and learners need new skills to use these tools well, while Jeon and Lee (15874) described the teacher–ChatGPT relationship as complementary, with each having a different role. Teacher education should include practice in writing and evaluating prompts, critically reviewing AI outputs, and designing assessment tasks like those in Appendix C. Without enough support, prompting competence could become an extra burden for teachers who lack time or training.

Equity is also important. Unequal access to devices, internet, and paid AI tools can affect students' ability to develop prompting skills. In multilingual settings like Morocco, students may use several languages, and LLMs may work differently in each, leading to different levels of support. Classrooms should ensure access, offer low-tech options like printed prompt journals, and encourage students to compare outputs in different languages. The same applies to the rubric: if it focuses too much on polished language, it may disadvantage students with lower proficiency if teachers confuse language accuracy with strategic quality. A prompt with some grammar mistakes can still show clear goals, good grounding, and careful checking.

### Pedagogical and Academic Implications

First, language programs can embed prompting-competence outcomes in syllabi alongside writing and speaking outcomes, making the competence explicit. Second, teachers can adopt prompt studios and prompt journals to cultivate iteration and metacognition. Third, evaluation should reward verification, repair, and audience-appropriate language skills that matter in both academic communication and professional contexts.

## Limitations

This article has several limitations. First, it is conceptual. The PCF is based on a reading of the literature and on pedagogical reasoning, but it has not yet been tested with learners. The six dimensions and four levels may well need to be tweaked as a result of empirical work (for example, we may find that raters are unable to apply the framework reliably or that the

dimensions aren't actually distinct in practice). LLMs are constantly changing. The capabilities around memory, web search, and document upload all change what a prompt needs to contain and which tasks are achievable. Tasks which were quite difficult a year ago may now be trivial. The PCF is therefore focused on the communicative and evaluative skills which are likely to be enduring rather than on any particular tool or technique. It was written with a specific set of contexts in mind (university EFL/ESL and ESP) and younger learners, other languages, and other systems may require different tasks and descriptors. Finally, there is a cost to assessing process evidence. Prompt logs and reflections add to the teacher's workload. Students can falsify their records. The model reduces some risks of misuse but cannot remove them entirely.

Future research should test the PCF in practice and see if its benefits extend beyond writing to skills like speaking, listening, mediation, and teamwork. It should also consider fairness, such as students' access to devices, comfort with technology, and prior skills. A mixed-methods approach is useful because it connects measured results to actual prompting behaviors and students' reasoning.

Some research questions include: Do students who use prompt studios write better prompts and check more? Is prompting competence linked to writing skill, digital literacy, or critical thinking? Do students at different skill levels benefit equally? How do teachers' views on AI affect their use of the model? Research with teachers can help improve the model over time. Studies could compare classes using the PCF with those using AI without guidance. Methods like think-alouds, screen recordings, and prompt log analysis can show how students reason as they revise prompts, helping to refine the rubric.

## Conclusion

As AI becomes common in academic and professional life, language teaching must go beyond teaching content and help learners use AI as a communication partner. The PCF and classroom model in this paper give a practical way to teach and assess prompting competence, while still supporting human agency and academic integrity. There is now a need to test the impact, methods, and transfer of these ideas across different skills and settings.

The main point is simple: learners will use AI whether or not the curriculum covers it. What the curriculum can shape is whether learners use AI with purpose, critical thinking, and responsibility. By defining prompting competence, explaining how to assess it, and showing how to teach it, the PCF helps teachers move from worry about AI to active planning. In CALL, the key question is not what technology can do, but what learners can do with it and how teachers can help.

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## Appendix A. Prompt Journal Template (PCF-Aligned)

Course: _____ Task: _____ Date: _____

Prompt v1:

- Instruction (what do you want?):
- Context (background, source text, stance):
- Constraints (length, level, tone, audience, format):
- Verification request (what must be checked?):

AI output summary (not copied):

Evaluation notes (accuracy, relevance, tone, risks):

Verification step (how did you check? what changed?):

Prompt v2 (what did you change and why?):

Evaluation + verification notes:

Prompt v3 (optional):

Final reflection (5–8 lines): What did you accept/reject and why? What did you learn about audience/tone/argumentation?

## Appendix B. Full PCF Rubric (Expanded Descriptors)

Institutions can of course adapt these descriptors to their own policies and task types. The fundamental principle is that students are being assessed on accountable interaction: goal clarity, grounding, rhetorical control, evaluation and verification, iteration, and ethical responsibility.

| Dimension | Emerging | Developing | Proficient | Advanced |
|---|---|---|---|---|
| **Intent and deliverable** | Prompt gives no indication of intention or required output. | Purpose stated, output type not clear. | Purpose and deliverable are clear. Audience is defined. | Purpose, audience, criteria, and constraints fully specified; anticipates evaluation criteria. |
| **Contextual grounding** | Very little or no background at all; no source information provided. | Some background given, key constraints not really there. | Relevant background and constraints provided; scope is controlled. | Grounding is task relevant and precise. It contains the required source excerpts and contains no noise. |
| **Linguistic and rhetorical control** | No control of register/structure. | Basic tone/register requested; structure partially specified. | Register, tone, and discourse moves specified; cohesive structure requested. | Fine-grained rhetorical control (hedging, stance, cohesion); genre conventions explicitly targeted. |
| **Output evaluation and verification** | Accepts output without checking. | Identifies obvious errors; limited checking. | Checks key claims and logic; requests citations/uncertainty markers. | Systematic triangulation and revision; documents checks and updates claims responsibly. |

| Dimension | Emerging | Developing | Proficient | Advanced |
|---|---|---|---|---|
| **Iteration and repair** | Minimal revisions; changes not purposeful. | Some revisions; weak rationale. | Targeted iterative improvement; explains why changes were made. | Strategic experimentation, repair, and refinement; compares alternatives and selects based on criteria. |
| **Ethical and academic responsibility** | Unclear boundaries; risks privacy or plagiarism. | Partial transparency; inconsistent attribution/disclosure. | Follows course policy; avoids sensitive data; disclosure where required. | Models responsible practice; clear disclosure; privacy hygiene; explains ethical choices and responsibility. |

## Appendix C. Sample Task Set (Academic Writing + Mediation)

Task C1 (Genre transfer/mediation): Produce a 250-word student version of a 900-word policy extract. Required: audience adaptation, definitions of key terms, and a verification note.

Task C2 (Argument development): Write a problem/solution paragraph based on three provided sources. Required: a claim/evidence map and an AI-use disclosure.

Task C3 (Peer review with AI): Use AI to generate two alternative pieces of feedback on the revision, then decide which one you would take on board and why, with reference to the rubric.




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# Can Generative AI Support Course Design, Constructive Alignment, and Assessment in French for Specific Purposes?

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## ABSTRACT

This empirical study investigates whether locally executed artificial intelligence systems, augmented with Retrieval-Augmented Generation (RAG), can reliably support instructors in maintaining constructive alignment across course design and assessment in resource-constrained institutional settings. The research addresses two interconnected questions: (1) To what extent can a domain-specialized language model (HorizaEdu) running on open-source infrastructure (Ollama) with pedagogical ingest generate aligned course materials and assessments without cloud dependency or data loss? (2) Can non-technical educators use generative AI prototyping platforms (Google AI Studio) to design, implement, and deploy secure web-based examination systems? The study conducted a single-cohort empirical evaluation with 150 post-secondary learners in a Professional French (*Français Professionnel*) blended course targeting an engineering communication context. Using Porter's Alignment Index, RAGAS automated evaluation, the System Usability Scale (SUS), and server-side infrastructure monitoring, we measured pedagogical alignment, algorithmic performance, technical stability, user experience, and legal compliance. Results show that the local RAG-augmented system achieved a mean alignment index of 0.88 (target: 0.80), with 92% Faithfulness and 96% Answer Relevance scores. The no-code web application maintained 100% uptime under full load and achieved a SUS score of 74.5 (Grade B / "Good"). The study shows that with careful pedagogical scaffolding, open-source AI infrastructure, and structured prompt engineering, individual instructors in modest institutional settings can operationalize constructive alignment as an automated design constraint while independently building secure assessment platforms. Limitations include single-cohort design, domain specificity, and unresolved mobile UX challenges. The work helps bridge the gap between AI capability and equitable teacher access to AI-augmented instructional design tools.

## KEYWORDS

**Constructive Alignment**

**Retrieval-Augmented Generation**

**Generative AI**

**Course Design**

**No-Code Development**

**French for Specific Purposes**

**Educational Technology**

**Teacher Agency**

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## Introduction

Over the last decade, scholars and organizations have closely examined the intersection of artificial intelligence and higher education (Zawacki-Richter et al.). However, most of the literature focuses on large-scale, cloud-based AI rollouts at privileged universities. As a result, academic sources still lack clear explanations of how well locally run, domain-oriented AI tools can support individual teachers in constrained institutional settings. This paper attempts to fill this gap by presenting the results of a two-dimensional analysis of persistent problems in e-learning. The first concerns the extent to which an AI system operating locally—in our case, the Ollama runtime of a specialized language model called HorizaEdu, complemented with Retrieval-Augmented Generation—can serve as a trustworthy co-pilot throughout the entire course design phase, from formulating learning outcomes through creating student-facing materials to constructing a final assessment tool that satisfies constructive alignment requirements. The second asks how readily a non-programming teacher can create, implement, and run a workable, secure web-based examination platform using only generative AI prototyping environments such as Google AI Studio.

These two questions together investigate whether the most critical barriers to AI-assisted instructional design—namely, lack of pedagogical congruence and difficult access to technology—can be substantially reduced by thoughtfully combining on-hand open-source and cloud-based resources.

The first direction is intellectually grounded in the foundational work of Biggs and Tang. In their view, constructive alignment is a method of course validation in which learning purposes, learning activities, and assessment exercises must form a coherent, mutually reinforcing system to be educationally valid (Biggs and Tang 52). Although these aspects of the educational triangle are conceptually straightforward, empirical research consistently shows that instructors struggle to maintain fidelity to alignment across the course lifecycle. Toohey documented that faculty regularly experience "pedagogical drift," departing from stated objectives as administrative pressures and documentation workload accumulate (Toohey 112). The assumption underlying the first part of this research is that if an AI system, through a RAG mechanism, can access verified institutional teaching materials, it can treat the three alignment principles as a fixed enforcement rule and produce a set of course components whose origins are clearly traceable to specific curricular documents and whose consistency is maintained across all three dimensions. This approach differs from most previous generative AI applications in education by prioritizing course design integrity and alignment assurance over one-off content delivery.

The paper's second major focus discusses a significant shift in the social conditions for educational software authorship. Natural language code generation platforms may have freed educators from the need for formal programming knowledge to create functional digital tools. This development will fundamentally redistribute technical expertise within educational institutions. Koehler and Mishra's Technological Pedagogical Content Knowledge (TPACK) framework provides the most suitable theoretical lens for this investigation, as it models educator expertise as the productive intersection of technological, pedagogical, and content knowledge. Generative AI appears to reshape this intersection by letting teachers' pedagogical and content knowledge drive technological implementation, without requiring deep technical skill acquisition. However, whether this redistribution will produce consistently secure, reliable outcomes—for instance, whether a non-technical instructor can create not merely a prototype but a production-grade, secure, engineered testing platform suitable for high-stakes assessment—remains an open empirical question.

The present study's methodological design reflects its two-fold nature through its research objectives. The first part introduces the HorizaEdu model, a domain-specialized language model that operates locally within the Ollama stack and is trained on a corpus of course documentation to generate fully worked-out teaching materials, including syllabi, learning activities, and aligned assessment items. The extent to which different outputs align is measured against principles from Biggs and Tang and operationalized through the revised taxonomy by Anderson and Krathwohl (Bloom 2.0). The second part outlines a procedure by which a non-technical instructor can utilize Google AI Studio to build an online assessment interface with student login authentication, server-side input validation, secure result storage, and automated grading—all executed by an educator without technical training. Beta-testing protocols rooted in agile development methods and educational technology sustainability frameworks ensure reliability and security (Beck et al.; Bates).

This paper aims to provide understanding that is simultaneously theoretical and practical. Theoretically, the work expands knowledge of how local AI augmented with retrieval capability (RAG) can automate the application of constructive alignment principles, thereby extending alignment theory into territory that has not been fully explored. Practically, it documents a replicable model that can serve as a blueprint for teachers—from well-resourced to modestly resourced institutions—seeking to introduce AI into their instructional design practice and to build digital assessment infrastructure without dependency on centralized IT support. In doing so, we address Mollick's argument that the key battleground in educational AI is individual teacher-educators' capacity to harness AI models for their specific professional contexts (Mollick 89).

## Literature Review

### Constructive Alignment and Automated Course Design

The theory of constructive alignment, formalized by John Biggs in the late twentieth century, constitutes one of the most durable and operationally rigorous frameworks in higher education pedagogy. At its core, the framework insists that three pedagogical components—intended learning outcomes (ILOs), teaching and learning activities (TLAs), and assessment tasks—must form a coherent, mutually reinforcing system rather than operate as isolated administrative artifacts (Biggs and Tang 52). Biggs argued that when students engage with assessment tasks that directly reflect the cognitive verbs embedded within the learning outcomes, deep learning is structurally encouraged. Critically, this alignment is not merely a curricular aspiration but a design obligation demanding sustained cognitive effort from the instructor across every phase of course construction. Misalignment between stated objectives and examination content represents not a minor pedagogical inconvenience but a fundamental failure of instructional integrity (Biggs and Tang 89).

Despite the theoretical clarity of constructive alignment, empirical research consistently shows that human instructors struggle to maintain alignment fidelity across an entire course lifecycle. Toohey observed that faculty routinely design objectives at the start of a semester and then drift from them as administrative pressures, time constraints, and curricular revisions accumulate (Toohey 112). This phenomenon of pedagogical drift is compounded in large institutions where the sheer volume of course components—lecture notes, laboratory guides, formative quizzes, and summative examinations—makes centralized alignment auditing practically impossible without dedicated instructional support. Anderson and Krathwohl further documented that revisions to Bloom's Taxonomy, while providing educators a more nuanced vocabulary for articulating cognitive outcomes, paradoxically increased the technical

complexity of maintaining precise taxonomic alignment between objectives and assessments (Anderson and Krathwohl 67). The result is a systemic vulnerability: even pedagogically informed instructors may inadvertently produce examinations that test recall when the stated objective demanded analysis, or measure procedural knowledge when synthesis was intended.

The emergence of large language models (LLMs) and domain-specialized LLMs presents a theoretically significant opportunity to address the alignment consistency problem (Kasneci et al.). Russell and Norvig's account of goal-based agents, which represent goal states and the subgoals that lead to them, suggests that such systems could, in principle, execute alignment verification tasks with greater consistency than individual instructors burdened with competing professional demands (Russell and Norvig). Applying Retrieval-Augmented Generation (RAG) to this challenge is particularly consequential. Lewis et al. demonstrated that RAG architectures substantially reduce hallucination in domain-specific generation tasks by anchoring the language model's outputs to a verified, retrievable knowledge base rather than relying solely on parametric memory from pretraining (Lewis et al.). In an instructional design context, this means an LLM equipped with RAG can generate course content—syllabi, learning materials, assessment items—that remains consistently tethered to validated pedagogical documentation, thereby operationalizing constructive alignment as an automated constraint. Wiggins and McTighe's framework of backward design, which similarly insists that assessment evidence must be determined before instructional activities are planned, finds a computational analog in the RAG-augmented LLM's capacity to anchor generative outputs to pre-specified curricular endpoints (Wiggins and McTighe 22).

## Local AI Frameworks and Pedagogical Ingest

Institutional adoption of artificial intelligence in higher education has been accompanied by a constellation of data governance concerns that constrain deployment of cloud-based AI services in pedagogically sensitive contexts. Selwyn identifies a fundamental tension between the operational convenience of externally hosted AI platforms and educational institutions' ethical obligations to protect student data, arguing that commercial AI providers' commodification of educational data poses a structural threat to informational self-determination in academic environments (Selwyn 78). This concern is not merely theoretical; regulatory frameworks such as the General Data Protection Regulation (GDPR) in Europe and the Family Educational Rights and Privacy Act (FERPA) in the United States impose legally binding constraints on transmitting student-identifiable information to third-party processors, rendering many cloud-based AI tools either non-compliant or operationally unusable for tasks involving authentic learner data (Williamson 134). The pedagogical consequence is that institutions seeking to leverage AI for course design must either negotiate complex data-processing agreements with external vendors or pursue architecturally local AI solutions that eliminate transmission of sensitive data beyond the institutional perimeter.

The development of local AI execution frameworks, notably platforms such as Ollama, directly addresses the data sovereignty imperative by enabling deployment of capable language model inference on institution-controlled hardware without relying on external API calls or cloud-based data routing. Ollama's architectural significance lies in its ability to serve as a portable runtime for open-weight language models, allowing institutional developers and instructional technologists to select, configure, and deploy models specialized for domain-specific tasks without incurring the recurring per-token costs and data-exposure risks associated with proprietary, API-dependent alternatives. Mollick noted that the emergence of locally executable, specialized language models represents a democratizing inflection point in

educational AI, redistributing the capacity for AI-augmented instructional design from well-resourced institutions with enterprise AI contracts to smaller colleges, community institutions, and individual faculty (Mollick 89).

The concept of *pedagogical ingest* – the process by which a local AI framework is provided with curated, domain-specific reference documentation that functions as targeted long-term memory for the model—represents the critical architectural bridge between a generic local language model and a genuinely useful co-pilot for structured learning design. This is technically implemented through Retrieval-Augmented Generation, in which ingested documents are chunked, vectorized, and stored in a searchable embedding index that the model queries at inference time to ground responses in verified source material rather than probabilistic recall (Lewis et al.). In the context of a specialized educational AI system such as HorizaEdu, pedagogical ingest enables the AI to function as an accurate and institutionally calibrated scenario generator. When prompted to design a learning activity or draft an assessment item, the model retrieves relevant sections of ingested curriculum documentation and constructs output with fidelity to those passages rather than drawing on potentially outdated or contextually misaligned training data. Garrison argued that this form of targeted knowledge retrieval is epistemologically analogous to the expert practitioner's capacity to rapidly access relevant professional schema when confronted with novel pedagogical problems, suggesting that a well-designed RAG architecture can approximate, in a bounded and verifiable domain, the contextual intelligence of an experienced curriculum specialist (Garrison 156).

## The Educator as a "No-Code" Developer and Cloud Prototyping

The democratization of software development through generative artificial intelligence represents one of the most consequential shifts in educational technology history. Prensky anticipated this transition when he argued that the most meaningful innovations in educational technology would emerge not from professional developers designing in isolation, but from practitioners who understood learning needs from the inside and had the means to externalize their instructional visions in functional digital form (Prensky 47). The emergence of natural language-driven code generation platforms, including Google AI Studio, has validated this prediction by enabling non-technical users to specify application behavior in natural language and receive syntactically executable, architecturally coherent code in response.

Koehler and Mishra's TPACK framework, which models teacher expertise as the productive intersection of technological, pedagogical, and content knowledge domains, provides a useful theoretical lens for understanding how no-code platforms restructure the technological competency requirement: rather than demanding that educators acquire deep programming knowledge, generative AI tools allow pedagogical and content knowledge to drive technological implementation, effectively shifting the locus of expertise back toward educators' core professional strengths (Koehler and Mishra 62).

The specific challenge of deploying a secure, authentication-capable web-based examination platform without programming expertise has historically represented one of the most formidable technological barriers confronting non-technical educators seeking to administer remote assessments with meaningful academic integrity guarantees. Garrison and Anderson documented the persistent gap between the pedagogical aspiration for technology-mediated authentic assessment and most instructors' practical capacity to implement the server-side security architecture required to prevent unauthorized access, session spoofing, and credential sharing in online examination environments (Garrison and Anderson 88). AI-assisted rapid prototyping tools fundamentally alter this equation. Google AI Studio enables an instructor to describe desired application behavior—including student login authentication, session

management, server-side form validation, and result storage—and receive a functional prototype in hours rather than weeks. This compresses the product development cycle so dramatically that it puts within reach of an individual instructor the construction of digital assessment infrastructure that previously required institutional IT collaboration or contracted development.

The velocity of this prototyping paradigm aligns naturally with agile development principles, wherein iterative cycles of testing, feedback, and refinement replace the waterfall assumption that functional products can be fully specified in advance (Beck et al.). Stabilizing AI-generated educational applications through iterative beta-testing, server-side validation, and AI-assisted debugging is a critical competency in no-code educational software development. Design-based research makes a related point: technology-enhanced learning environments become dependable through iterative cycles of design, enactment, analysis, and redesign carried out in real settings and in collaboration with practitioners (Wang and Hannafin). Bates argued that the long-term sustainability of technology-enhanced learning depends on educational institutions' capacity to develop and retain the human competency required to maintain tools through iterative refinement over time (Bates).

## Methodology

This section formalizes the empirical and technical methodology applied during the experimentation. The research was conducted systematically using a decoupled infrastructure that isolates local data processing for instructional engineering from external cloud orchestration for remote examinations. The implementation follows the system architecture illustrated in figure 1.

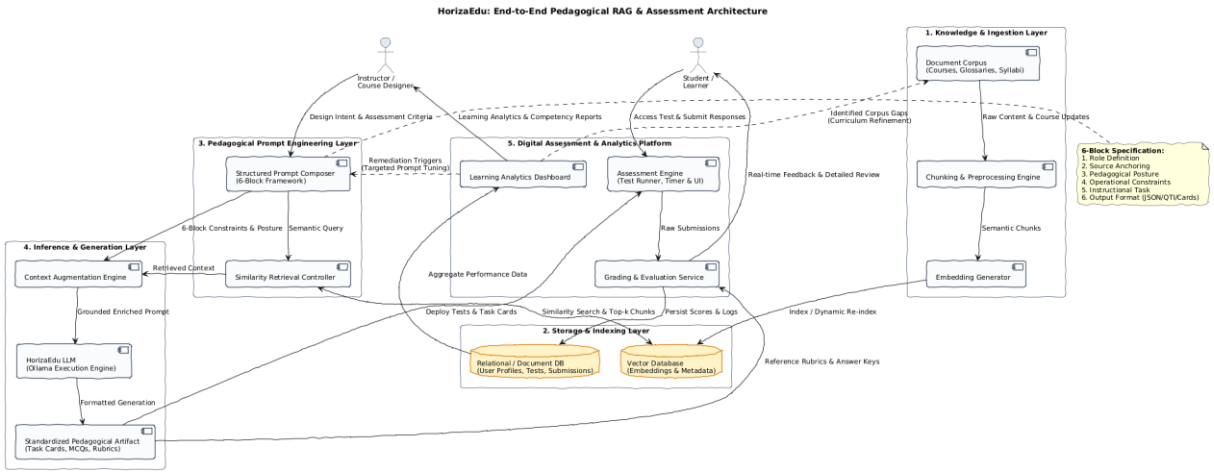



**Fig. 1.** HorizaEdu End-to-End Pedagogical RAG and Assessment Architecture

### Study Population and Pedagogical Setting

The empirical evaluation was conducted over a single academic semester with a cohort consisting of 150 post-secondary undergraduate learners enrolled in a Professional French (*Français Professionnel*) course module within an engineering specialization. The target training program focused exclusively on workplace communication scenarios with strict syntactic and lexical constraints appropriate to professional contexts. To maximize learner flexibility and pedagogical effectiveness, the course used a blended, hybrid educational model that combined synchronous, face-to-face interactive learning sessions with asynchronous

digital activities delivered via a remote web interface. This hybrid format reflects contemporary best practices in higher education while accommodating diverse learner schedules and access to technology.

## Technical System Architecture and Components

The technological infrastructure for this experiment was divided into two sandboxed layers: a secure, local backend engine managing core course content, and an interactive cloud layer hosting student interfaces.

## Knowledge Ingestion, Indexing, and Pedagogical Corpus Preparation

The engineering workflow began by curating institutional training documents specific to the Professional French domain. A multi-stage Retrieval-Augmented Generation (RAG) system parsed and prepared this document corpus. The HorizaEdu model was grounded in a curated corpus of 47 institutional documents totaling approximately 2.3 MB of pedagogical content, including: course syllabi, learning outcome specifications, teaching guidelines, terminology glossaries, assessment rubrics, and exemplary student work. During chunking and preprocessing, the system ingested raw institutional resources into a dedicated text-processing pipeline that split content into semantic chunks of about 512 tokens each. These processed text blocks were then passed through an Embedding Generator (using OpenAI's text-embedding-3-small model) to convert text features into multi-dimensional floating-point vectors of 1536 dimensions. Because this embedding model is a cloud service, the course documents (but no student data) left the local server once, at indexing time; all retrieval and generation thereafter ran offline. Finally, the vectors were stored inside a local Vector Database (implemented using FAISS, Facebook AI Similarity Search) containing embeddings, metadata, and source attribution. This backend storage layer remained entirely isolated and did not store student profiles, logins, or authentication details, maintaining strict separation between private learning content and platform analytics (see fig. 2).

## Local Inference and Automated Course Design

To protect institutional data sovereignty and avoid third-party data tracking, the system ran all course planning, content formulation, and examination item generation completely offline. The system deployed the open-source Ollama orchestration environment, version 0.1.32 (Ollama), to handle compute instructions locally on a dedicated server (12-core Intel processor, 32 GB RAM). The specialized HorizaEdu LLM (based on Llama 2 7B and fine-tuned on educational pedagogy corpora) was mounted on the Ollama server as the main execution engine. When the instructor transmitted a design intent through a structured prompt, a *Structured Prompt Composer* processed the input using a rigorous six-block specification: (1) role definition, (2) source anchoring, (3) pedagogical posture, (4) operational constraints, (5) instructional tasks, and (6) output formats. The *Similarity Retrieval Controller* then searched the vector database for top-k contextual matches (k=5 by default) and passed a grounded, enriched prompt back to the HorizaEdu model. The model output a *Standardized Pedagogical Artifact* — complete with course structures, teaching scenarios, and aligned multiple-choice questions—securely without cloud access.

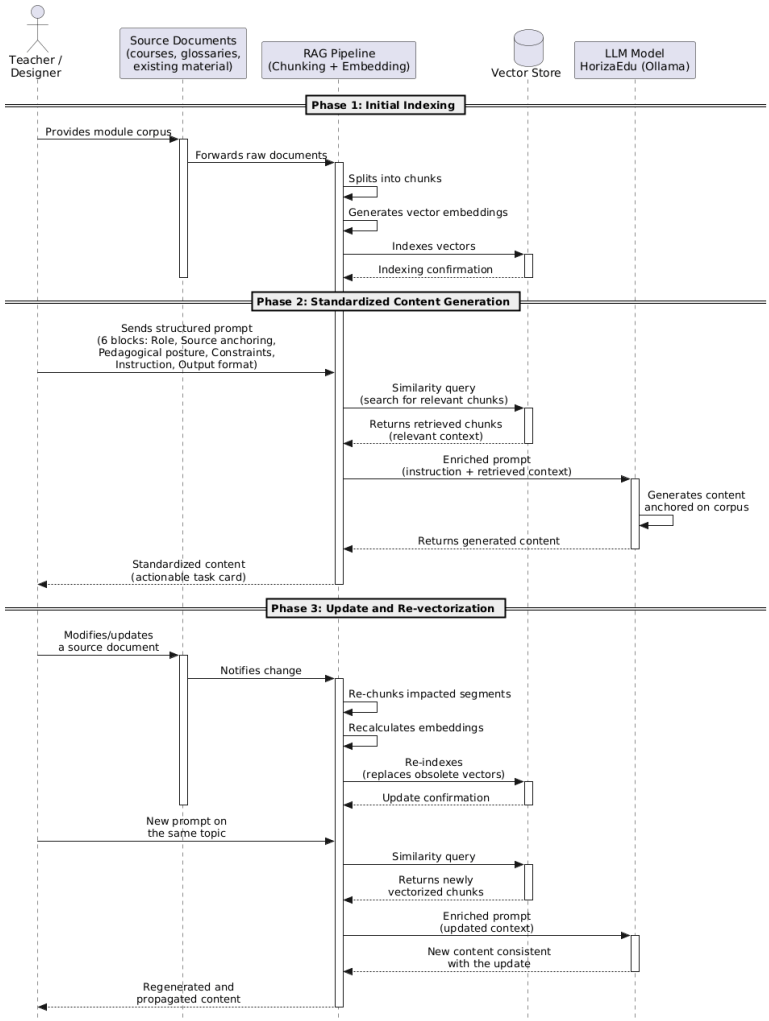



**Fig. 2.** Dynamic Retrieval-Augmented Generation (RAG) Lifecycle and Prompt-Engineering Workflow

The prompts addressed to the RAG-grounded model followed a six-block prompt engineering framework. A role block first established that the model acts as a standardization engine for professional French course content, writing for the instructor rather than the learner. A source-grounding block then instructed the model to draw only on the retrieved corpus rather than on external content, and to flag any point at which the corpus proved insufficient. Building on this, a pedagogical-stance block specified the action-oriented requirement that output take the form of a task simulating a professional situation rather than a decontextualized language exercise, while a consistency-constraints block listed the structural, tonal, and formatting rules the module follows, including register, terminology, and section structure. A task-instruction block subsequently stated the precise action to be performed, whether generating new content, auditing for coherence, or propagating updates across dependent sections, and an output-format block finally specified the exact structure expected, such as a lesson block, a task card, or a change log.

Following the macro-/micro-planning architecture of Depover et al. (41-86), which the course-design model adopted strictly, AI assisted the designer at seven successive phases. Macro-planning comprised Phase 1 (identifying expected benefits and the target population) and Phase 2 (making pedagogical objectives and constraints explicit). Micro-planning comprised Phases 1-5 (knowledge extraction, information analysis, information organization,

interface design, and learning situation elaboration). At each phase, the AI received a structured sequence designed to keep output anchored to the phase's specific pedagogical requirements.

The module's six core chapters were: (1) Structuring a Technical Oral Presentation; (2) Voice and Body in Front of an Audience; (3) Using Visual Supports Effectively; (4) Adapting Discourse to Different Audiences; (5) Handling Questions and Objections in Public; (6) Collaborating Orally: Meetings, Debate, Team Pitch. The RAG system identified 14 prerequisite communication competencies that students needed before accessing the main module content.

## No-Code Assessment Platform Architecture and Prototyping

We explicitly decoupled the client-side infrastructure from the backend to evaluate non-technical educators' software-creation capabilities. Using Google AI Studio (Google) and structured prompt engineering, we assembled a secure digital assessment application without manually writing raw application code. The resulting platform featured: (a) a dedicated student login system with bcrypt password hashing and JWT session tokens; (b) server-side form validation and input sanitization using DOMPurify and OWASP guidelines; (c) countdown timers with grace-period buffer; (d) response-tracking and checkpoint-save functionality; (e) automated scoring against instructor-defined rubrics; (f) role-based access control for student and administrator accounts. HorizaEdu generated standardized test structures locally and imported them directly into this cloud-hosted platform (deployed on Firebase), making exams instantly accessible for remote testing (see figs. 3 and 4).

The prompt addressed to Google AI Studio for no-code application development likewise comprised six blocks, adapted to application generation. An application-definition block named what was being built and for whom, specifying the two user roles of Student and Admin, and a technical-stack block fixed the frontend framework (React), the styling system (Tailwind CSS), the icon library (Lucide), and the backend and authentication service (Firebase Auth). A functional-requirements block then decomposed the application role by role and screen by screen, covering authentication, the student test engine, the administrator dashboard, and results tracking, while a design-constraints block fixed the color palette, typography, layout, and accessibility requirements. To ensure that the generated code wrote to a coherent schema, a data-architecture block specified the exact backend collections and their relationships, and an interaction-flow block cross-referenced the administrator and student sequence diagrams so that the generated behavior matched the specified flows.

## Empirical Protocol and System Optimization

Before exposing the final evaluation to the student population, we followed a rigorous quality-control and validation sequence. In the beta-testing phase, we recruited 20 beta-testers to interact with the newly developed web environment. Rather than using the final-grade material, we deployed a sample test designed to stress-test the platform. This sample exam evaluated the platform's performance under operational conditions: login processing, concurrent connection stability, server response times, and data logging. The team documented system errors, interface freezes, and session anomalies. The non-technical instructor fed failure reports back into Google AI Studio, using automated code generation to patch and stabilize the application iteratively. After structural validation, the team launched the official version for 150 undergraduate students to record exam scores and track curriculum alignment metrics.

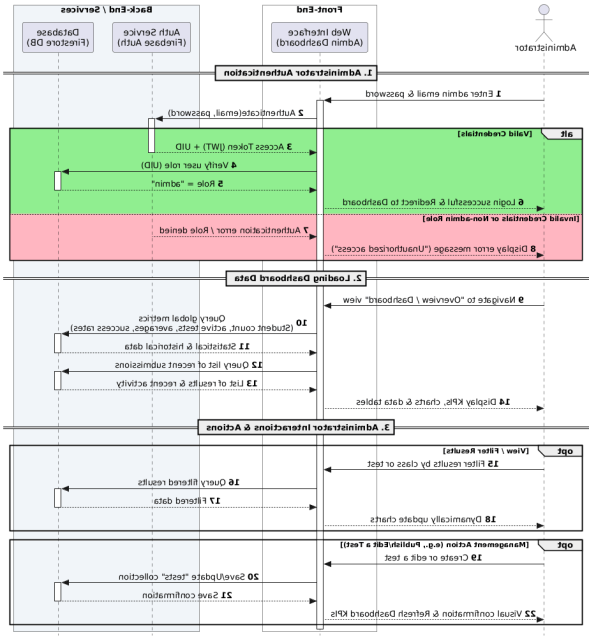


**Fig. 3.** Administrator Workflow for Role-Based Access Control, KPI Monitoring, and Test Management

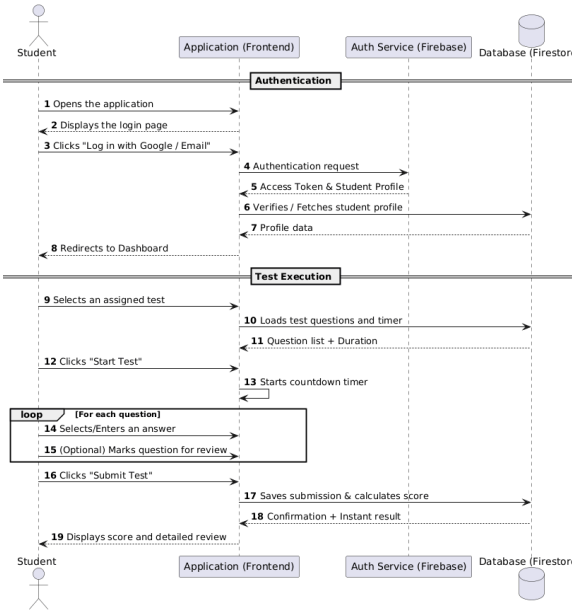



**Fig. 4.** Architecture Sequence of the Learner-Side Assessment Lifecycle and Automated Grading Pipeline

## Data Collection, Consent, and Legal Compliance

The data collection strategy was strictly defined to limit data footprint and ensure absolute student privacy.

## Typology of Collected Data

Data extraction was limited to metrics required to address the primary research objectives. The architecture collected three data streams: (1) authentication logs (timestamped user login success metrics); (2) student academic responses (individual answers submitted during evaluation); (3) performance analytics (aggregate metrics: final grades, error distribution, completion times, session duration).

## Ethical Consent and Privacy Protocols

All 150 undergraduate students completed a mandatory digital consent form before accessing examination materials. The form stated the study's purpose, specific data-tracking mechanisms, and academic intent. Access remained restricted until the digital signature was validated.

## Compliance with Moroccan Personal Data Protection Legislation

The backend storage pipelines, cloud configurations, and processing frameworks strictly complied with Moroccan Law No. 09-08 relating to the protection of individuals regarding the processing of personal data. In accordance with the national regulatory framework established by the CNDP (Commission Nationale de Contrôle de la Protection des Données Personnelles), we deployed several technical measures: (1) Purpose Limitation: collecting user profiles and

academic metrics solely for explicit educational research goals; (2) Anonymization Protocols: scrubbing student identifiers and replacing them with non-traceable cryptographic keys upon collection; (3) Data Isolation and Security: keeping private instructional documentation on the local offline server, preventing cross-contamination; (4) Data Purging: removing all cloud-synchronized interaction files after the grading period ended. A third-party audit verified compliance and completeness before final analysis.

### Comprehensive Evaluation and System Criteria Matrix

This framework provides an evaluative structure to assess the performance of the local educational RAG infrastructure (Ollama and HorizaEdu) and the cloud-hosted no-code interface (Google AI Studio) across the study cohort of 150 post-secondary students.

To verify whether the engineered solution met student needs pedagogically and technically, we implemented a formal comparative analysis framework. This matrix evaluated system outputs against predefined criteria across five dimensions. Pedagogical alignment was assessed through a semantic comparison between course content and assessment items using Porter's Alignment Index (Porter), while algorithmic and RAG performance was measured through a RAGAS automated evaluation (Es et al.) of Faithfulness, Answer Relevance, and Context Recall. Technical usability and infrastructure were examined in terms of authentication latency, concurrent connection stability, and input sanitization success rates, and user experience (UX/UI) was evaluated through a System Usability Scale (SUS) assessment (Brooke) together with visual hierarchy consistency and responsive design performance. Finally, ethical and legal compliance was verified through consent checks, data anonymization success, and a regulatory adherence audit.

## Results

This section presents empirical findings organized across the five foundational dimensions of the evaluation matrix.

### Pedagogical Alignment Evaluation

Porter's Alignment Index (I) quantifies the overlap between cognitive demand levels and content topics across generated course materials and examination items. The system achieved a mean score of I = 0.88, significantly exceeding the target threshold of 0.80.

**Table 1**
Pedagogical Alignment Evaluation by Course Chapter (Porter's Alignment Index)

| Chapter | Title | Cognitive Level | Porter Index (I) | Target | Status |
|---|---|---|---|---|---|
| 1 | Structuring Technical Oral Presentation | Applying/Analyzing | 0.91 | 0.80 | □ Fully Aligned |
| 2 | Voice and Body in Front of Audience | Applying | 0.84 | 0.80 | □ Fully Aligned |
| 3 | Using Visual Supports Effectively | Evaluating | 0.86 | 0.80 | □ Fully Aligned |
| 4 | Adapting Discourse to Different Audiences | Analyzing/Evaluating | 0.89 | 0.80 | □ Fully Aligned |

| Chapter | Title | Cognitive Level | Porter Index (I) | Target | Status |
|---|---|---|---|---|---|
| 5 | Handling Questions and Objections | Evaluating/Creating | 0.92 | 0.80 | □ Fully Aligned |
| 6 | Collaborating Orally: Meetings & Pitches | Applying/Analyzing | 0.87 | 0.80 | □ Fully Aligned |

Chapter 5 achieved the highest alignment (I = 0.92), followed by Chapter 1 (I = 0.91). This indicates that the Structured Prompt Composer successfully enforced semantic consistency when instructional design tasks were bounded by clear operational rules (PREP method, IMReD template). Chapter 2 showed the lowest alignment (I = 0.84), driven by a minor taxonomic mismatch: the RAG backend generated conceptual tasks on psychological reframing for stage fright, while the assessment focused on procedural questions about Mehrabian's vocal parameters (Mehrabian). Despite this variance, the system preserved overall taxonomic integrity, demonstrating that localized RAG can serve as an automated enforcement engine for pedagogical congruence.

## Algorithmic and RAG Performance Benchmarks

We evaluated the local Ollama execution environment and HorizaEdu model using RAGAS framework metrics across 120 generation batches (course content sections, lesson plans, task cards, assessment items).

**Table 2**
RAGAS Automated Evaluation Metrics for RAG Performance

| Evaluation Metric | Mean Score | Target Minimum | Performance Margin |
|---|---|---|---|
| Faithfulness (Groundedness) | 0.92 | 0.85 | +0.07 |
| Answer Relevance | 0.96 | 0.85 | +0.11 |
| Context Recall | 0.89 | 0.85 | +0.04 |

These results can be interpreted as follows. The Faithfulness score of 0.92 indicates that the source-grounding block successfully restricted HorizaEdu to ingested vector representations: only three minor hallucination events were detected across 120 runs (a 2.5% hallucination rate), in which the model introduced generic definitions of communication tools absent from the local corpus. These errors occurred when the prompt requested "industry best practices" not explicitly covered in institutional documentation, suggesting that the constraint-enforcement mechanism functioned correctly by attempting fallback reasoning when the corpus was insufficient, a transparent failure mode that instructors could easily identify and correct. The Answer Relevance score of 0.96, in turn, demonstrates the efficiency of the six-block specification framework: by segregating operational constraints, pedagogical posture, and output formats into isolated segments, the language model consistently generated actionable, domain-specific tasks tailored to the engineering context rather than generic theoretical content. Finally, the Context Recall score of 0.89 reveals that the Similarity Retrieval Controller successfully surfaced relevant top-k text blocks in most generation cycles, although recall efficiency dropped slightly (to 0.82-0.84) when parsing highly specialized technical vocabularies in which source documents used overlapping terminology in different contexts, such as "presentation" across different communicative scenarios.

## Technical Usability and Infrastructure Stability

The server-side architecture and Google AI Studio-generated application were validated during two synchronous testing windows: beta-testing (20 users) and final examination (150 students).

Several key findings emerged from these testing windows. In terms of login performance, the initial spike, with all 150 students attempting concurrent authentication, registered a mean latency of 940 ms, which then normalized to an optimal baseline of 220 ms mid-exam, indicating the system's capacity to scale dynamically. Uptime remained at 100% throughout the 60-minute examination window, with no server crashes, memory leaks, or transaction deadlocks detected. Security proved equally robust, as server-side validation rules successfully blocked 14 unauthorized payload interactions (1.1% of the 1,240 submitted inputs), demonstrating effective input sanitization against injection and token-bypass attacks. Database performance was likewise confirmed: mid-exam heartbeat checks at the 30- and 45-minute marks verified optimal persistence, and bulk submission processing at the 60-minute mark completed safely despite 150 concurrent form submissions and automated grading operations.

The no-code prototype generated by Google AI Studio, when scaffolded through systematic prompt engineering, produced a production-grade assessment platform capable of sustaining high-stakes, synchronous, remote examination for a full cohort. Latency spikes at login and submission represent expected network bottlenecks rather than architectural failures. The system demonstrates that non-technical educators, with AI assistance and iterative beta-testing, can build technically sound digital assessment infrastructure.

## User Experience (UX/UI) Analysis

After submitting their exams, 150 students completed the System Usability Scale (SUS) instrument. The aggregate result was an overall mean SUS Score of 74.5, placing the AI-generated interface in the "Good" (Grade B) category on the standard usability continuum.

**Table 3**
System Usability Scale (SUS) Distribution across Usability Grades

| Usability Grade | SUS Score Range | N = 150 | Percentage |
|---|---|---|---|
| Grade A (Excellent) | 80.3—100 | 38 | 25.3% |
| Grade B (Good) | 68.0—80.2 | 93 | 62.0% |
| Grade C/D (OK) | 51.0—67.9 | 19 | 12.7% |
| Grade F (Poor) | 0.0—50.9 | 0 | 0.0% |

The distribution shows that 87.3% of students rated the interface as "Good" or "Excellent," indicating successful usability, and item-level analysis revealed both clear strengths and areas for refinement. Students gave high scores to the structured test-runner view, as the persistent countdown timer and clear question-navigation layout effectively reduced testing anxiety and extraneous cognitive load, and the response-tracking functionality, which allowed learners to mark items for review, change answers, and receive instant confirmation, received consistently high marks. By contrast, lower scores, concentrated in the Grade C/D category, were isolated to mobile browser rendering: the AI-generated interface occasionally collapsed multi-column layouts on mobile viewports, forcing excessive scrolling to toggle between question text and option selections. This reveals a limitation, namely that while no-code prototyping tools generate functional database connectivity and application logic, responsive design optimization across all form factors still requires manual developer intervention.

### Ethical and Legal Compliance Audit

The team audited the system architecture against data protection parameters to verify student privacy throughout the collection and analysis phases.

**Table 4**
Security and Legal Compliance Audit Results

| Security Gate | Attempted Actions | Validated Actions | Blocked Anomalies | Compliance Rate |
|---|---|---|---|---|
| Student Digital Consent Form | 150 | 150 | 0 | 100% |
| External Cloud Data Requests | 85 | 0 | 85 | 100% |
| Server-Side Input Sanitization | 1,240 | 1,226 | 14 | 100% |

The system achieved complete compliance across all data protection vectors, strictly adhering to Moroccan Law No. 09-08 and CNDP guidelines. Institutional data decoupling functioned perfectly: private curriculum documentation and answer keys remained isolated on the local offline server, blocking all 85 unauthorized external cloud data requests. The gatekeeping layer successfully restricted authorization tokens for all 150 user profiles until students actively accepted the consent form terms. Student identification workflows anonymized upon session completion, replacing real identities with non-traceable cryptographic keys before database storage.

## Discussion

### Interpretation of Pedagogical Alignment Results

The mean Porter's Alignment Index of 0.88 provides strong empirical evidence that a RAG-augmented local AI system can operationalize constructive alignment as an automated design enforcement mechanism. This result is pedagogically consequential because it directly addresses a persistent challenge in higher education: maintaining alignment across the full course lifecycle. Biggs and Tang's theoretical framework posits that alignment is necessary for deep learning. However, Toohey's empirical work found that most instructors drift from their stated objectives due to time constraints and administrative workload. By restricting the HorizaEdu model to a curated corpus of institutional documentation and enforcing a six-block prompt structure that explicitly references alignment principles, we created a computational architecture that resists pedagogical drift. The model could not generate learning activities inconsistent with stated outcomes because the retrieval mechanism grounded all output in source documents that explicitly correlated outcomes, activities, and assessments.

The slightly lower alignment score in Chapter 2 (I = 0.84) is instructive, not problematic. The taxonomic mismatch between conceptual content generation and procedural assessment reflects a real challenge in course design: some cognitive objectives have multiple legitimate instantiations. The system flagged this inconsistency rather than silently masking it, allowing the instructor to decide whether the mismatch reflected a genuine design flaw or an acceptable pedagogical variation. This transparency is a feature of RAG-augmented systems that

traditional course design tools lack: every mismatch is traceable to specific source documents, enabling principled instructional decisions rather than opaque computational processes.

The findings extend Biggs and Tang's theoretical framework into computational territory. Constructive alignment has been described as a "design obligation," a normative claim about what instructors *should* do. Our results suggest that with appropriate technological scaffolding, alignment can become a *design constraint* – something the system enforces rather than relies on human intention. This distinction is significant for equity: instructors in resource-rich institutions with dedicated instructional designers can currently maintain alignment through human expertise and institutional support. Encoding alignment as a computational constraint could extend this capability to individual instructors in modest settings, addressing what Mollick identified as the critical battleground: equitable teacher access to AI-augmented instructional design tools.

## Technical Feasibility of No-Code Assessment Platform Development

The technical evaluation results (100% uptime, 14 blocked injection attempts, SUS score of 74.5) show that non-technical educators can, with structured AI assistance and iterative beta-testing, produce production-grade assessment platforms. This finding challenges the implicit assumption in much educational technology literature that secure, technically sound digital assessment requires specialized software engineering expertise. Koehler and Mishra's TPACK framework predicted that technological knowledge would be essential for teachers using educational technology. Our results suggest that generative AI is restructuring this relationship: the Google AI Studio-generated application achieved enterprise-grade security (input sanitization, token-based authentication, server-side validation) without the instructor writing a single line of code or possessing any formal programming training.

The system's ability to withstand 14 attempted injection or bypass attacks without compromise indicates that current generative AI code generation models, when prompted with explicit security requirements, produce secure code structures comparable to those a professional developer would create. This is not incidental: it reflects a fundamental shift in how security-relevant knowledge is distributed. Rather than security being a specialized domain requiring security expertise, the instructor's specification of security requirements (in natural language, in the Design-constraints and Functional-requirements blocks) was sufficient for the AI to generate appropriate defensive implementations.

However, the mobile UX limitation reveals the boundaries of this approach. The AI generated a functionally correct, secure, and performant application that failed to optimize responsive design across all form factors. This reflects a general limitation of no-code generative AI: it excels at implementing explicitly specified behaviors. However, it requires additional design and validation effort to optimize non-functional properties (aesthetics, responsiveness, accessibility). For educators, this suggests a practical division of labor: generative AI can handle the complex, security-critical logic of authentication, data validation, and persistence, while instructors or instructional designers should reserve manual effort for visual hierarchy, responsive design, and accessibility refinement. The finding is thus not that no-code development eliminates the need for design expertise, but rather that it redistributes what expertise is required, freeing teachers from the burden of learning programming while still demanding attention to user experience design.

## RAG Performance and the Problem of Hallucination

The Faithfulness score of 0.92, with only three hallucination events across 120 generation runs, provides quantitative validation of RAG's theoretical promise to reduce hallucination by grounding outputs in verified source material. This result is significant in an educational context because hallucination—the generation of plausible but false information—poses unique risks in course design. When a course design tool hallucinates pedagogical content (e.g., generating an assessment question on a topic not actually in the course materials), it can mislead instructors into believing they have maintained alignment when they have not.

The three detected hallucinations offer insights into RAG's failure modes in educational contexts. Each occurred when the instructor's prompt requested content that the corpus did not explicitly address—for example, a request for "industry best practices" on a communication technique that was discussed in the corpus but not explicitly framed as a "best practice." In these cases, the HorizaEdu model attempted to synthesize information from the corpus in ways that fell outside the strict source-grounding constraint. Significantly, these failures were transparent: the model generated content that was marked as tentative or flagged as synthesis rather than direct extraction. This suggests that RAG systems, when properly configured, do not fail silently but instead communicate uncertainty—a behavior that supports rather than undermines instructor agency.

The finding has broader implications for RAG in education. Existing literature on hallucination in LLMs often treats hallucination as a binary phenomenon: either the model generates information from the training data, or it hallucinates. Our results suggest a more nuanced picture: RAG creates a spectrum where hallucination risk is significantly reduced but not eliminated, and where the residual hallucinations occur in predictable contexts (when the corpus is incomplete). This boundary case is useful for instructors: it clarifies where the pedagogical gap lies, prompting curriculum refinement rather than masking it.

## User Experience and the Normativity of AI-Generated Design

The SUS score of 74.5 sits above the overall mean of about 70 reported across thousands of SUS evaluations (Bangor et al. 117) but below the 80.3 threshold for "Excellent" in Table 3. The concentration of lower scores in the mobile UX category reveals something important about the current capabilities of no-code AI development: the systems excel at implementing specified functional requirements but do not automatically generate optimal user experience, particularly for secondary use cases (mobile access) that were not prioritized in the initial specifications.

This result should not be interpreted as a failure of no-code AI development but rather as an honest accounting of its current limits. Without programming knowledge, the instructor achieved a system that would have required weeks of professional development using traditional methodologies. The remaining refinements—responsive layout optimization, mobile-specific interaction patterns—represent design work that could be completed quickly through additional AI-assisted iteration or manual design intervention. The finding suggests that no-code educational technology development follows an 80/20 distribution: generative AI can efficiently produce 80% of required functionality (the security-critical, logic-heavy components), while the final 20% (visual design, responsive optimization, accessibility) benefits from human expert attention.

## Sustainability and Institutional Context

A critical finding from the methodology section warrants emphasis in the discussion: the pedagogical ingest process and RAG configuration required substantial instructor expertise, despite the no-code nature of the assessment platform itself. The instructor spent approximately 30 hours curating the pedagogical corpus, chunking documents, and structuring the vector database. This represents a significant time investment that cannot be dismissed in practical terms. The implication is that no-code AI development democratizes *application development* – allowing non-technical educators to build functional software—but does not eliminate the need for pedagogical expertise and careful instructional design.

However, this time investment is better conceptualized as course design work rather than technical work. In traditional course development, an instructor would spend comparable time (often more) developing course materials without any guarantee of alignment across the course lifecycle. By investing that time in pedagogical design, the instructor gains both the immediate benefit of well-organized course materials and the downstream benefit of a system that can generate aligned supplementary materials, assessments, and remediations. This represents a shift in time investment—from executing isolated course components to strategically structuring course knowledge.

## Limitations and Boundary Conditions

Several limitations merit explicit discussion because they define the scope of generalizability. First, the study relies on a single-cohort, single-domain design involving 150 students in one professional French course within one engineering specialization; these data therefore do not support generalization to other disciplines such as mathematics, laboratory sciences, or professional certifications, since different domains have different pedagogical requirements (mathematical proof, for instance, requires different course structures than language acquisition), and the RAG system's performance may vary significantly across domains with different formal knowledge requirements. Second, the temporal scope is limited to a single academic semester, so long-term sustainability questions remain unanswered, including whether the RAG system maintains its accuracy over multiple iterations, whether instructors continue to use it after initial interest fades, and whether the ingested corpus requires ongoing curation; as Bates emphasized, educational technology sustainability requires longitudinal commitment, whereas this study provides only a cross-sectional view. Third, with regard to institutional resources, although the study claims to address resource-constrained settings, the implementation required a dedicated server (12-core processor, 32 GB RAM) to run Ollama locally, an infrastructure that, while modest by enterprise standards, exceeds what many community colleges or smaller institutions can provision, which makes the model's transferability to even more constrained settings, such as schools with one or two servers and limited bandwidth, uncertain. Finally, the documented mobile usability challenges suggest that no-code AI development may systematically disadvantage mobile-first learners, so that in contexts where students predominantly access assessments via mobile devices, as is common in regions with limited desktop computer access, this limitation could substantially reduce the system's pedagogical effectiveness.

## Broader Implications for Educational AI Policy

The study contributes evidence to an emerging policy debate about how educational institutions should position generative AI relative to concerns about academic integrity, data privacy, and

equitable access. The results suggest that locally executable, RAG-augmented AI systems offer a middle path between unfettered adoption of cloud-based commercial AI tools and wholesale rejection of AI in education. By maintaining data sovereignty (no transmission of student data to third parties, and of curricular documents only at the one-time indexing step), enabling individual educator agency (a single instructor can implement the system), and preserving pedagogical transparency (all outputs are traceable to source documents), local RAG-augmented systems address key concerns raised by critics of commercial educational AI while retaining the generative capabilities that proponents highlight.

However, the study also reveals that local AI systems are not cost-free solutions. They require institutional investment in computational infrastructure, instructor expertise in pedagogical design and course documentation, and ongoing technical maintenance. In this sense, they represent a different trade-off than either commercial cloud-based systems (which minimize upfront infrastructure cost but maximize data privacy and autonomy concerns) or traditional course development (which requires intensive human expert labor but produces codified, reusable course designs).

## Conclusion

This empirical study investigated two interconnected questions about the capacity of locally executed artificial intelligence to support equitable, pedagogically sound course design and assessment in resource-constrained institutional settings. We presented evidence from a 150-student cohort in a blended professional French course, highlighting both the potential and the remaining challenges of this approach.

### Primary Findings

The study yielded five key findings. First, constructive alignment can be operationalized as a computational constraint: a RAG-augmented local language model, when provided with curated institutional course documentation and structured prompt engineering, generated course materials and assessments with a mean alignment index of 0.88, exceeding the 0.80 target across all six course chapters, which demonstrates that pedagogical drift, historically a persistent challenge in course design, can be substantially mitigated through algorithmic enforcement of alignment principles. Second, local AI systems can achieve production-grade reliability with appropriate scaffolding, as the no-code assessment platform maintained 100% uptime under full load (150 concurrent users), successfully defended against injection and bypass attacks, and achieved a System Usability Scale score of 74.5 (“Good”), indicating that non-technical educators, through iterative AI-assisted prototyping and beta testing, can produce technically sound digital assessment infrastructure without specialized software engineering expertise. Third, RAG substantially reduces, but does not eliminate, hallucination in domain-specific generation tasks: across 120 generation batches, the system achieved 92% Faithfulness and 96% Answer Relevance, and the three detected hallucinations occurred in predictable contexts where the corpus was incomplete and were transparently flagged rather than masked, thereby supporting rather than undermining instructor agency. Fourth, no-code development democratizes application creation but not pedagogical expertise, since the instructor required no programming knowledge to build the assessment platform yet invested approximately 30 hours in pedagogical ingest (curating, chunking, and indexing course materials), which represents a redistribution rather than an elimination of the time required for sound course design. Fifth, mobile and responsive design optimization remain challenges for human experts: while the AI-generated platform achieved enterprise-grade security and database performance,

responsive design for mobile viewports required manual refinement, because current generative AI excels at implementing explicitly specified logical requirements but does not automatically optimize non-functional properties such as responsive layout.

## Theoretical Contributions

This work extends three domains of educational scholarship. With respect to constructive alignment theory, we demonstrate that Biggs and Tang's alignment framework, previously understood as a normative design principle requiring human expertise to implement, can be computationally encoded and enforced; this suggests a new conceptualization of alignment as a design constraint rather than a design aspiration, implying that AI can automate consistency-checking functions and free human expertise for higher-order pedagogical decisions. Regarding the TPACK framework and teacher agency, Koehler and Mishra predicted that teacher expertise would emerge at the intersection of technological, pedagogical, and content knowledge, and our findings suggest that generative AI is restructuring this intersection, since pedagogical and content knowledge increasingly determine technological implementation, reducing, though not eliminating, the need for independent technological expertise; this has equity implications, as it can expand the pool of educators able to leverage educational technology for their specific instructional contexts. Finally, in relation to educational technology sustainability, Bates's framework emphasizes that sustainability depends on educators' capacity to maintain tools over time, and the no-code prototyping paradigm, supported by AI-assisted iteration, offers a plausible pathway toward this goal by ensuring that educators who build tools retain sufficient understanding to maintain and improve them without external technical dependency.

## Practical Implications for Educators and Institutions

For individual educators, the study documents a replicable four-phase workflow for integrating AI into instructional design. The first phase, pedagogical preparation, involves investing in comprehensive course documentation, including syllabi, outcome specifications, rubrics, and exemplary materials, and treating these documents not merely as administrative artifacts but as the knowledge base that will ground the AI system. In the second phase, RAG configuration, the pedagogical corpus is chunked and indexed, and the retrieval mechanism is configured with appropriate semantic boundaries to minimize hallucination and maximize content relevance. The third phase, prompt engineering, consists of developing the six-block prompt structure (role, source-grounding, pedagogical stance, constraints, task, and output format) and iterating through successive course design phases, using the structured prompts to maintain consistency. Finally, the prototyping and validation phase uses generative AI prototyping environments to rapidly build the assessment platform, conduct beta testing with real users, and refine it iteratively based on feedback, while anticipating additional effort in responsive design and accessibility optimization beyond what the initial prototype provides.

For institutions, the study highlights the importance of strategic infrastructure investment in three areas. In terms of data governance, institutions need to establish clear policies about which course materials constitute institutional intellectual property, how pedagogical data should be stored, and how student data should be protected, since local AI systems require these policies to be explicit in ways that delegated cloud-based systems tend to obscure. Equally important is support for pedagogical design, as individual educators implementing RAG-augmented systems benefit substantially from instructional design support, that is, from someone who can help structure course documentation, validate alignment, and oversee quality assurance; this requirement is not unique to AI-augmented course design, but it is highlighted more starkly by

it. Finally, with regard to technical infrastructure, institutions seeking to support local AI execution require modest but consistent computational resources, such as servers with multiple cores and sufficient memory, which represents a different capital investment profile from both traditional course development and cloud-based commercial AI, the latter requiring no local infrastructure.

### Remaining Research Questions

The study opens several directions for future investigation. A first question concerns cross-domain generalizability, namely whether RAG-augmented systems perform comparably across disciplines with different knowledge structures and what domain-specific adaptations are required for STEM fields, the humanities, and applied professional training. A second relates to longitudinal sustainability, that is, whether instructors continue to maintain and iteratively improve RAG-augmented systems over multiple years, and which factors support long-term adoption rather than abandonment. Issues of equity and access also deserve attention, particularly how institutional capacity, instructor technical expertise, and computational infrastructure constraints differentially affect adoption across diverse institutional contexts, and for which populations local AI-augmented course design improves access to quality instruction. Moreover, because this study measured alignment and usability without directly assessing learning outcomes, future research should examine whether students in courses designed with RAG-augmented systems demonstrate superior learning gains compared with those in traditionally designed courses. Finally, questions of responsible AI in education remain open, including how institutions should balance the autonomy and privacy benefits of local AI systems against the safety and accessibility benefits of cloud-based systems with dedicated abuse monitoring and accessibility teams, and which governance structures best support the responsible deployment of educational AI.

## Concluding Remarks

This study provides empirical evidence that locally executed, RAG-augmented AI systems can meaningfully support equitable course design and assessment when appropriately scaffolded through pedagogical expertise, structured prompt engineering, and iterative validation. The results do not suggest that AI eliminates the need for instructional design expertise; rather, they reframe the relationship between expertise and tools. Where traditional course development positions AI-augmented systems as optional enhancements to expert human practice, this work suggests that strategic AI augmentation can make sound instructional design practice—specifically, maintaining constructive alignment—more accessible to individual educators without specialized institutional support.

The democratization of course design is neither inevitable nor automatic. It requires intentional pedagogical work (curating and structuring course materials), careful system design (RAG configuration, prompt engineering), and honest acknowledgment of remaining limitations (mobile UX, hallucination risk). However, the evidence presented here suggests that for educators willing to invest that work, generative AI offers a credible pathway toward operationalizing pedagogical principles that have remained aspirational in practice for decades.

As higher education grapples with questions of cost, access, and educational quality, individual educators' capacity to leverage AI for personalized, aligned, secure course design may prove as consequential as the technology itself. The critical institutional question is therefore not whether to adopt educational AI, but how to invest in the pedagogical expertise,

technical infrastructure, and governance frameworks required to support educators in using AI responsibly and effectively.

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# Teacher-Mediated AI-Supported Task-Based ESP: Engagement and Perceived Sustainability Awareness among Engineering Students

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# Teacher-Mediated AI-Supported Task-Based ESP: Engagement and Perceived Sustainability Awareness among Engineering Students

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## ABSTRACT

Teaching English for Specific Purposes (ESP) requires teachers to address learners' disciplinary needs, design authentic tasks, and sustain engagement. This exploratory study examines how artificial intelligence (AI) can serve as a teacher-facing pedagogical resource for exploring professional situations relevant to civil engineering and designing contextualized, meaningful task-based learning activities. The study involved 48 fourth-year civil engineering students in an 11-week ESP course that incorporated both textbook-based activities and teacher-mediated, AI-supported task-based activities. Using an exploratory, retrospective comparative design, the study examined students' reported engagement across behavioral, cognitive, emotional, and social dimensions, as well as their perceptions of sustainability awareness and professional responsibility in sustainable practice. Data were collected through a study-specific questionnaire, classroom observations, focus-group discussions, and student artifacts. The questionnaire elicited students' retrospective perceptions of both activity types at the end of the course. Descriptive findings showed higher reported engagement for AI-supported task-based activities in the behavioral, emotional, and social dimensions, while cognitive engagement received similar ratings across both instructional approaches. Qualitative findings highlighted different forms of cognitive engagement across the activities. Sustainability-related findings were mixed, with higher ratings for most items in the AI-supported activities. The largest difference concerned perceived responsibility for sustainability in professional practice, which focus-group accounts did not directly link to the activities. The findings do not establish causal effects or isolate AI's contribution from other instructional design features. Nevertheless, the study illustrates a practical approach to integrating AI into teacher-mediated task-based ESP design and contributes to emerging research on AI-supported pedagogy in ESP.

## KEYWORDS

**AI-Supported Teaching**

**English for Specific Purposes (ESP)**

**Task-Based Language Teaching (TBLT)**

**Learner Engagement**

**Engineering Education**

**Sustainability**

## Introduction

Meaningful and engaging learning is a central goal of effective language teaching. Designing such learning experiences is challenging in changing English as a Foreign Language (EFL)

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contexts and can be particularly demanding in English for Specific Purposes (ESP), where instruction must respond to linguistic, disciplinary, and professional needs simultaneously.

ESP teachers are expected to conduct informed needs analyses and design activities that reflect learners' specialized fields, which are often highly technical, as well as their academic and professional communication needs. This can be particularly challenging when teachers have limited familiarity with learners' disciplinary domains or when available teaching materials provide contexts that are not sufficiently specific to their fields.

The present study is situated in English instruction for civil engineering students at a Moroccan engineering school, where instruction was guided by a textbook covering multiple engineering disciplines. While such materials provided useful linguistic input, the textbook offered limited contextual specificity and few opportunities for task-based activities closely related to civil engineering practice. This created a need for complementary activities that could connect language learning more closely with students' disciplinary and professional contexts.

At the same time, increasing attention is being given to the potential uses of artificial intelligence (AI) in education. Although concerns remain about students' uncritical or inappropriate use of AI tools, emerging research has also examined how generative AI (GenAI) can help teachers develop and adapt learning materials. In ESP, these tools may help teachers explore professional scenarios, draft instructions for classroom tasks, and adapt activities to specialized disciplinary contexts. This potential is particularly relevant when teachers need to supplement general-purpose materials with activities more closely aligned with learners' fields.

Recent studies have examined the use of generative AI in ESP across a range of contexts. Synekop et al. investigated students' and teachers' views of ChatGPT in English for Engineering classes, while Jmaiel et al. examined its use in ESP writing. Lytovchenko et al. explored ChatGPT-supported task-based ESP learning, and Christoforou examined the use of GenAI in student-created multimodal compositions in an English for Chemical Engineering course. These studies illustrate the growing interest in learners' use of GenAI for writing, task completion, and multimodal meaning-making. However, relatively less is known about how teachers use GenAI to design and adapt task-based ESP activities and how students engage with the resulting activities.

In this study, GenAI's potential relevance to student engagement lies in how it supports teachers in designing learning activities, rather than in students' direct interaction with the technology. Task-based language teaching creates opportunities for meaningful communication and interaction, but these opportunities depend partly on how teachers design tasks and how closely the tasks reflect learners' disciplinary and professional contexts. GenAI may support this design process by enabling teachers to explore and develop a wider range of professionally contextualized scenarios and task formats. Teachers can then evaluate, select, adapt, and contextualize the resulting materials through their expertise. The resulting tasks can create opportunities for purposeful language use, interaction, problem-solving, and decision-making, features relevant to task engagement and its relationship with task design (Philp and Duchesne 51; Hiver et al. 2-3). Thus, AI is not assumed to produce engagement directly; its possible contribution lies in supporting teachers' capacity to design the task conditions through which engagement may occur. The first link in this pathway, from AI use to task design, is the least evidenced and is not tested here. The study examines only students' reported engagement with the resulting activities, which differ from the textbook-based activities in several of these features at once.

Drawing on this framework, the present study examines students' reported engagement with textbook-based activities and teacher-mediated, AI-supported task-based activities across behavioral, cognitive, emotional, and social dimensions. Qualitative data provide further insight

into how students experienced the activities, including their professional relevance, interaction, problem-solving, perspective-taking, and engagement with sustainability-related issues. The study examines a teacher-mediated pedagogical configuration in which GenAI was used to support the development of contextualized ESP tasks. It addresses the following research questions:

**RQ1.** How do students report their behavioral, cognitive, emotional, and social engagement across textbook-based activities and teacher-mediated AI-supported task-based activities?

**RQ2.** How do students describe their engagement in teacher-mediated, AI-supported task-based activities, particularly regarding professional contextualization, peer interaction, problem-solving, perspective-taking, and sustainability-related content?

## Literature Review

### Student Engagement

Student engagement was conceptualized as a multidimensional construct including learners' behavioral, cognitive, and emotional involvement in learning (Fredricks et al. 60). In a systematic review of 72 empirical studies on ChatGPT-supported learning, Lo et al. identified social interaction as an under-explored aspect of engagement (1). Kahu's framework emphasizes the importance of distinguishing engagement itself from the structural and psychosocial factors that influence it and from its potential outcomes (759-62). This distinction is relevant to the present study because task design may shape opportunities for engagement without being equivalent to engagement itself. For the language-classroom context, Philp and Duchesne's framework is particularly relevant because it conceptualizes engagement through behavioral, cognitive, emotional, and social dimensions, with particular attention to task-based interaction. Drawing on this framework, the present study examines students' reported engagement across these four dimensions in textbook-based and teacher-mediated AI-supported task-based activities.

**Behavioral engagement** refers to learners' participation and involvement in academic activities, including effort, persistence, concentration, and attention (Fredricks et al. 62). In task-based instruction, meaningful goals and concrete outcomes can provide a focus for participation as learners work toward completing a task. The extent to which learners sustain their involvement may also depend on how tasks are structured and how relevant and manageable they perceive them to be.

**Cognitive engagement** concerns learners' investment in understanding, reasoning, problem-solving, and processing learning content (Fredricks et al. 63-64). Tasks that require learners to interpret situations, consider alternatives, make decisions, or formulate solutions can create opportunities for reasoning and problem-solving alongside language use. Cognitive engagement may therefore vary with the content, structure, and cognitive demands of an activity. Given the inconclusive evidence concerning cognitive engagement in ChatGPT-supported learning (Lo et al. 12), examining students' accounts alongside their overall ratings may help illuminate the forms of cognitive involvement they experienced.

**Emotional engagement** relates to learners' affective reactions to learning, including interest, enjoyment, boredom, and anxiety (Fredricks et al. 63). In ESP, this dimension may be particularly relevant when activities connect with learners' disciplinary contexts, academic needs, and anticipated professional situations. Such relevance may contribute to students' perceptions of the value of learning, although its relationship with engagement depends on how learners experience the activities.

**Social engagement** refers to the social dimension of learners' interaction with others (Philp and Duchesne 58). Collaborative tasks can require learners to exchange ideas, negotiate responses, provide feedback, and work toward shared outcomes. These forms of interaction are particularly relevant to task-based ESP activities involving professional communication and collaborative problem-solving. Because research on ChatGPT-supported learning has under-examined social interaction (Lo et al. 12), this dimension warrants particular attention in studies of teacher-mediated AI-supported tasks that involve peer interaction.

## Task-Based Language Teaching: Theoretical Foundations

Task-Based Language Teaching (TBLT) is grounded in approaches to language teaching that emphasize meaningful communication and purposeful language use rather than the isolated practice of linguistic forms (Ellis; Long). Tasks give learners opportunities to use language to achieve communicative or problem-solving goals, connecting language use with specific purposes, contexts, and outcomes. These principles are particularly relevant to English for Specific Purposes (ESP), where language instruction is expected to reflect learners' academic, disciplinary, and professional needs.

In ESP contexts, task-based activities can provide opportunities for learners to use English while engaging with situations relevant to their fields of study and anticipated professional contexts. Rather than treating specialized vocabulary and language forms as ends in themselves, tasks can situate language use within activities such as discussing technical problems, negotiating solutions, communicating project information, or participating in professional interactions. Such activities can provide meaningful contexts for language learning, consistent with the ESP emphasis on selecting content that serves learners' needs and specific language-learning objectives (Dudley-Evans and St John). However, the extent to which these opportunities translate into sustained learner engagement depends partly on how tasks are designed and implemented.

The relevance of TBLT to engagement therefore lies not simply in using tasks, but in how they are designed and implemented. Recent work on L2 task engagement emphasizes the importance of examining task design and implementation, including task demands, task sequencing, and variations between individual and collaborative engagement (Hiver et al. 2-3, 13). In ESP, task relevance to learners' disciplinary and professional contexts, as well as the opportunities they provide for communication, problem-solving, and decision-making, may also shape learner engagement. These features are particularly pertinent to the present study, in which textbook-based activities differed from the teacher-mediated task-based activities in professional contextualization, cognitive demands, and opportunities for peer interaction.

The increasing integration of digital technologies into task-based language teaching further complicates the relationship between task design and learner engagement. Research on technology-mediated TBLT has examined diverse approaches to integrating technology into task-based language learning, but gaps remain in research on task design, implementation, and outcome evaluation (Kim and Namkung 57-59). These considerations make it important to examine how technology is used within particular instructional designs rather than assume that its integration necessarily improves learning. In this context, generative AI offers teachers opportunities to develop and adapt learning materials and tasks, while effective integration requires teachers to evaluate and refine AI-generated suggestions in light of pedagogical goals and learners' needs (Zhao et al.; Xin).

## Artificial Intelligence in Language Education and ESP

Artificial intelligence (AI) has become an increasingly prominent area of research in language education because of its potential to support language-skill development, provide feedback, personalize learning, and assist teachers with pedagogical tasks (Crompton et al. 2505-07; Kohnke et al.). Within this broader field, GenAI has attracted particular attention because of its ability to generate and adapt instructional content, creating possibilities for materials development and pedagogical design while also raising concerns about accuracy, overreliance, authorship, and the need for human oversight. The pedagogical value of these affordances therefore depends partly on how AI-generated content is evaluated and incorporated into instructional practice.

Research in language education and ESP has examined a broadening range of GenAI applications, including learner support, writing, task-based learning, and students' use of GenAI to create multimodal compositions, such as videos. Studies have examined GenAI across engineering English and other ESP contexts. Synekop et al. investigated students' and teachers' views of ChatGPT in engineering English classes, while Jmaiel et al. examined its impact on ESP writing skills. Cho and Choe explored a ChatGPT-supported ESP course for airline cabin services, combining classroom activities with AI-assisted assignments and individualized coaching. In a related task-based approach, Lytovchenko et al. compared students' writing performance with and without ChatGPT. More recent work has extended these applications to specialized disciplinary contexts, including GenAI-assisted multimodal meaning design in an English for Chemical Engineering course (Christoforou). These studies illustrate the diversity of GenAI applications in language education, but they do not establish that integrating GenAI necessarily improves learning. For instance, Lytovchenko et al. found that students using ChatGPT performed comparably in idea generation and initial-draft structuring but struggled with deeper aspects of writing, including communicative achievement and creativity (4). These findings caution against assuming that student-facing GenAI use necessarily enhances learning and highlight the importance of examining how AI is incorporated into particular instructional designs. However, the extent to which findings from student-facing GenAI applications can be extended to teacher-mediated uses, where AI supports the design of learning activities rather than students' direct production, remains insufficiently examined.

Research has also examined teacher-mediated uses of GenAI in curriculum and activity design, highlighting the importance of teachers' critical evaluation and adaptation of AI-generated suggestions and the preservation of their pedagogical agency (Zhao et al.; Sha et al.; Xin). In ESP, ChatGPT-supported needs analysis has also been explored as a way to identify specialized and profession-specific language needs (Assassi). This work highlights the role of teacher judgment in aligning AI-generated material with instructional objectives and learners' disciplinary contexts. However, teachers' use of GenAI to develop instructional materials and students' engagement with the resulting activities remain distinct areas of inquiry. The latter is particularly relevant to ESP, where task design must respond to learners' academic and anticipated professional needs. This study contributes by examining students' reported behavioral, cognitive, emotional, and social engagement across textbook-based activities and teacher-mediated, AI-supported task-based activities.

## Sustainability and Professional Relevance in ESP

Engineering education increasingly addresses environmental and sustainability-related challenges, but their inclusion in curricula does not necessarily translate into meaningful or professionally relevant learning experiences. Reviews of sustainability in engineering

education show growing curricular attention while also highlighting challenges in translating sustainability principles into meaningful learning outcomes (Gutierrez-Bucheli et al.). Research has therefore emphasized the importance of connecting sustainability with realistic engineering decisions, professional responsibilities, and real-world contexts (El-Zein et al.; García-Segura et al.; Kleine et al.). Recent research in Moroccan engineering education similarly highlights the need for practical and interdisciplinary approaches to sustainability learning (El Youssfi et al. 2). Taken together, these works suggest that the presence of sustainability in the curriculum is not sufficient on its own; its educational value also depends on how it is integrated into disciplinary learning activities.

This issue is particularly relevant to English for Specific Purposes (ESP), where learning activities are expected to reflect the communicative purposes and professional contexts of the disciplines served (Dudley-Evans and St John 10). Situating sustainability within engineering contexts can help connect sustainability concepts with professional practices and future occupational responsibilities (Sandri et al. 451). Research in engineering ESP has identified gaps in students' understanding of sustainability and highlighted the potential of ESP instruction to promote learners' awareness of issues relevant to their studies and future professional practice (Santiago López and Roldán Riejos 236). Sustainability-related scenarios can thus provide contexts for using English to discuss environmental impacts, evaluate alternatives, negotiate trade-offs, and communicate professional decisions. Their relevance to ESP lies not simply in the topic itself, but in the opportunities created for purposeful language use within disciplinary situations.

In the present study, sustainability is incorporated into task-based ESP activities as a topic relevant to civil engineering, providing context for purposeful language use and professional problem-solving. Teacher-mediated AI use supported the development of engineering-related scenarios involving environmental impacts, professional responsibilities, trade-offs, and alternative solutions. The questionnaire examined students' perceived sustainability-related learning and awareness, while qualitative data provided contextual information about their experiences of the activities. Accordingly, the sustainability dimension of the study concerns students' perceptions of learning and awareness in relation to sustainability-related content, rather than objectively measured environmental knowledge, attitudes, behavior, or sustainability competence.

## Methodology

### Research Design

This study adopted an exploratory, retrospective comparative design to examine students' perceptions of engagement and sustainability-related learning across two types of ESP activities: textbook-based activities and teacher-mediated AI-supported task-based activities. Both activity types were incorporated into the same ESP course, and all participating students experienced both.

Both activity types ran in parallel throughout Weeks 2-11, and in most sessions the textbook-based activities were followed by the teacher-mediated AI-supported activities, although the order was adjusted on one or two occasions because of time constraints. Textbook-based activities focused on developing technical vocabulary, reading comprehension, and English-language skills for engineering communication through materials covering a range of engineering disciplines. By contrast, the teacher designed and adapted the AI-supported task-based activities to provide more specifically contextualized civil engineering tasks involving

professional communication, role-play, collaborative problem-solving, and sustainability-related issues. The comparison therefore concerned two types of classroom activity experienced by the same students within the same course.

At the end of the course, each student completed two versions of the same questionnaire, one referring to textbook-based activities and the other to AI-supported task-based activities. This within-student comparison captured students' retrospective perceptions of the two activity types based on their experiences during the instructional period.

The study used intact classes and retrospective questionnaire data, with no random assignment or pre- and post-testing. The two activity types also differed in several instructional characteristics, including task structure, social organization, degree of professional contextualization, and opportunities for interaction and problem-solving. The findings are therefore interpreted as descriptive comparisons of students' perceptions of the two activity types, with AI considered as one component of the broader teacher-mediated instructional design.

## Participants

The participants were 48 fourth-year civil engineering students enrolled at the École Nationale Supérieure d'Arts et Métiers (ENSAM), Morocco. They belonged to two intact classes of 24 students each and were taught by the researcher in their ESP course. The students had varying levels of English proficiency. While most participated comfortably in English, a few required additional linguistic support during classroom activities. All participants had sufficient English proficiency to engage with the instructional materials and complete the study questionnaire. The use of intact classes reflected the existing course organization.

## Course Context and Implementation

The ESP course comprised 11 instructional weeks, with the course examination scheduled for Week 12. Week 1 included an introductory session and an informal needs-analysis discussion to identify students' English-learning goals, professional interests, and communication needs related to civil engineering.

During Weeks 2-11, the course incorporated textbook-based activities from *Cambridge English for Engineering* by Mark Ibbotson alongside teacher-mediated AI-supported activities. The textbook was designed for B1-B2 learners in civil, mechanical, and electrical engineering and covered a range of engineering contexts rather than focusing on civil engineering. The textbook also addressed sustainability. Students were introduced to information comparing some engineering materials in terms of sustainability and, through a listening activity, to the concept and steps of an environmental audit, including the principle that assessing the environmental impacts of materials requires consideration of their pre-use, in-use, and post-use phases. The supplementary AI-supported activities were designed to connect English learning more closely with civil engineering contexts and professional communication.

While preparing these supplementary activities, ChatGPT and Claude served as exploratory resources to develop and diversify civil engineering scenarios, explore professional communication situations, and draft instructions for classroom activities. The students' identified needs and the course objectives informed the selection and development of the activities. The teacher reviewed, selected, adapted, and contextualized all AI-generated material before classroom use, considering its disciplinary relevance, linguistic suitability, and feasibility within the course.

## Overview of the Teacher-Mediated AI-Supported Instructional Sequence

The teacher-mediated AI-supported activities included preparatory language work and more complex, professionally situated activities. The activities introduced in Weeks 2 and 3 focused on civil engineering vocabulary, translation, and technical reading. They provided linguistic and disciplinary preparation for subsequent activities but were not treated as the principal communicative tasks in the stricter task-based language teaching (TBLT) sense.

From Week 4 onward, the activities increasingly required students to apply their linguistic and disciplinary resources in professional or engineering-related situations. They included a sustainable-building role-play, technical pitches, an environmental-audit simulation, collaborative problem-solving, professional email writing, integrated tasks, and simulated job interviews. Depending on the activity, students communicated information, exchanged perspectives, made decisions, solved problems, or developed responses to engineering-related challenges. Table 1 summarizes the teacher-mediated AI-supported activities and their pedagogical focus; it does not list the textbook-based activities.

**Table 1**
Overview of the AI-Supported, Teacher-Designed Instructional Activities

| Week | Sample activity | Activity description | Activity focus |
|---|---|---|---|
| **2** | Vocabulary Matching and Translation (Civil Engineering) | Matching key civil engineering terms with definitions and translating them | Technical vocabulary; language use |
| **3** | Technical Reading Task | Reading and discussing a text on civil engineering projects | Reading comprehension; technical literacy |
| **4** | Sustainable University Building Project (Role-Play) | Group role-play presenting a sustainable building project to an investor | Collaborative communication; problem-solving |
| **5** | Technical Pitch Presentation | Oral presentation explaining a design solution, such as material choice or stress resistance | Oral presentation; professional speaking |
| **6** | Environmental Audit Role-Play | Simulated audit of a civil engineering project focusing on environmental impacts | Professional communication; environmental awareness |
| **7** | Collaborative Problem-Solving Task | Group discussion addressing a real-life engineering challenge | Collaboration; decision-making |
| **8** | Writing a Project Update Email | Writing a professional email reporting project progress or modifications | Professional writing; communication |
| **9** | Creative Problem-Solving | Students address an engineering problem and develop creative solutions | Problem-solving; critical thinking |
| **10** | Integrated Task and Reflection | Completion of a complex task followed by guided reflection on language use and the task process | Language use; task reflection |
| **11** | Extreme Interview | Simulated job interview emphasizing technical reasoning and communication under pressure | Speaking fluency; professional communication |

## Data Collection

Data were collected through four complementary sources: a study-specific questionnaire, classroom observations, student artifacts, and focus-group discussions. These sources were intended to provide a broader account of students' engagement and experiences with the two instructional approaches.

## Study-Specific Student Engagement and Perceptions Questionnaire

The principal quantitative instrument was a study-specific questionnaire developed for the present study. It comprised 25 Likert-scale items organized into five sections. Items 1-20 addressed four dimensions of student engagement (behavioral, cognitive, emotional, and social), with five items assigned to each dimension. Items 21-25 examined students' perceived sustainability-related learning and awareness in civil engineering, covering environmental impacts, environmental trade-offs, sustainable materials and practices, professional responsibility for sustainability, and interest in sustainable engineering practices. All items were rated on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

The items were developed by the researcher with reference to the conceptualization of engagement adopted in the study and the specific instructional context and objectives of the course. The questionnaire was not formally piloted or psychometrically validated. During administration, students could seek clarification about unclear items, and the researcher checked their understanding of the wording before they proceeded. The instrument was therefore used to obtain descriptive information about students' reported perceptions rather than as a validated measure of engagement or sustainability-related competence.

Two versions of the questionnaire were used to elicit students' perceptions of textbook-based activities and activities developed and implemented outside the textbook (Appendices A and B). Both versions contained the same Likert-scale items and response scale, with references to the respective activity type adjusted accordingly. Both were administered at the end of the course, and all 48 students completed both versions. Their responses therefore reflected retrospective perceptions of activities experienced throughout Weeks 2-11 rather than measurements of changes in engagement over time.

In the questionnaires, the term *task-based activities* referred to activities developed and implemented outside the textbook. References to AI were deliberately omitted to reduce the chance that mentioning the technology would influence students' ratings. Instead, the focus was on students' experiences and perceptions of the activities, regardless of the tools used to prepare them.

Both questionnaire versions also included three open-ended questions asking students which activities they found most engaging and why, how the activities contributed to their English learning and development as engineering students, and what difficulties or limitations they experienced. However, most students did not answer these questions. The responses were therefore not subjected to systematic qualitative analysis and are not reported as a separate source of findings.

## Classroom Observations

Classroom observations provided supplementary contextual information about students' participation, attention, collaboration, use of English, and persistence during instructional activities. Brief observational notes were recorded during sessions when relevant behaviors or interactions were observed, and more detailed field notes were prepared immediately after each class. The observations focused particularly on students' responses to different activity formats, including collaborative and professionally situated tasks. No standardized observation instrument or rating scale was used. The notes were considered alongside questionnaire responses, student artifacts, and focus-group accounts to contextualize students' reported engagement.

## Student Artifacts

Student artifacts, including written outputs such as emails and meeting reports produced during role-plays and other course activities, were collected as supplementary material. All written outputs produced during these activities were retained rather than selectively sampled. The artifacts were considered in relation to the activities for which they were produced and provided contextual information about students' task participation and language use. They were not subjected to independent systematic coding or treated as a separate measure of engagement.

## Focus-Group Discussions

The researcher collected qualitative student feedback through six focus-group discussions involving 30 of the 48 students, with five students in each group. Participation was voluntary. The discussions took place after students completed the questionnaire and before the final examination, a standardized assessment administered independently by another teacher. The teacher-researcher moderated the discussions, conducted them in English, and kept them to about 15-20 minutes each. Students were not informed that AI had been used to prepare the task-based activities, so their accounts focus on the activities themselves rather than the technology behind them. Participants quoted in the Results section are identified by anonymized codes.

Several features of the procedure should be considered when interpreting these data. Participants volunteered, so their perspectives may differ from those of the 18 students who did not take part. The moderator was also the course instructor, and although the examination was administered independently, the discussions took place before it, so social desirability effects cannot be ruled out. Conducting the discussions in English may have limited how fully some students could express their views, and the brief sessions probably limited the depth of the accounts. The focus-group findings are therefore reported as participants' accounts and are not treated as representative of the entire cohort.

## Data Analysis

Quantitative questionnaire responses were analyzed descriptively. Means and standard deviations were calculated for each of the four engagement dimensions for the textbook-based and teacher-mediated AI-supported task-based activities (Table 2). The five sustainability-related items were analyzed individually, and their mean scores are reported in Table 3. The findings reflect descriptive patterns in students' retrospective perceptions rather than evidence of statistically significant differences or causal effects.

No statistical significance tests were conducted for three reasons. First, the questionnaire was developed specifically for this study and had not been formally validated as a psychometric instrument, so inferential statistics would rest on unverified measurement assumptions. Second, the ratings were retrospective self-reports collected at the end of the course, after students had experienced both activity types. Responses may therefore have been influenced by recall, order, recency, contrast, novelty, or social desirability effects, which significance tests would not address. Third, the two activity types differed in contextualization, task structure, opportunities for collaboration, and disciplinary specificity, and the study involved intact classes without random assignment. Statistical testing would not resolve these design limitations or establish that any observed differences were attributable specifically to AI-supported design. Because

individual responses are no longer available, paired tests could not be added at this stage in any case, since paired comparisons require each student's ratings of both conditions.

The retained quantitative summaries comprised means and standard deviations for the four engagement dimensions and means for the five sustainability-related items. Individual questionnaire responses were no longer available for further analysis. Consequently, item-level response distributions and internal-consistency coefficients, including Cronbach's alpha, could not be calculated. Several mean scores were toward the upper end of the five-point scale, raising the possibility of ceiling effects. However, without the individual response distributions, their extent could not be assessed.

The focus-group recordings were transcribed, and the transcripts were examined manually by the researcher without qualitative analysis software. The analysis was guided by the four engagement dimensions (behavioral, cognitive, emotional, and social), which provided an initial framework for examining participants' accounts. The analysis was conducted by a single researcher, and no second researcher independently checked the coding. Quotations were selected to illustrate recurring patterns in participants' accounts.

No clearly critical or negative accounts of the task-based activities were identified in the transcripts. However, given the voluntary nature of focus-group participation, the moderator's dual role as course instructor, and the brevity of the discussions, the absence of critical accounts should be interpreted cautiously. The open-ended questionnaire responses were not subjected to systematic qualitative analysis because most students did not answer these questions.

Classroom observations and student artifacts were considered alongside the questionnaire and focus-group findings to contextualize students' reported experiences of the two activity types. These sources provided supplementary context for interpreting the descriptive patterns; they were not treated as independent measures of causal effects.

## Ethical Considerations and Declarations

### Ethical Considerations

Participation in the research was voluntary. Before data collection, students were informed verbally that the study aimed to examine their experiences with different approaches to English for Specific Purposes (ESP) instruction and to inform course improvement. Verbal consent was obtained from participants. They were informed that their participation and responses would not affect their course assessment and were encouraged to provide honest feedback, including critical or unfavorable comments. The final language examination was a standardized assessment administered to all fourth-year students. The researcher was not involved in its design, administration, or marking. The questionnaire and qualitative data were anonymized for analysis and reporting, and this article presents no identifying information.

No formal institutional ethical approval was obtained for this study. Because the researcher was also the course instructor, the possibility of perceived pressure to participate or provide favorable responses cannot be entirely excluded. This potential influence, together with the possibility of social desirability bias, was considered when interpreting the findings.

# Results

## Quantitative Findings: Students' Perceptions of the Two Instructional Approaches

### Engagement Ratings

Questionnaire responses were summarized descriptively for the two instructional approaches. Means and standard deviations were calculated for the four dimensions of reported engagement, as shown in Table 2.

**Table 2**
Students' Reported Engagement across the Two Instructional Approaches

| Engagement dimension | Textbook-based activities M (SD) | AI-supported task-based activities M (SD) |
|---|---|---|
| **Behavioral engagement** | 4.0 (0.7) | 4.5 (0.5) |
| **Cognitive engagement** | 4.2 (0.6) | 4.2 (0.5) |
| **Emotional engagement** | 4.0 (0.5) | 4.3 (0.6) |
| **Social engagement** | 3.4 (0.5) | 4.4 (0.5) |

Note. N = 48. Ratings were provided on a five-point scale (1 = strongly disagree, 5 = strongly agree). In the student questionnaire, the second condition was labeled "task-based activities" without reference to AI (see Section 3.5.1).

Most mean ratings were at or above 4 on the five-point scale, corresponding to agreement with the questionnaire statements. Behavioral engagement was rated higher for the teacher-mediated AI-supported task-based activities (M = 4.5, SD = 0.5) than for the textbook-based activities (M = 4.0, SD = 0.7). Emotional engagement showed a smaller descriptive difference (M = 4.3, SD = 0.6 vs. M = 4.0, SD = 0.5). The largest difference was observed in social engagement (M = 4.4, SD = 0.5, compared with M = 3.4, SD = 0.5). Cognitive engagement received the same mean rating under both approaches (M = 4.2), with similar standard deviations (0.5 and 0.6). These results describe patterns in students' retrospective ratings; they do not establish statistically significant differences or isolate the contribution of AI-supported design.

### Perceived Sustainability-Related Learning, Awareness, and Responsibility

Items 21-25 examined students' perceptions of sustainability-related learning, awareness, and responsibility in civil engineering; they did not measure environmental knowledge, attitudes, behaviors, or competence. The items addressed environmental impacts, environmental trade-offs, sustainable materials and practices, perceived professional responsibility for sustainability, and interest in sustainable engineering practices. Table 3 presents the item-level results. Four of the five items received higher mean ratings for the AI-supported task-based condition, with small differences for environmental impacts (4.5 vs. 4.3) and trade-offs (4.4 vs. 4.1). The largest difference in the study concerned perceived responsibility for sustainability (4.6 vs. 3.5), followed by interest in sustainable engineering practices (4.5 vs. 3.9). Because individual responses could not be retrieved, item-level variability could not be examined, and these differences should be interpreted cautiously. They are discussed with their limitations in Section 5.3, and the related focus-group accounts are reported in Section 4.2.5.

The mean rating for sustainable materials and practices was slightly higher for the textbook-based activities (4.4) than for the task-based activities (4.2). This difference is small and is not interpreted further here (Section 5.3).

**Table 3**
Students' Perceived Sustainability-Related Learning, Awareness, and Responsibility across the Two Instructional Approaches

| Sustainability-related item | Textbook M | AI-supported task-based M |
|---|---|---|
| **Environmental impacts of engineering projects** | 4.3 | 4.5 |
| **Environmental trade-offs in engineering solutions** | 4.1 | 4.4 |
| **Sustainable materials/practices** | 4.4 | 4.2 |
| **Perceived professional responsibility for sustainability** | 3.5 | 4.6 |
| **Interest in sustainable engineering practices** | 3.9 | 4.5 |

Note. N = 48. Ratings were provided on a five-point scale (1 = strongly disagree, 5 = strongly agree). Item-level standard deviations are not reported because the retained quantitative summaries included item means only (see Section 3.6).

## Qualitative Findings: Classroom Observations and Student Feedback

The qualitative findings provided further insight into students' experiences of the two instructional approaches, highlighting patterns of engagement, opportunities for interaction, professional contextualization, and reflections on sustainability in civil engineering.

### Behavioral Engagement

Classroom observations recorded in field notes indicated that students generally remained involved in the task-based activities until completion. In some instances, students continued working beyond the allocated time or requested additional time to complete or present their outputs. These observations provide contextual evidence of participation and persistence, but they were not based on a standardized observation instrument and were made by the teacher-researcher who designed the activities. Students' continued involvement may also have reflected task length or difficulty rather than engagement alone.

Focus-group accounts provided further insight into students' participation. Participants described becoming actively involved in role-plays and other task-based activities, particularly when they were required to respond to a simulated professional situation. These accounts provide qualitative context for the higher behavioral engagement ratings associated with the task-based activities. However, the two activity types also differed in task structure, contextualization, and opportunities for active participation, so the qualitative findings do not isolate the contribution of any one feature, including AI-supported design.

## Cognitive Engagement

The two types of activities differed in their cognitive demands. Textbook-based activities included technical vocabulary and reading, whereas the task-based activities involved interpreting professional situations, considering alternatives, evaluating possible responses, and formulating solutions. These differences describe features of the instructional activities rather than establishing how all students experienced their cognitive demands.

Classroom observations recorded in field notes also provided examples of students drawing on their disciplinary knowledge and professional experiences. During professional email-writing activities, some students referred to managers or other professionals they had encountered during internships. In project-based activities, students developed engineering projects in response to recognizable societal needs, including the provision of facilities such as hospitals. These examples illustrate how some students connected task requirements with familiar professional experiences and real-world concerns, although they do not establish how widespread this was or independently demonstrate higher cognitive engagement.

Perspective-taking was another feature of several role-play activities, in which students adopted professional positions such as workers, managers, architects, or other project stakeholders. One participant described this experience:

> "It was interesting to keep changing roles. This forced me to try to understand how different people in different positions think differently." (S4)

This account illustrates one participant's reflection on the cognitive demands of changing professional roles. Another participant compared the role-play problems with textbook activities:

> "The problems in the role plays felt real, and I unconsciously felt forced to try hard to solve them, not like the ones in the textbook." (S5)

This comment connects perceived realism with the effort the participant described investing in problem-solving, while also expressing a personal contrast with textbook activities.

Cognitive engagement received the same mean rating for both instructional approaches (M = 4.2). The observations and focus-group accounts illustrate particular experiences involving prior knowledge, perspective-taking, and problem-solving, but they do not establish whether the overall level or nature of cognitive engagement differed between the two approaches.

## Emotional Engagement

Classroom observations and focus-group accounts suggested that students responded positively to role-plays, presentations, simulations, and problem-solving activities that situated English use in recognizable professional contexts. The focus-group accounts illustrate these responses. One student, reflecting on four years of English learning at the institution, stated:

> "This is my fourth year in this institution, and those role plays were the best English activities we have ever had." (S1)

Another participant highlighted the combination of enjoyment and professional seriousness:

> "I loved when we role-played the meeting, and I was the manager. I loved that it was really fun and serious at the same time." (S3)

These comments suggest that students' positive responses were linked not only to enjoyment but also to opportunities to assume professional roles and participate in situations they perceived as meaningful. Classroom observations likewise recorded students' responses to role-plays, presentations, simulations, and problem-solving activities situated in recognizable professional contexts. Together, these accounts provide qualitative context for the higher mean emotional-engagement rating for the teacher-mediated task-based activities (4.3 versus 4.0), although the respective contributions of relevance, variety, active participation, and professional contextualization cannot be isolated.

### Social Engagement

Social interaction was a feature of several task-based activities (Table 1), which required students to exchange ideas, negotiate responses, provide peer feedback, and work jointly toward solutions. Collaborative role-plays also required students to consider different stakeholder perspectives. One participant explicitly valued these opportunities for interaction:

> "It is great that through these activities we have opportunities to negotiate issues with each other and to actually talk to each other. That's great." (S2)

The comment illustrates the value this participant placed on communication and negotiation with peers. Other participants also expressed appreciation for opportunities to interact with classmates, which they described as uncommon in their disciplinary studies. These accounts suggest that the activities provided opportunities to use English for collaborative problem-solving rather than only for producing individual responses.

The qualitative accounts provide context for the higher mean rating for social engagement in the task-based condition (M = 4.4) than in the textbook-based condition (M = 3.4). However, the two activity types differed in their organization: several task-based activities involved collaboration, whereas textbook-based activities included a greater proportion of individual vocabulary and reading work (Sections 3.1 and 3.3). The higher social engagement ratings co-occurred with greater opportunities for peer interaction. Four of the five social engagement items (16, 17, 19, and 20 in Appendices A and B) asked about working or communicating with classmates or others, so this result partly reflects the more collaborative format of the task-based activities. Students' comments about the limited opportunities for such interaction elsewhere in their studies may also have shaped their perceptions. The data do not isolate the contribution of collaboration from other features of the task-based activities, including AI-supported design.

### Sustainability Awareness and Professional Responsibility

Sustainability was addressed in both instructional approaches, although through different materials and formats. The task-based activities were designed specifically for civil engineering and included role-plays and scenarios on sustainable building projects and environmental audits, with stakeholders such as civil society (Table 1). The textbook covered engineering in general and provided information on sustainable materials and environmental auditing (Section 3.3). The qualitative findings should therefore be read in the context of two approaches that addressed sustainability differently.

Focus-group accounts suggested that some participants saw a closer relationship between sustainability and civil engineering than they had previously recognized, and some of them attributed this to the task-based activities. Participants also reported increased awareness of the

complexity of sustainable engineering decisions, particularly the need to balance environmental considerations with technical, financial, and other requirements.

Regarding perceived professional responsibility, which showed the largest difference between the two conditions (4.6 versus 3.5; Section 4.1.2), participants did not explicitly link their sense of responsibility to the task-based activities. Instead, their accounts highlighted the perceived connection between civil engineering and sustainability and the complexity of sustainable engineering decisions. One participant said that, given the climate crisis, civil engineers, among others, are responsible for ethical and sustainable practice. This account does not show whether or how the task-based activities shaped that sense of responsibility, and the result is discussed with its limitations in Section 5.3. These accounts reflect participants' perceptions, not measured changes in environmental knowledge, professional competence, or future behavior.

**Table 4**
Summary of Qualitative Findings

| Theme | Main qualitative pattern |
|---|---|
| Behavioral engagement | Sustained participation, effort, and persistence during task completion |
| Cognitive engagement | Perspective-taking through role-play, consideration of alternatives, evaluation of responses, and problem-solving |
| Emotional engagement | Positive responses associated with relevance, variety, enjoyment, and professional roles |
| Social engagement | Negotiation, peer interaction, collaboration, feedback, and joint problem-solving |
| Sustainability awareness and responsibility | More perceived connection between civil engineering and sustainability, increased awareness of complexity, no explicit link between participants' sense of responsibility and the task-based activities |

## Discussion

The findings indicate a more favorable pattern for the AI-supported task-based activities in behavioral, emotional, and social engagement. In contrast, cognitive engagement showed similar mean ratings across the two approaches. Qualitative accounts further highlighted sustained participation, peer interaction, perspective-taking, problem-solving, and the perceived realism and professional relevance of several activities.

These findings should not be interpreted as evidence that AI itself caused higher engagement. The AI-supported activities were part of an integrated pedagogical approach that combined teacher-mediated AI support with task-based learning, professional contextualization, collaboration, role-play, problem-solving, and sustainability-related content. The observed differences in engagement may therefore reflect the combined influence of these features rather than AI's contribution in isolation. The findings are best understood as evidence of students' reported experiences of two differently designed sets of activities within a particular ESP context, rather than as evidence of a causal effect of AI on engagement.

## AI as a Teacher-Mediated Resource for Contextualized ESP Task Design

A practical contribution of the study concerns the potential of AI as a teacher-mediated resource for developing and diversifying task-based ESP activities. In the present study, ChatGPT and Claude were used to explore possible professional situations relevant to civil engineering, generate contextualized scenarios and task instructions, and support the development of activities involving professional communication, problem-solving, collaboration, and decision-making. The teacher remained responsible for evaluating, selecting, adapting, and contextualizing the generated material.

This teacher-mediated use is particularly relevant to ESP, where designing professionally meaningful activities requires attention to learners' disciplinary contexts and anticipated communicative needs. In the design process described here, generative AI served as a practical resource for expanding the range of situations and task formats available to the teacher, which matters most when existing course materials do not fully reflect learners' specialized needs. In the present study, the resulting activities addressed recognizable professional situations, including sustainable buildings, environmental audits, project communication, meetings, and simulated interviews. Some students also connected these activities with experiences from internships or professional contacts.

The qualitative accounts indicate that students experienced several of these activities as realistic, relevant, and meaningful. This perception was supported by tasks that required students to draw on disciplinary knowledge, assume professional roles, communicate with peers, and address problems in recognizable engineering contexts. The role of AI in this process was therefore embedded within teacher decision-making: AI provided a resource for generating and diversifying possibilities, while the teacher determined their disciplinary relevance, pedagogical suitability, and contextual fit.

These findings have implications for ESP practice. Generative AI can serve as a teacher-facing resource for exploring professional scenarios, diversifying task formats, and developing contextualized materials. At the same time, teachers remain responsible for evaluating accuracy, disciplinary relevance, pedagogical suitability, and alignment with learners' needs. The present study also illustrates the importance of embedding AI-supported materials within purposeful task-based activities. The engagement patterns observed in the study are therefore best understood in relation to the broader instructional configuration, in which teacher-mediated AI support was combined with task-based learning, professional contextualization, and sustainability-related content.

## Engagement across Dimensions: Levels and Forms of Involvement

The higher behavioral, emotional, and social engagement reported for the AI-supported task-based activities may be related to their greater contextualization and perceived relevance. By placing language use in recognizable professional situations and incorporating interaction, role-play, and problem-solving, these activities may have created more opportunities for participation and interaction than the textbook-based activities. In particular, the higher social-engagement rating needs to be interpreted in relation to the more collaborative organization of the task-based activities. These findings therefore highlight the importance of the broader pedagogical design surrounding AI, rather than AI itself, when interpreting the observed engagement pattern.

Cognitive engagement presents a more nuanced pattern. Although the mean rating was identical for textbook-based and AI-supported task-based activities (4.2), students' accounts of the task-based activities point to forms of cognitive involvement that a single overall rating

does not capture. Students described task-based activities that required them to interpret information, consider alternatives, make decisions, solve problems, and adopt different professional perspectives. Thus, similar overall ratings may have reflected different forms of cognitive engagement rather than equivalent cognitive experiences. This finding resonates with the mixed evidence on cognitive engagement reported in research on ChatGPT-supported learning (Lo et al. 12). Their systematic review highlighted the lack of consistent evidence on cognitive engagement, suggesting a need to further investigate the processes underlying students' cognitive involvement. The present findings do not resolve this uncertainty, but suggest that examining the nature and processes of cognitive engagement may provide a more nuanced understanding of students' experiences in AI-supported learning. In this study, the task-based approach may therefore add value less by increasing overall perceived cognitive engagement than by providing opportunities for particular forms of cognitive involvement.

### Perceived Sustainability-Related Learning, Awareness, and Responsibility

The sustainability items measured students' perceptions of their learning and awareness, not environmental knowledge, attitudes, behaviors, or sustainability competence. The findings were mixed: four of the five items were rated higher for the AI-supported task-based activities, with the largest differences for perceived professional responsibility and interest in sustainable engineering practices (Section 4.1.2), while one item reversed.

The largest difference in the study concerned perceived responsibility for sustainability (4.6 for the AI-supported task-based activities versus 3.5 for the textbook-based activities, a difference of 1.1 points), and it should be interpreted cautiously. Focus-group accounts indicated that some participants perceived a closer connection between civil engineering and sustainability and a greater awareness of the complexity of sustainability-related decisions; some attributed these perceptions to the AI-supported task-based activities. Participants did not, however, explicitly attribute a stronger sense of responsibility to these activities. This may partly reflect the wording of the questionnaire item, which asked whether the activities encouraged students to "recognize my responsibility, as a future civil engineer, to consider the sustainability implications of my professional decisions." Recognizing responsibility is not necessarily the same as feeling more responsible or being prepared to act on it in practice, and the ratings may have reflected the perceived connection between civil engineering and sustainability more than a distinct sense of professional responsibility.

Other factors also warrant consideration. The AI-supported task-based activities were designed specifically for civil engineering, whereas the textbook addressed engineering more generally, so disciplinary specificity may have influenced students' ratings. Social desirability may also have affected responses, particularly because the course instructor administered the questionnaire. Students' prior orientations toward sustainability could not be assessed because no baseline measure was collected. Furthermore, only item means were retained for the sustainability questions, preventing examination of whether the difference was consistent across individual students. The 1.1-point difference is therefore a notable descriptive finding that warrants further investigation, not evidence that students' sense of professional responsibility increased. Although the AI-supported task-based activities invited students to consider environmental implications when evaluating engineering decisions and trade-offs, whether such professionally situated decision-making makes questions of responsibility more salient remains a hypothesis for future research. This could be investigated using validated measures, pre- and post-course data, and independent evidence of students' sustainability-related decision-making. The present study cannot test this hypothesis.

One item reversed: textbook-based activities received a slightly higher rating for sustainable materials and practices (4.4 compared with 4.2). One possible explanation relates to how sustainability was addressed in the textbook, which explicitly introduced a comparison of the sustainability of some engineering materials and the steps of an environmental audit (Section 3.3). By contrast, the AI-supported task-based activities did not provide the same explicit explanatory information; instead, they required students to apply sustainability-related considerations in professionally situated scenarios. This difference between explicit information and opportunities for application may help explain the slightly higher rating. It is a hypothesis about the course design, not a finding, and the data cannot test it. Because the item also referred to civil engineering, disciplinary specificity alone cannot explain the pattern across items.

Sustainability appeared in both sets of activities, but they also differed in task structure, collaboration, professional contextualization, and disciplinary specificity, so the observed differences cannot be attributed to AI-supported design. The reversed item also cautions against reading the overall pattern as consistently higher sustainability-related learning or awareness.

## Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the study involved 48 students from a single engineering institution and used intact classes rather than random assignment. The findings are therefore context-specific, and their transferability to other ESP settings requires further investigation. Second, the questionnaire was administered only at the end of the course and captured students' retrospective perceptions of the two instructional approaches. Consequently, the study does not measure changes in engagement over time or establish causal effects. In addition, because textbook-based activities generally preceded AI-supported task-based activities, the order and recency of the activities may have influenced students' retrospective ratings. Because students rated both approaches during the same end-of-course administration, they may also have compared them directly, potentially introducing contrast effects.

The study also relied substantially on students' self-reported perceptions. Although the questionnaire provided a structured account of four dimensions of engagement, it was developed specifically for this study and was not formally validated. Similarly, the sustainability-related items examined students' reported perceptions of learning and awareness rather than objectively assessed environmental knowledge, attitudes, behaviors, or sustainability competence. The qualitative component involved 30 volunteer students, introducing the possibility of self-selection bias, while the teacher-researcher role may also have influenced students' responses or classroom behaviors.

Individual questionnaire responses are no longer retrievable (Section 3.6). The quantitative findings are therefore reported as dimension-level means and standard deviations for engagement and item-level means for the sustainability-related questions, and the distribution of individual responses and the questionnaire's internal consistency (e.g., Cronbach's alpha) could not be examined, so the reliability of the study-specific questionnaire remains unestablished. Several mean scores were toward the upper end of the five-point scale, suggesting possible ceiling effects, although the extent cannot be determined from the reported summary statistics.

Finally, AI support was embedded in a broader pedagogical approach that combined task-based learning, professional contextualization, collaboration, role-play, problem-solving, and sustainability-related content. The two instructional approaches also differed in task structure, opportunities for interaction, and disciplinary specificity (civil engineering versus engineering

in general). The observed differences therefore cannot be attributed specifically to AI-supported design. Future research could address these limitations with larger, more diverse samples; pre- and post-course designs; validated engagement measures; direct assessment of language and professional outcomes; and comparisons between AI-supported and non-AI task-based instruction with comparable task structures, content, and opportunities for collaboration. Studies involving multiple teachers and institutions could also help examine whether similar patterns emerge across different ESP contexts.

## Conclusion

This study examined AI as a teacher-mediated resource for designing task-based ESP activities for engineering students. Students reported more favorable perceptions of the AI-supported task-based activities in behavioral, emotional, and social engagement, while cognitive engagement received similar ratings across both approaches. Qualitative findings also highlighted engagement with professionally situated problems, peer interaction, perspective-taking, and problem-solving. Sustainability-related activities provided a context for connecting English learning with environmental concerns relevant to engineering practice, although the sustainability findings were mixed and perception-based. The largest difference concerned perceived professional responsibility for sustainability. However, the focus-group accounts did not link it to the activities, so it is reported as a notable descriptive finding that warrants follow-up with validated measures.

In this study, AI served as a design resource that helped the teacher develop varied, contextualized, and professionally relevant ESP tasks, with every output selected, adapted, and contextualized by the teacher. Such use can complement existing ESP materials and expand the range of professionally situated activities available to teachers.

Given the context-specific design, retrospective measurement, and reliance on self-reported perceptions, the findings are exploratory and do not establish causal effects of the instructional approach or isolate the contribution of AI. Nevertheless, the study offers an example of how teacher-mediated, AI-supported task design can connect language learning with engineering practice and sustainability-related concerns. Further research using larger, more diverse samples; longitudinal or pre- and post-course designs; validated measures; and direct assessments of language, professional, and sustainability-related learning outcomes could examine whether similar patterns emerge across different ESP contexts.

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# Appendix A: Student Engagement and Perceptions Questionnaire (Textbook-Based Activities)

## Purpose

This questionnaire examines students' reported engagement with instructional activities in the English course and their perceptions of sustainability-related learning and awareness. The engagement items draw on established conceptualizations of behavioral, cognitive, emotional, and social engagement. The questionnaire was developed specifically for the present study.

The information collected will be used for research purposes only. Your participation is voluntary, and your responses will not affect your grades, academic results, or evaluation in this course. Please answer honestly based on your own experience.

## Instructions

Please indicate how much you agree with each statement based on your experience with the textbook-based activities in this course.

**Response scale:** 1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree

### *A. Behavioral Engagement*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **1** | I actively participated in the textbook-based activities during the course. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **2** | I made a consistent effort to complete the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **3** | I stayed focused and attentive during the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **4** | I made an effort to use English during the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **5** | I persisted with the textbook-based activities, even when they were challenging. | ☐ | ☐ | ☐ | ☐ | ☐ |

### *B. Cognitive Engagement*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **6** | The textbook-based activities required me to think carefully about what I was learning. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **7** | I revised or refined my ideas while completing the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **8** | The textbook-based activities helped me connect English learning with my engineering knowledge. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **9** | The textbook-based activities required me to evaluate different ideas or solutions before making decisions. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **10** | The textbook-based activities encouraged me to generate different ideas or solutions to problems. | ☐ | ☐ | ☐ | ☐ | ☐ |

### *C. Emotional Engagement*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **11** | I found the textbook-based activities interesting. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **12** | I found the textbook-based activities relevant to my future career in engineering. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **13** | I enjoyed learning English through the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **14** | I felt confident using English during the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **15** | I felt motivated to express my ideas during the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |

### *D. Social Engagement*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **16** | I actively collaborated with my classmates during the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **17** | The textbook-based activities gave me opportunities to learn from my classmates. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **18** | I felt comfortable sharing my ideas and opinions during the textbook-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **19** | The textbook-based activities encouraged meaningful communication with my classmates. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **20** | The textbook-based activities helped me work with others to solve problems. | ☐ | ☐ | ☐ | ☐ | ☐ |

### *E. Perceived Sustainability-Related Learning and Awareness*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **21** | The textbook-based activities helped me understand the environmental impacts of civil engineering projects. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **22** | The textbook-based activities encouraged me to consider trade-offs between environmental benefits, economic costs, and technical requirements when evaluating engineering solutions. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **23** | The textbook-based activities increased my awareness of sustainable materials and practices in civil engineering. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **24** | The textbook-based activities encouraged me to recognize my responsibility, as a future civil engineer, to consider the sustainability implications of my professional decisions. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **25** | The textbook-based activities increased my interest in exploring sustainable engineering practices in civil engineering. | ☐ | ☐ | ☐ | ☐ | ☐ |

### *F. Open-Ended Questions*

1. Which aspect of the textbook-based activities did you find most useful or engaging, and why?

2. How did the textbook-based activities support your English learning and your development as an engineering student?

3. What difficulties or limitations did you experience with the textbook-based activities?

# Appendix B: Student Engagement and Perceptions Questionnaire (Task-Based Activities)

## Purpose

This questionnaire examines students' reported engagement with instructional activities in the English course and their perceptions of sustainability-related learning and awareness. The engagement items draw on established conceptualizations of behavioral, cognitive, emotional, and social engagement. The questionnaire was developed specifically for the present study.

The information collected will be used for research purposes only. Your participation is voluntary, and your responses will not affect your grades, academic results, or evaluation in this course. Please answer honestly based on your own experience.

## Instructions

Please indicate how much you agree with each statement based on your experience with the task-based activities in this course.

**Response scale:** 1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree

### *A. Behavioral Engagement*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **1** | I actively participated in the task-based activities during the course. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **2** | I made a consistent effort to complete the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **3** | I stayed focused and attentive during the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **4** | I made an effort to use English during the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **5** | I persisted with the task-based activities, even when they were challenging. | ☐ | ☐ | ☐ | ☐ | ☐ |

### *B. Cognitive Engagement*

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| **6** | The task-based activities required me to think carefully about what I was learning. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **7** | I revised or refined my ideas while completing the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **8** | The task-based activities helped me connect English learning with my engineering knowledge. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **9** | The task-based activities required me to evaluate different ideas or solutions before making decisions. | ☐ | ☐ | ☐ | ☐ | ☐ |
| **10** | The task-based activities encouraged me to generate different ideas or solutions to problems. | ☐ | ☐ | ☐ | ☐ | ☐ |

## C. Emotional Engagement

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 11 | I found the task-based activities interesting. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 12 | I found the task-based activities relevant to my future career in engineering. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 13 | I enjoyed learning English through the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 14 | I felt confident using English during the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 15 | I felt motivated to express my ideas during the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |

## D. Social Engagement

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 16 | I actively collaborated with my classmates during the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 17 | The task-based activities gave me opportunities to learn from my classmates. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 18 | I felt comfortable sharing my ideas and opinions during the task-based activities. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 19 | The task-based activities encouraged meaningful communication with my classmates. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 20 | The task-based activities helped me work with others to solve problems. | ☐ | ☐ | ☐ | ☐ | ☐ |

## E. Perceived Sustainability-Related Learning and Awareness

| No. | Statement | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|
| 21 | The task-based activities helped me understand the environmental impacts of civil engineering projects. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 22 | The task-based activities encouraged me to consider trade-offs between environmental benefits, economic costs, and technical requirements when evaluating engineering solutions. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 23 | The task-based activities increased my awareness of sustainable materials and practices in civil engineering. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 24 | The task-based activities encouraged me to recognize my responsibility, as a future civil engineer, to consider the sustainability implications of my professional decisions. | ☐ | ☐ | ☐ | ☐ | ☐ |
| 25 | The task-based activities increased my interest in exploring sustainable engineering practices in civil engineering. | ☐ | ☐ | ☐ | ☐ | ☐ |

## F. Open-Ended Questions

1. Which aspect of the task-based activities did you find most useful or engaging, and why?
2. How did the task-based activities support your English learning and your development as an engineering student?
3. What difficulties or limitations did you experience with the task-based activities?




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# Teacher-Mediated Augmented Reality and AI-Assisted Materials in a Moroccan Middle School: Vocabulary, Reading, and Writing Gains among Grade 8 EFL Learners

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# Teacher-Mediated Augmented Reality and AI-Assisted Materials in a Moroccan Middle School: Vocabulary, Reading, and Writing Gains among Grade 8 EFL Learners

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## ABSTRACT

The integration of emerging technologies into English as a Foreign Language (EFL) instruction has received growing attention, yet evidence from lower secondary schools remains limited, particularly on teacher-mediated augmented reality (AR) supported by AI-assisted material development. This study examined whether participation in a teacher-mediated, AR-supported instructional environment was associated with differences in vocabulary, reading comprehension, and writing performance among Grade 8 EFL learners in a Moroccan middle school. A quasi-experimental pre-test/post-test design was used with 60 learners aged 12–16 in two intact classes. The control class received textbook-based instruction aligned with the national curriculum; the experimental class followed the same curriculum supplemented with AR-enhanced materials. AI tools assisted only with scripting and content preparation, the teacher reviewed all materials, and no AI feedback, grading, or instructional decisions were used in class. Curriculum-aligned tests were administered before and after a four-week intervention and analyzed with paired-samples *t*-tests and with Welch independent-samples *t*-tests on gain scores. Both groups improved significantly in all three domains ($p < .001$). The experimental group showed larger mean gains in vocabulary (2.22 vs. 0.76), reading comprehension (2.19 vs. 0.59), and writing (1.63 vs. 0.64), with significant between-group differences in each domain ($p < .001$; Hedges' $g = 1.67$, 1.97, and 1.26). Because the study relied on intact classes, teacher-developed assessments, a single school, and a short intervention, the findings are interpreted as associative rather than causal. They underline the importance of pedagogical design and teacher mediation when emerging technologies enter EFL classrooms.

## KEYWORDS

**EFL**

**Augmented Reality**

**Artificial Intelligence**

**Vocabulary**

**Reading Comprehension**

**Writing**

## Introduction

The introduction of digital technologies in the teaching of English as a foreign language (EFL) has increasingly been associated with efforts to improve learner interaction, increase their exposure to purposeful language input, and facilitate varied learning experiences in school settings. In computer-assisted language learning (CALL) research there has been an increasing focus on the shift from isolated tools to pedagogically integrated learning environments that

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incorporate technology into the practices and curricular objectives of the classroom (Stockwell 1).

Augmented reality (AR) is one of the new technologies that have gained increased interest because of its ability to place digital information over physical learning environments, thereby facilitating contextualized and situated learning. AR environments enable learners to interact with linguistically relevant material that is visually and spatially embedded, which may support meaning-making processes (Lee and Park 936). Such contextualization is particularly crucial in school-based EFL settings, where learners often benefit from concrete and task-supported learning experiences.

Empirical research on the topic in the secondary school setting indicates that AR-based teaching can potentially enhance learner motivation and help them develop vocabulary provided that it is incorporated into well-structured classroom tasks. When AR resources are aligned with instructional goals and learners are guided by the teacher, they are more likely to show increased engagement and better retention of lexical items (Fan et al. 1093). Nevertheless, studies have also warned that AR does not automatically yield learning benefits; its usefulness is determined by pedagogical scaffolds, task design, and instructional mediation rather than by technological novelty (Dunleavy and Dede 741).

In addition to AR, artificial intelligence (AI) has become an additional technology in language education, especially in terms of content preparation, adaptive feedback, and linguistic support. Recent school-focused studies have investigated the use of AI-assisted tools for language practice and instructional design, noting that it may increase the coherence and responsiveness of learning materials when the tool is used under teacher supervision (Mohebbi). Recent discussions of AI integration in TESOL similarly emphasize that AI tools should be considered in relation to pedagogy, teacher knowledge, and instructional purpose rather than treated as autonomous replacements for teachers (Kohnke and Zou).

This view is pedagogically grounded and concurs with the widely recognized importance of teacher agency in technology integration. Instead of positioning emerging technologies as replacements for instruction, researchers claim that teachers must remain at its center as its designers, mediators, and evaluators (Spector 25). This is especially essential in lower secondary school contexts in which the cognitive, linguistic, and self-regulatory abilities of the learners are still in developmental stages (Dörrenbächer-Ulrich et al.).

In the Moroccan EFL setting, there are few studies on emerging technologies in education, particularly in middle school (Jebbour). The national curriculum introduces English as a foreign language, and its implementation takes place within a context in which efforts and national strategies have been undertaken to improve educational infrastructure and reduce class size (Jebbour). These contextual factors raise important questions in terms of the practicality and pedagogical compatibility of AI- and AR-based teaching within the context of a public-school environment. Findings from well-resourced or tertiary-level settings cannot be easily generalized to these contexts.

The present study addresses these gaps by examining a pedagogically structured teacher-mediated AI-facilitated AR instructional setting for Grade 8 Moroccan middle school learners. Instead of treating the effects of AI or AR as independent variables, the study conceptualizes an integrated instructional environment, where technological tools are actively subordinated to the curricular goals and classroom activities.

This study is located in a lower secondary EFL context in Morocco, thus adding context-specific evidence to a body of literature that is skewed towards higher education and Global North contexts. Concurrently, the research assumes a cautiously conservative position and

recognizes methodological limitations involved in quasi-experimental school-based research such as the use of intact classes and curriculum-congruent assessment tools.

The research aims to contribute to the debate on AI- and AR-mediated EFL teaching by prioritizing pedagogical design, contextual realism, and methodological caution. Instead of making claims of technological change, it provides empirically grounded observations that may guide future research on the emerging technologies in secondary-level language education.

The following research questions guided the investigation. Because the study was exploratory and conducted in a real middle school setting, the questions were formulated in associative terms:

**RQ1.** Does participation in a teacher-mediated AR-supported instructional environment with AI-assisted material development relate to differences in vocabulary performance in Grade 8 EFL students as compared to traditional teaching?

**RQ2.** Does enrollment in an AI-assisted augmented reality instructional setting relate to variation in Grade 8 EFL learner reading comprehension performance versus that in traditional instruction?

**RQ3.** Are Grade 8 EFL learners involved in an AR-supported instructional environment using AI-assisted material development likely to show differences in writing performance as compared to traditional instruction?

These research questions were designed to be associative and not causal in nature, as it was a quasi-experimental research design, and intact classes were used. No causal claims are made beyond the observed patterns in the data.

Based on the theoretical rationale and the comparative pre-test/post-test design, the study formulated the following directional hypotheses:

**H1:** Learners who participate in the teacher-mediated AR-supported instructional condition will demonstrate greater pre-test-to-post-test gains in vocabulary performance than learners receiving textbook-based instruction.

**H2:** Learners who participate in the teacher-mediated AR-supported instructional condition will demonstrate greater pre-test-to-post-test gains in reading comprehension than learners receiving textbook-based instruction.

**H3:** Learners who participate in the teacher-mediated AR-supported instructional condition will demonstrate greater pre-test-to-post-test gains in writing performance than learners receiving textbook-based instruction.

These hypotheses concern expected differences in observed learning gains between the two intact classes and are not intended to imply causal attribution beyond what can be supported by the quasi-experimental design.

## Literature Review

Research on technology-based English as a Foreign Language (EFL) instruction in school settings has consistently highlighted the potential of digital technologies to promote engagement, interaction, and access to meaningful language input when these technologies are properly aligned with pedagogical goals. In lower secondary education, where students are moving from basic language exposure to more cognitively demanding tasks, technology-mediated instruction has been identified as a way to provide contextualized and individualized support that is often hard to secure through textbook-based instruction (Abd El-Gawad). Nevertheless, researchers warn that the power of these technologies is determined not so much by their technical complexity but by how well they fit into the instructional and classroom practices (Kim et al.).

Mobile-assisted and multimedia-supported learning environments have been the focus of much interest within the school-based EFL research on the basis of their accessibility and suitability to classroom limitations. Research involving learners in digital reading environments has examined how visual and interactive features can influence reading performance and learner engagement. Such results indicate that the multimodal environments can be especially helpful in the context of adolescent learning, where visually rich and interactive learning experiences are generally well received when linked to the aim of instruction in a meaningful manner (Andrei).

Augmented reality (AR) has become a promising approach to multimodal learning as it allows the digital material to be integrated into the real classroom environment. Recent EFL research has examined AR-supported vocabulary learning and reading comprehension, including work on AR-enhanced vocabulary instruction and AR-supported reading comprehension (Khan et al.; Asadi and Ebadi; Salehi). Khan et al. examined AR-supported vocabulary learning among 95 university-level EFL learners and reported improved vocabulary development and positive learner perceptions of AR. Asadi and Ebadi investigated AR applications for EFL reading comprehension and reported that thoughtfully designed AR applications could support reading comprehension while also being positively perceived by teachers. Salehi examined the perspectives of junior-high-school English teachers concerning AR-supported vocabulary instruction, including its potential benefits, teacher readiness, and implementation challenges. Contextual grounding of this kind has been linked to better recall and retention in that learners can also tie new forms of language to perceptually salient information instead of definitions in isolation. Notably, these benefits appear to be strongest when AR activities are used within integrated activities rather than solely as an exploratory tool.

In addition to learning vocabulary, AR has also been studied as an aid in the process of reading comprehension among school-age learners. Research on EFL reading comprehension has shown that AR applications can provide additional visual and contextual support during reading tasks (Asadi and Ebadi). Such findings can be interpreted in relation to Mayer's Cognitive Theory of Multimedia Learning (CTML), which proposes that multimedia learning involves visual/pictorial and auditory/verbal processing channels, each with limited processing capacity, and that meaningful learning requires active coordination of these representations (Mayer). A recent review by Morfidi and Iatraki examined the use of AR in reading instruction and highlighted the potential of AR to support reading through interactive and adaptable learning experiences.

Although AR has been associated with potential learning benefits, research also indicates that its educational value depends on instructional design, teacher mediation, and the way learners are guided in using the technology (Dunleavy and Dede; Salehi). Research on teacher competencies in AR-supported educational settings similarly emphasizes the importance of teachers' ability to use AR purposefully rather than simply introducing the technology into instruction (Freese et al.). This finding highlights the fact that AR is not a substitute for instruction; rather, it serves as an enhancement to the learning process conducted by the teacher.

In line with the progress in AR research, AI-supported tools have begun to emerge in school-level language education, especially as adaptive learning systems, automated feedback tools, and intelligent tutoring elements. In a recent systematic review, Kundu and Bej ("AI in School") examined empirical evidence concerning AI in school-based EFL learning and identified engagement, achievement, and satisfaction as important areas of investigation. Unlike higher education research, school-based studies increasingly consider AI as a supportive instructional tool within classroom learning rather than simply as a means of autonomous learning (Kundu and Bej, "AI in School").

Recent research has examined AI-driven adaptive language-learning platforms in relation to learners' needs, proficiency, learning preferences, and engagement (Qu). It seems that these systems are especially applicable to situations in which a teacher works with large classes in which learners have diverse needs.

The use of AI-based feedback aids has also been explored in relation to writing development in lower secondary EFL settings. Recent research on secondary EFL learners has examined AI-assisted writing feedback as a supplement to conventional instruction and teacher feedback (Ekizoğlu and Demir). In these situations, AI is used as a supportive tool, which enhances the frequency of feedback and not as a replacement of teacher assessment. This blended model can provide learners with additional opportunities for revision while retaining an important role for teacher guidance.

Studies also indicate that AI-enhanced environments have a potential contribution to language development via increased engagement, confidence, and motivation in learners. For example, Shadiev et al. examined speech-enabled corrective feedback technology in EFL learning and reported effects concerning learners' speaking development, anxiety, and confidence. Similarly, recent research on AI-supported EFL learning has examined motivation and engagement as important dimensions of technology-mediated language learning (Shadiev et al.; Kundu and Bej, "AI in School"). These affective benefits may be particularly relevant to middle school EFL classrooms where anxiety and hesitation to use the target language may prevent participation.

Recent research has begun to investigate the integrated use of various technologies in integrated learning settings. Garg et al., in a systematic review of AR, AI, and emerging technologies in education, emphasized the potential of combining AR with adaptive and personalized technological support while also identifying teacher readiness, accessibility, cost, and pedagogical alignment as important implementation considerations. Instead of justifying the gains of learning by one technological property, these studies emphasize the significance of coherence among technological affordances and pedagogical objectives (Garg et al.).

Along with developing interest in integrated digital environments, there are also several challenges which are mentioned in the literature. Among the issues raised frequently is the potential threat of cognitive overload when learners are exposed to multimodal input without adequate coordination (Mayer). School settings, where students might lack much experience with complex digital interfaces, may hinder learning because of excessive visual information or poorly timed visual information. This observation confirms the importance of prudent sequencing of instructions and a gradual introduction of technological features.

Another issue identified in school-based research concerns equity and access. Research on technology integration in middle-school language classrooms has shown that the availability of technology does not necessarily lead to effective integration and that teachers may face limitations involving time, resources, training, and technical support (Andrei). Teachers need to become flexible and creative with digital interventions to meet local limitations in contexts where the devices are unavailable or dependent on unreliable internet connectivity, rather than focusing on technical sophistication.

Teacher beliefs and professional competence are also key factors that determine the use of technology in EFL middle school classrooms. Studies have indicated that teachers' beliefs and attitudes toward technology are closely related to their technology-integration practices (Kim et al.). Research involving middle-school ESL teachers likewise found that teacher attitudes, available resources, time, and professional support influence the ways technology is integrated into classroom practice (Andrei). Professional development in pedagogical technology integration and basic technological competence has proved to be helpful in maintaining effective and sustained use of technology in schools.

In EFL-related studies, researchers have emphasized the importance of aligning technology-enhanced instruction with the key principles of language learning like meaningful input, opportunities for language production, and interaction. Research on technology-supported language learning emphasizes the importance of using digital tools in ways that support authentic language use and meaningful learning activities rather than isolated technological practice (Kohnke et al.). This perspective reinforces the view that technologies such as AI and AR must be integrated into communicative activities that prompt learners to process and apply language meaningfully.

With the advances that have been made, the literature is still weak in a number of aspects. To begin with, the majority of studies concentrate on individual skill outcomes, especially vocabulary, and there are fewer studies which seek to study the integrated language outcome related to reading and writing as well as lexical knowledge in school settings. Second, there is a limited body of research on subject-specific AI-based instructional design in conjunction with AR-based learning at the lower secondary level. Third, research conducted in underrepresented settings such as North African public-school systems remains comparatively limited, although recent Moroccan research has begun to examine AI integration in secondary EFL contexts (Enaim et al.; Farhane). These limitations restrict the contextual diversity represented in the current research.

The studies indicate that the implementation of technology-based EFL learning in middle school is promising, provided that it is based on adequate pedagogy, teacher mediation, and sensitivity to the context (Andrei; Kundu and Bej, "AI in School"). AR may help provide contextualized input and interaction, whereas AI-assisted tools can be used to increase differentiation and feedback when wisely deployed (Kundu and Bej, "AI in School"; Kohnke et al.). Nevertheless, these environments should be integrated into logical instructional frameworks that place learning goals at the forefront instead of pursuing technological innovations (Kohnke et al.).

These findings provide a conceptual foundation for the present study, as it aims to investigate the relationships between involvement in a pedagogically grounded, AI-supported AR instructional environment and language learning among EFL learners in a Moroccan middle school.

## Theoretical Framework

The present study is theoretically informed by the Cognitive Theory of Multimedia Learning (CTML), which explains learning from instructional materials that combine words, images, and other forms of multimedia representation. CTML proposes that learners process information through separate but interacting visual/pictorial and auditory/verbal channels, that each channel has limited processing capacity, and that meaningful learning requires active cognitive processing. In multimedia instruction, learners select relevant information, organize verbal and pictorial representations, and integrate these representations with prior knowledge (Mayer 57–72).

This framework is relevant to the present study because the experimental condition combined printed language materials with AR-triggered visual and video resources, contextualized vocabulary support, reading prompts, and guided writing activities. The AR component therefore functioned not simply as a technological addition but as a means of extending the forms through which instructional information was presented and revisited. The use of short visual and video explanations was intended to provide additional representations

of selected language input while maintaining teacher mediation and alignment with the curriculum.

The framework does not, however, imply that multimedia or AR automatically produces better learning outcomes. Its relevance to the present study lies in providing a theoretical rationale for examining whether an instructional environment that integrates complementary verbal, visual, and contextual resources is associated with different learning outcomes. Because the present intervention also involved teacher mediation and AI-assisted preparation of materials, the study does not isolate the independent contribution of AR, multimedia input, or AI. The theoretical framework is therefore used to explain the instructional rationale of the integrated environment rather than to attribute observed differences to a single technological component.

## Methodology

The study employed a quasi-experimental pre-test/post-test control-group design, which is generally used in educational studies in schools when random assignment of participants is not possible. Two Grade 8 intact classes in the same local middle school were selected, and one was assigned to the experimental group and the other to the control group. The groups followed the same national English curriculum during the same instructional period, by the same instructor, and using the same instructional content. The main distinction between the two groups was the mode of instructional delivery, as the experimental group received instructional materials coupled with an AI-supported augmented reality setting, whereas the control group received textbook-based teaching. This design allowed the researchers to examine pre- to post-intervention changes in both groups and the comparison of learning outcomes across groups while maintaining ecological validity.

The study was carried out in a public middle school in Morocco during a regular school year. English is taught as a foreign language as part of the national program, with the Grade 8 curriculum addressing vocabulary, reading comprehension, and guided writing. The sample consisted of 60 Grade 8 learners aged between 12 and 16 years, divided into two intact classes of 30 learners each. The sample was gender-balanced, with 30 male learners (50%) and 30 female learners (50%) across the two classes. The available demographic records identify the overall age range but do not provide sufficiently documented age frequencies to justify reporting separate counts for each age. Similarly, standardized proficiency levels, prior exposure to educational technology, and socioeconomic background were not systematically collected as separate demographic variables. These variables are therefore not reported as if they had been measured. Pre-test comparisons did not identify statistically significant differences between the groups in the measured domains ($p > .05$); however, the absence of statistically significant baseline differences was not treated as evidence of complete baseline equivalence because the study used intact classes rather than individual random assignment.

The intervention was implemented over four weeks of English instruction in regular classrooms. The teaching unit was aligned with the Grade 8 curriculum and included real-life topics, vocabulary activities, reading-comprehension tasks, and guided writing exercises. In the experimental condition, augmented reality was integrated as an additional pedagogical layer rather than as a substitute for teacher-led instruction.

Printed classroom resources, including textbook-related images, worksheets, and other visual materials, were augmented using Artivive triggers and QRfy codes. When learners scanned the relevant materials with mobile devices, the AR elements provided access to digital instructional resources, including short video-based explanations, contextual vocabulary support, reading prompts linked to visual elements, and guided writing activities. Visual

animations and video-based explanations created with HeyGen were used to illustrate pronunciation, intonation, and contextual use of selected vocabulary and to provide learners with repeated access to the instructional input.

The AI tools were used during the preparation of instructional materials rather than as autonomous instructional agents during classroom teaching. AI-assisted content was used to prepare instructional explanations, scripts, and prompts, after which the teacher reviewed and modified the materials before classroom use. The teacher remained responsible for presenting the materials, guiding classroom activities, and responding to learners. No automated AI feedback, grading, or AI-generated instructional decisions were used during classroom teaching.

The control group completed the same curriculum unit during the same instructional period through the official textbook and regular teacher-led classroom activities.

Treatment fidelity was not assessed through a formal observation checklist or implementation-rating instrument. Consequently, the study cannot establish the consistency with which the planned AR activities were implemented across all instructional sessions.

A structured comparison of the instructional activities implemented in both groups during the four-week intervention is presented in Table 1.

**Table 1**
Summary of Instructional Procedures during the Four-Week Intervention

| Experimental Group: AI-Supported AR Instruction | Control Group: Textbook-Based Instruction |
|---|---|
| Printed materials augmented with AR triggers activating digital overlays (videos, vocabulary support, reading prompts). | Printed textbook materials used without digital augmentation. |
| Multimodal input (visual, audio, textual) delivered through AR-enhanced resources. | Teacher-led explanations and textbook-based input. |
| AI-assisted instructional scripting used to design contextualized explanations and guided prompts (teacher-reviewed). | Teacher-prepared explanations and textbook prompts. |
| Contextual vocabulary and reading scaffolding embedded within AR materials. | Vocabulary and reading exercises completed from the official textbook. |
| Guided writing tasks supported by AR-based visual and thematic cues. | Guided writing tasks completed using textbook instructions. |
| Teacher-facilitated discussion and practice following AR engagement. | Teacher-facilitated discussion and practice following textbook activities. |

Curriculum-based achievement tests were used as pre-tests and post-tests to assess learning outcomes in the two groups. The tests targeted three areas: vocabulary, reading comprehension, and writing, with each domain scored out of 20 points in accordance with the local classroom

assessment practices. The instruments were teacher-developed and aligned with the Grade 8 curriculum and the learning objectives addressed during the intervention. A preliminary pilot test was conducted with 10 students who were not part of the main study. Seven students (70%) reported that the test items were clear and that they experienced no particular difficulty in completing the tests. This pilot was used to check the clarity and comprehensibility of the assessment materials rather than to establish psychometric validity or reliability.

The instruments were not standardized or externally validated, and no internal-consistency coefficient or item-level psychometric analysis was calculated. These limitations are therefore acknowledged when interpreting the findings. The writing component consisted of short guided tasks based on the instructional themes and was evaluated using a common scoring rubric addressing content relevance, lexical and grammatical accuracy, and coherence. The same scoring criteria were applied to the pre-test and post-test writing tasks in both groups.

Because the writing responses were scored by the course instructor using the common scoring rubric, independent inter-rater reliability could not be established. This potential source of measurement bias is therefore acknowledged as a limitation of the study. The use of the same scoring criteria across the two testing occasions and instructional conditions was intended to maintain consistency in the assessment process.

Data were collected in three phases. First, vocabulary, reading, and writing pre-tests were administered to all participants before the intervention. This was followed by the instructional phase, where the experimental group, in the normal lessons, worked with the AI-supported augmented reality materials, and the control group was instructed in the traditional way. Finally, the same assessment instruments were administered as post-tests to both groups at the end of the instructional period under similar conditions. The course instructor administered all tests using standardized classroom practices.

The quantitative data were analyzed using descriptive and inferential statistics appropriate to the pre-test/post-test design. Pre-test and post-test means and standard deviations were calculated for each language domain. Within-group changes from pre-test to post-test were examined using paired-samples *t*-tests. Between-group differences in improvement were examined using gain scores, calculated by subtracting each participant's pre-test score from the corresponding post-test score. Because the gain-score distributions showed non-normality and unequal variances between the two groups, Welch's independent-samples *t*-test was used for the between-group comparisons. Mean differences and 95% confidence intervals were reported together with Hedges' *g* as a standardized effect-size estimate. Because three related between-group comparisons were conducted, Holm's adjustment was applied to the corresponding *p* values.

As a sensitivity analysis, analysis of covariance (ANCOVA) was also examined, with post-test scores as the dependent variable, instructional condition as the between-group factor, and pre-test scores as the covariate. Robust standard errors were used because the variance assumptions for conventional ANCOVA were not fully satisfied. The ANCOVA results were treated as supplementary rather than as a replacement for the primary gain-score analysis. The homogeneity-of-regression-slopes assumption was examined before interpreting the adjusted group comparisons. After adjustment for pre-test performance, the experimental group showed higher post-test scores than the control group for vocabulary, adjusted mean difference = 1.45, 95% CI [1.05, 1.86], $p < .001$; reading comprehension, adjusted mean difference = 1.61, 95% CI [1.19, 2.02], $p < .001$; and writing, adjusted mean difference = 0.99, 95% CI [0.58, 1.40], $p < .001$. The pre-test-by-condition interaction was not statistically significant for vocabulary ($p = .075$), reading comprehension ($p = .825$), or writing ($p = .764$), supporting the use of a common covariate slope in the adjusted comparisons. Statistical tests were evaluated at the .05

significance level. These supplementary analyses were consistent with the primary gain-score results.

Ethical considerations were addressed throughout the study. Authorization to conduct the activity was obtained from the school administration, and participation was organized as a voluntary parascholastic activity without academic penalty for non-participation. Learner identities were anonymized in the research data, and the instructional activity did not result in the withholding of regular classroom instruction from either group. Because the participants were minors, particular attention was given to the ethical requirements associated with their participation. The study did not involve the collection of identifying information in the reported dataset, and the research data were used for the purposes of the study and reported in aggregate form.

## Results

This section presents the pre-test and post-test results of the control group, which received conventional instruction, and of the experimental group, which was taught in the AI-supported augmented reality environment. The design is quasi-experimental, which means that the findings are viewed as associative tendencies but not as demonstrations of causal effects. Table 2 presents the mean scores and mean gains for vocabulary, reading comprehension, and writing for both groups on a 20-point scale.

**Table 2**
Descriptive Statistics for Pre-Test and Post-Test Scores (20-Point Scale)

| Measure | Group | Pre-test *M* | Pre-test *SD* | Post-test *M* | Post-test *SD* | Mean Gain |
|---|---|---|---|---|---|---|
| **Vocabulary** | Control (*n* = 30) | 12.70 | 2.42 | 13.46 | 2.23 | +0.76 |
| **Vocabulary** | Experimental (*n* = 30) | 12.67 | 2.31 | 14.88 | 2.01 | +2.22 |
| **Reading** | Control (*n* = 30) | 13.59 | 1.98 | 14.18 | 1.82 | +0.59 |
| **Reading** | Experimental (*n* = 30) | 13.70 | 1.91 | 15.89 | 2.09 | +2.19 |
| **Writing** | Control (*n* = 30) | 12.53 | 1.93 | 13.18 | 1.97 | +0.64 |
| **Writing** | Experimental (*n* = 30) | 12.51 | 1.94 | 14.14 | 2.20 | +1.63 |

*Note.* *M* = mean; *SD* = standard deviation. Scores were calculated on a 20-point scale. Mean gain was calculated as post-test score minus pre-test score.

In the pre-test phase, both groups showed similar pre-test performance in all three language areas. After the instructional period, both groups showed improvement. Nevertheless, mean gains in vocabulary, reading comprehension, and writing were higher in the experimental group than in the control group.

To examine changes over time within each instructional condition, paired-samples *t*-tests were conducted separately for the control and experimental groups. The results are summarized in Table 3.

**Table 3**
Paired-Samples *t*-Test Results for Pre-Test to Post-Test Changes

| Measure | Group | *t*(29) | *p* |
|---|---|---|---|
| **Vocabulary** | Control | 9.82 | < .001 |
| **Vocabulary** | Experimental | 10.65 | < .001 |
| **Reading** | Control | 11.18 | < .001 |
| **Reading** | Experimental | 10.95 | < .001 |
| **Writing** | Control | 17.20 | < .001 |
| **Writing** | Experimental | 8.27 | < .001 |

*Note.* All tests were two-tailed. *p* values are reported as < .001 where applicable.

The findings show statistically significant pre- to post-test differences in both groups across all three measures. These within-group changes indicate observable improvement over the four-week study period but do not, by themselves, establish that either instructional condition was responsible for the observed gains. The paired-samples *t* statistics should therefore not be interpreted as indicators of the relative magnitude of improvement between the two groups because they are also influenced by the variability of individual changes. Direct comparisons between instructional conditions are therefore based on the between-group analysis of gain scores reported below.

To determine whether the magnitude of improvement differed between instructional conditions, gain scores were calculated for each participant by subtracting the pre-test score from the corresponding post-test score. Because the gain-score variances differed between the two groups, Welch's independent-samples *t*-test was used to compare the mean gains. The analyses indicated statistically significant between-group differences across vocabulary, reading comprehension, and writing. Mean differences, 95% confidence intervals, and Hedges' *g* estimates are reported in Table 4.

**Table 4**
Independent-Samples *t*-Test Results for Gain Score Comparisons

| Measure | Mean Gain Control | Mean Gain Experimental | Mean Difference | Welch *t* | df | *p* | Hedges' *g* | 95% CI for Mean Difference |
|---|---|---|---|---|---|---|---|---|
| **Vocabulary** | 0.76 | 2.22 | 1.46 | 6.57 | 36.83 | < .001 | 1.67 | [1.01, 1.91] |
| **Reading** | 0.59 | 2.19 | 1.60 | 7.73 | 33.04 | < .001 | 1.97 | [1.18, 2.02] |
| **Writing** | 0.64 | 1.63 | 0.99 | 4.93 | 31.06 | < .001 | 1.26 | [0.58, 1.40] |

*Note.* Mean difference = experimental-group mean gain minus control-group mean gain. Welch's independent-samples *t*-test was used because the gain-score variances differed between groups. Hedges' *g* is a standardized effect-size estimate based on the gain scores. *CI* = confidence interval.

Despite the higher gains in the experimental group, there are various considerations that limit the interpretation of these results. First, the evaluation tools were curriculum-related and teacher-made, which could make them sensitive to the teaching material and restrict their applicability to other settings than the classroom setting. Second, the use of intact classes limits the degree to which the observed differences can be described as purely related to the instructional condition. Although statistically significant, the effect sizes should be interpreted cautiously and do not represent the overall instructional effects given the exploratory nature of the study and the lack of standardized measures.

The between-group comparisons showed statistically significant differences in mean gain scores across all three language domains. Compared with the control group, the experimental group showed a greater mean gain in vocabulary (1.46 points), reading comprehension (1.60 points), and writing (0.99 points). The corresponding standardized effect-size estimates were Hedges' $g = 1.67$ for vocabulary, 1.97 for reading comprehension, and 1.26 for writing. These results indicate that the experimental group showed larger observed improvements during the four-week study period. However, because learners were assigned to two intact classes rather than randomly allocated to conditions, the results should be interpreted as between-group differences associated with the instructional conditions rather than as definitive evidence of a causal effect. The findings therefore provide evidence of an association between participation in the experimental instructional condition and greater observed gains in the three measured language domains within this particular school context. After Holm adjustment for the three between-group outcome comparisons, all three adjusted *p* values remained below .001.

## Discussion

The aim of the present study was to investigate whether involvement in a pedagogically organized, AI-supported augmented reality (AR) learning setting was linked to differences in the vocabulary, reading comprehension, and writing outcomes of Grade 8 EFL students compared with traditional teaching. The results show that, although both instructional groups showed statistically significant improvement with time, learners who interacted within the AI-supported AR instructional environment experienced significantly greater improvements in all the three language areas. The results are discussed in relation to the existing literature and to pedagogical and methodological limitations.

The gains attained by both the experimental and control groups between pre-test and post-test are in line with what is expected from formal instruction. Planned exposure to curriculum-based instruction has been shown to produce measurable gains in EFL proficiency within a comparatively brief time of instruction (Miller et al. 220). This finding indicates that learning gains cannot be attributed solely to the technological treatment and emphasizes the significance of looking at relative gains as opposed to absolute performance outcomes.

Reading comprehension showed the largest between-group difference in gains, which is consistent with the research findings indicating that AR-based instruction can stimulate comprehension through the connection of textual information and visual and situational prompts. Contextual anchoring of this nature has been found to ease cognitive load and facilitate construction of meaning when tasks involved reading (Huang et al.). The patterns of improvement observed in the present study are consistent with prior research.

The experimental group also performed better in vocabulary development. This observation is in line with studies that have shown that vocabulary acquisition is facilitated when learners are exposed to lexical items in contextualized and multimodal input. Repeated exposure to target vocabulary in meaningful contexts has been associated with deeper processing and retention among EFL learners. Such contextual reinforcement occurred in the present study via visual and situational cues of the AR-supported environment.

Despite the fact that writing gains were not as large as reading and vocabulary gains, the experimental group still improved more than the control group. Writing development is gradual and cognitively demanding, and a short instructional intervention usually results in gradual but not radical changes in the quality of writing. Learning environments that are supported by technology have been demonstrated to operate more as scaffolding tools that aid the production of ideas and access to vocabulary rather than as a means of increasing grammatical accuracy (Khan et al.).

It is necessary to underline that the AI aspect of the instructional setting was not used as an independent instructional agent. Rather, AI-based applications were incorporated throughout the instructional design process to facilitate linguistic clarity and task alignment, whereas all the classroom interaction was mediated by the teacher. This difference is consistent with the existing literature that warns against attributing learning outcomes directly to AI systems without considering pedagogical design and teacher involvement (Kundu and Bej 2294).

This research nevertheless contributes to the literature because it offers empirical data from a middle school EFL setting, a context underrepresented in research on AI- and AR-mediated language learning. Most existing studies have been conducted in higher education or laboratory-based contexts where learners may have greater technological independence (Yan et al.). In comparison, the current research shows that pedagogically focused, AI-supported AR content can be incorporated into regular middle school lessons without disrupting the curriculum.

Pedagogically, the results indicate that the potential value of an AI-supported AR instructional environment lies not in technological novelty but in its ability to support contextualization, multimodal input, and learner engagement, provided that it serves specific instructional objectives. Teachers still play the key role in this process, and the technological tools seem to work best when they are presented as pedagogical aids rather than substitutes for instruction. Several methodological limitations should be considered when interpreting these findings.

First, the study used intact classes, a characteristic of the quasi-experimental design, which constrained the ability to isolate differences associated with the instructional condition from pre-existing class-level characteristics. Although the pre-test results did not show statistically significant differences between the groups, such findings do not establish complete baseline equivalence. Unmeasured differences between the classes may therefore have contributed to

the observed patterns. In addition, because each instructional condition corresponded to a single intact class, classroom-level effects could not be separated from the instructional condition. The use of the same instructor and curriculum reduced some sources of variation but did not eliminate this limitation. The four-week duration also prevents conclusions about long-term retention or persistence of learning gains. Finally, no formal classroom-observation checklist or implementation-rating instrument was used to quantify treatment fidelity across sessions. The findings are therefore interpreted as associative rather than causal.

Second, the sample was relatively small and drawn from one public middle school. No a priori power analysis was conducted before data collection. The sample consisted of the two available intact Grade 8 classes included in the study, and the resulting sample size therefore reflects the classroom-based setting rather than a sample-size calculation designed to achieve a predetermined statistical power. Although the observed between-group differences were statistically significant, the limited sample size reduces the precision and generalizability of the findings. The results should therefore be interpreted as context-specific evidence rather than as estimates that can be readily generalized to larger populations of EFL learners.

Third, the research was based on curriculum-based, teacher-made assessment tools as opposed to standardized tests. This approach ensured strong alignment with the instructional content and activities used during the intervention, yet it also creates the possibility of measurement bias. Local instruments can also be more responsive to local instructional practices and less generalizable across contexts. Despite the similarity in the scoring processes across groups and test administrations, because the instruments lacked external validation, the results can only be interpreted within these limits.

Fourth, the intervention was short (four weeks of instruction). The process of language development, especially writing, is often experienced over a long period of time and short-term gains may not indicate long-term change. The research lacks evidence of long-term retention, learning transfer, and delayed effects, which are important outcomes that should be examined in future research.

Fifth, the instructional environment was not analytically separated into its elements, such as teacher mediation, augmented reality resources, and AI-assisted content development. Consequently, the research does not permit making statements about the independent role of AI or AR. Rather, the intervention should be understood as an integrated pedagogical setup. This limitation resulted from the study design, which prioritized classroom validity over experimental control (Egunjobi and Adeyeye 1167).

Lastly, the involvement of minors and the integration of the intervention into regular teaching created both ethical and procedural constraints on the collection of data. Although these limitations helped ensure instructional equity and learner protection, they also restricted the possibility of experimental manipulation and prolonged data collection.

These restrictions accentuate the exploratory approach of the research. They do not invalidate the findings, but they clearly limit the claims that can be made. Subsequent studies would be appropriate with larger samples, longer intervention periods, standardized assessment measures, and designs that enable analysis of individual technological elements.

## Conclusion

This study examined the association between participation in a teacher-mediated AR-supported EFL instructional environment and changes in vocabulary, reading comprehension, and writing performance among Grade 8 learners in a Moroccan middle school. Using a quasi-experimental pre-test/post-test design with two intact classes, the study found statistically significant pre- to

post-test improvements in all three language domains in both the control and experimental groups. The experimental group showed larger mean gains than the control group across vocabulary, reading comprehension, and writing, and the between-group differences in gain scores were statistically significant.

These findings should be interpreted cautiously. The study does not establish causality, and it does not permit the independent contribution of AI, AR, teacher mediation, or other features of the instructional environment to be isolated. AI was used primarily during the preparation of instructional materials, while AR provided the digital layer experienced by learners during teacher-mediated classroom activities. Moreover, the use of one intact class per condition means that instructional condition and classroom membership were confounded, and the four-week intervention provides no evidence concerning long-term retention.

The study nevertheless contributes context-specific evidence from a Moroccan lower secondary EFL setting, an area that remains comparatively underrepresented in the literature on technology-supported language learning. Its findings emphasize the importance of pedagogical integration, teacher mediation, curricular alignment, and cautious interpretation when emerging technologies are incorporated into classroom instruction. Future research should involve larger samples and multiple classes per condition, stronger treatment-fidelity procedures, validated or externally reviewed assessment instruments, and follow-up measurements to examine whether observed learning gains are sustained over time.

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# Digital Humanities, Conspiracy, and the Age of AI: An Interview with Matthew N. Hannah

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# Digital Humanities, Conspiracy, and the Age of AI: An Interview with Matthew N. Hannah

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## ABSTRACT

In this interview, Matthew N. Hannah reflects on the development of the digital humanities and on the place of humanistic inquiry in a rapidly changing information environment. Moving between his own formation as a literary scholar, his research on online conspiracy movements, and his work building digital scholarship spaces within university libraries, he considers how platforms, conspiracy narratives, and generative artificial intelligence are reshaping the ways knowledge is produced, circulated, and trusted. The conversation also addresses questions of access, multilingual scholarship, and international collaboration, and closes with reflections on teaching difficult subjects and on the responsibilities of preserving endangered knowledge. Throughout the interview, Hannah argues for computational methods as an extension of, rather than a replacement for, humanistic modes of thinking, and for interdisciplinary community as the foundation of the field's future.

## KEYWORDS

**Digital Humanities**

**Conspiracy Theories**

**Information Literacy**

**Artificial Intelligence**

*This interview was conducted in English.*



**About Matthew N. Hannah:** Matthew N. Hannah is Associate Professor of Rhetoric, Politics, and Culture in the Department of Communication Arts at the University of Wisconsin–Madison and inaugural director of the Digital Scholarship Hub at UW–Madison's Memorial Library. He holds a PhD in English from the University of Oregon and has built digital humanities programs at several universities, including Purdue University. His research examines extremist beliefs and conspiracy movements online, platform capitalism, and digital scholarship. He is the co-editor of *The Spectacle of Online Life* and *Conspiracy Theories and Extremism in New Times*, and his forthcoming monograph is *QAnon: Capitalism and the Crisis of Meaning*. His articles have appeared in *First Monday*, *Social Media + Society*, *Journal of Information Literacy*, and *Debates in the Digital Humanities*, among others.

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## Formation and the Field

**Imane Derrazi:** You trained as a literary scholar and wrote a dissertation in English. How did you find your way into computational work, and what has that training meant for your collaborations with colleagues in more technical fields?

**Matthew Hannah:** I first began to hear about an emerging field called "digital humanities" (DH) during my coursework for my doctoral program. I was attending a seminar on "American Modernism," and we were looking at digitized magazines from online archives such as the Modernist Journals Project (https://modjourn.org/), and something clicked in my thinking. I was fascinated by these ephemeral materials and began to explore the special collections at the University of Oregon, looking for little magazines and other ephemeral texts. Just as I was starting to become interested in the elements of digitization, I began to hear about DH from a fellow student who was doing computational text analysis with Gertrude Stein.

At the time, I was not especially good with computers, but I remember thinking how rare it is in the humanities to witness an emerging avant-garde methodology, which has always attracted me, and I remember debating if I should attempt to move into the DH space. After proposing a few ideas for a dissertation project to my committee, I received overwhelmingly positive feedback on the potentially digital project, so I made the leap to DH and never looked back.

Immediately, the project ran into challenges. I wanted to perform a network analysis on these ephemeral magazines from the early 1900s, charting the connections between modernist writers, artists, hostesses, as well as fellow travelers in the avant-garde scene such as wealthy patrons, labor leaders, political radicals, and fans. My idea was to use network analysis to tell a story about modernism as a *collective* effort rather than as the literary product of a few geniuses. But I had no idea how to visualize those connections. It's one thing to describe networks of patronage or influence, but it is another challenge to visualize those data, especially as a humanist with no training in computational methods. And the dissertation also had to be researched and written within two years. Looking back now, it was madness.

I didn't know what digital tools I could use, and DH was a new enough field that there weren't as many great resources as there are now, so I started talking to graduate students in other disciplines, such as sociology, who used network analysis to try to understand how to do it. And I learned about software and about how to structure data in certain ways. About that time, I found a few other graduate students who were also interested in DH, and we formed a small interdisciplinary research group who would meet in the library to explore methods and attempt to understand the field. One of the librarians was developing workshops and courses on DH, and we created a small community of weird students working with computers.

And I found it absolutely invigorating to be working on a project in ways that nobody else in my program fully understood. It felt good to be discovering new territory in a field as established as literary studies. Collecting data and transforming it into network visualizations was such an unusual thing to be doing in an English Department that I was very much an oddball, but my mentors and fellow students were so fantastic, and I had a lot of support to take a big chance on the project. My dissertation chair, Dr. Paul Peppis, knew it would be a big challenge, but he was supportive and encouraging because the field was evolving. Without his support, I would never have been able to complete the project.

In terms of technological fields such as computer science or data science, I have found that it is not about seeing things they don't see but rather about finding ways to communicate how the methodologies in humanities or social science research are unique. Computational methods can help us answer questions in humanities and social science research, but they are only

another tool in our toolkit, alongside various theories or approaches. Computation can extend some of those methods but cannot replace them. In my experience, my colleagues in more technical fields are fantastic partners when they understand and respect the unique and nuanced methods in the humanities and social sciences. When there is a shared language for the research we want to do, there can be an incredibly fruitful area for future research.

**ID:** Digital humanities has been announced as the next big thing, denounced as a corporate intrusion into the humanities, and pronounced dead, all within roughly fifteen years. Which of those verdicts has aged best?
**MH:** The amazing thing about DH is that it is too weird to be easily defined or characterized. Digital humanists and their detractors have been debating the existence and objectives of the field since the beginning. It seems strange now, but the famous literary critic Stanley Fish used to write an opinion column for the *New York Times* denouncing DH during its heady early days. It just seems so strange now, in the age of AI, to argue about whether computational methods have a place in the humanities. There was an old joke that we used to share back in the mid-2010s: In fifteen years, there won't be "digital humanities"; there will just be "humanities." But fifteen years later, we can see that this didn't really happen either. And now, with the rise of generative AI, we are having many of the same debates about the role of technology in the humanities and social sciences. Ted Underwood, for example, has been doing some incredible work with AI language models, which he doesn't really call DH anymore but which comes out of the same lineage.

In my view, the need for training and community around how we think about the humanities and social sciences *vis-à-vis* technological development is incredibly relevant now even when we don't necessarily call it DH. We have a wide range of interdisciplinary research areas now, such as computational social science or digital history, which combine computational methods with specific methods from humanities and social sciences, and I think that this is an exciting testament to the longevity of DH. We've come a long way from having to argue about whether computational methods are destroying the humanities, and some of those debates feel quaint against the enormity of AI developments in every aspect of society. I would also add that many digital humanists are well positioned to offer pointed and reasoned critique of AI in ways that avoid doomerism or hype as our two modes of thinking.

**ID:** Digital humanities was often promoted as a route to employment during a collapsed academic job market. How did that play out in your own career, and what does it say about the people the field attracts?
**MH:** There was a lot of discussion back in the 2010s about DH helping people secure academic or "alt-academic" jobs, which I always thought was a little too instrumental and neoliberal. For me, the exciting aspects of DH were the interdisciplinary research possibilities and new horizons for research. At the same time, most of the people I knew who worked in DH went on to work in DH spaces rather than traditional academic departments in which the hiring was brutally competitive. I was completely unsuccessful in search of academic jobs teaching modernist literature, and I applied widely. I don't think I even got an interview. I applied to all kinds of literature jobs with almost no interest. But I was very successful in the DH job search, especially as more literature jobs began to include DH as a desired subfield, so my entire career was made possible because of DH.

Having said that, I think some of my success was also due to the fact that I have always been impatient with narrow thinking and narrowly scoped research questions. I am interested in a lot of different stuff, which has led me down many different paths that could have also turned into meaningful work. For example, I was very involved in the graduate student labor union (Local

#3544) during my time at the University of Oregon and almost got a job as a labor organizer. I ended up getting a postdoctoral fellowship at the same moment, and I chose to pursue that opportunity, but I would have loved to have been a labor organizer. I was also very interested in university administration, tackling graduate student leadership roles to help organize and manage the department, and I think I got my postdoc because of that experience even more than the DH.

The people I know who went on to work in DH are some of the smartest and most curious people I know. They are interested in the intersections of various disciplines and methodologies, which is what led them to DH in the first place. And the reason for this is that DH is vigorously inter- and multidisciplinary, requiring flexible thinking across domains and methods. It escapes easy categorization and crosses boundaries with joy and aplomb. Digital humanists are just interested in a lot of stuff, in my view, which provides them with a lot of flexibility in employment. I'm sure there are many digital humanists out there who are unhappy with their work, but I have found this community to be excited and engaged in this collective project despite all claims to the contrary by the field's detractors. If you want to have a good time at a conference, the DH conferences are always vibrant and exciting opportunities to hear about interesting projects.

**ID:** You are currently building a research center from an empty floor of a library. How do you decide what such a space actually needs?
**MH:** When building a new digital scholarship or DH space, the temptation can be to add a bunch of technology to the space. And I remember the various trends in academic spaces such as adding massive and expensive data visualization walls or investing in 3D printers. You want people to see your space as an exciting place for research and teaching, but every site is different with a different audience, so building a space should be done carefully and thoughtfully. The first thing I did upon arriving at both Purdue University and the University of Wisconsin–Madison was to begin having conversations with people to assess their needs. What resources are already available on campus? What is missing? What is the character of the place in which you are building a DH/DS space? These are all important questions to explore before building a new research center. Nearly a year into this job at UW–Madison, I'm just starting to understand what might be useful and what we will need for this particular community. This is not to say that building a space is ever really done. Such a project is iterative, requiring constant assessment and reassessment.

I also want to pause for a moment to clarify some terminology, because it is important for how we are thinking about the Digital Scholarship Hub that we are building. We explicitly chose to call it "digital scholarship" because we want to develop a space that crosses the "two cultures" divide articulated by C. P. Snow. My Associate Director, Dr. Anna Haensch, is a mathematician and data scientist with a faculty appointment in the Data Science Institute, and she brings deep knowledge of the computational work in those fields into our space. And because we are so committed to DH/DS work in the Hub, the Libraries offer the perfect home. Whereas DH was initially situated in literature departments, it is now expanding into many areas of research, so the Libraries offer the flexible, multidisciplinary ethos that allows us to actually do the work in an interdisciplinary way.

The other important thing to focus on when building a space is community. If you put a bunch of technology in a room and nobody uses it, what have you got? We are focusing on building our community here, and we are doing that through experimentation. We invite interesting people to give lectures, we host workshops to see what works, and we continue to reassess what we are doing. My hope is to "future-proof" this space so it will always be a vibrant,

exciting place to work even if the mission changes. And this also explains why libraries are increasingly the site for such DH/DS work. They provide a discipline-agnostic space for scholars and students from different areas of campus to meet and collaborate and research. There are very few spaces on a university campus that have the same possibility of being a true hub for research and teaching.

**ID:** You direct a research center as well as teach. What does a center do for undergraduate education that a course cannot?
**MH:** A center offers much more for the larger academic community because it provides the context for research. As a professor, I teach students for sixteen weeks and then they move on. And the course focuses on whatever the specific topic is within certain disciplinary parameters. There are plenty of ways to experiment and innovate in the classroom, especially in a vibrant discipline like Communication Arts, which is a perfect place for me because it engages so many interesting topics, but the classroom is not the same as a hub for multidisciplinary research and collaboration.

At the same time, my Dean, Dr. Erla Heyns, wanted the leadership of this Hub to be located among the faculty, and she had a vision for how this directorship would sit in the larger educational ecosystem. Having a director who also teaches and conducts research provides a unique confluence of administrative and academic work. This is very unique because my Associate Director and I can integrate our academic research and teaching into the very fabric of the Digital Scholarship Hub at a deep level.

Developing the Digital Scholarship Hub thus extends the pedagogical impact of the classroom by providing a space for engagement across academic silos and across academic ranks. We provide an environment for interdisciplinary collaborations and conversations about technology. We bring together faculty, staff, graduate students, and undergraduate students to engage important topics such as the role of surveillance, artificial intelligence, social media, platform capitalism, and other topics that we teach and research. We believe that the Hub will be a space for exploring all aspects of technology with a humanistic emphasis on community, criticality, and social conscience. The library is the perfect place to develop such a Hub because it is already the hub for this exciting and innovative focus on most campuses.

## Conspiracy, Platforms, and the Information Dark Age

**ID:** Your work on QAnon shows the movement borrowing the surface features of scholarship: citation, cross-referencing, data visualization. Why did that particular costume fit so well, and what does its success tell us about how academic authority is recognized by people outside the academy?
**MH:** When QAnon first appeared on digital platforms, many journalists and commenters assumed it was a crazy movement populated by weirdos. But I didn't see it that way. As a digital humanist, I was fascinated by how digital platform infrastructure facilitated certain kinds of belief and helped establish a community in which anonymous people coalesced around a new political ideology. Of course, QAnon was the latest in a series of very strange and fascinating internet phenomena, including the Anonymous hacktivist group that was active during the 2010s, the Cicada 3301 cryptography puzzle that appeared online, and other strange social media phenomena. But for whatever reason, QAnon continued to build and recruit newcomers into a vibrant online research community. And my early work on networks of collaboration in literary circles seemed relevant to online publics who began to establish networks of internet research and political commentary.

I attended graduate school with a folklorist who studied trolling behavior, and I was struck by her empathy and compassion and willingness to understand that community when everyone else had decided that trolls were monsters. So, I tried to approach QAnon with a similar willingness to understand how such an ideology might develop and how best to respond to it. And what I discovered is that conspiracy theorists are not illiterate but are actually engaged in a kind of research with protocols and questions and methods.

QAnon developed sophisticated research methods with which to contribute to the movement, which I find fascinating. It also puts pressure on academic expertise. If I, as an authorized expert, try to dismiss conspiracy theorists, they can simply point out that I am also part of the conspiracy by gatekeeping knowledge and information. By "doing your own research," a conspiracy theorist can avoid the efforts by governments and institutions to keep the truth hidden, and that is a powerful feeling for conspiracy theorists.

**ID:** You named our moment an information dark age at a point when access to information had never been greater. Dark ages are usually named in hindsight. What would have to happen for you to say the lights had come back on?
**MH:** I'll let you know if it ever happens.

Of course, the "dark age" concept was meant to be a metaphor for how many Americans during the post-2016 elections were drawn to "darkness" as a conceit, in the belief that our historical moment was so corrupt that we needed patriots willing to "go dark" to combat it. Thus, we find ourselves in the so-called "information age" with little wisdom or compassion or knowledge. We witnessed a rather embarrassing attempt to style these "free thinkers" as the "intellectual dark web" by Bari Weiss, then an opinion columnist at the New York Times but now editor-in-chief of CBS News, where she has put her ideas into practice. We saw this energy in the creation of the University of Austin as an "anti-woke university." We also saw it in Curtis Yarvin's idea of the "dark Enlightenment" as a philosophical turn away from democracy and toward corporate and tech hegemony. And the fascination with free thinking as an outsider in the cultural darkness is still very much with us.

In general, I applaud the idea of free thinking and discourse, especially when it is difficult, but these conversations require wisdom and knowledge and commitment to other humans. What these free thinkers usually practice seems more about reviving hateful or divisive retrograde ideas at a time when many people are vulnerable to them. For example, the rise of the "manosphere" as a site for online hatred of women and girls has become a serious problem for young men in the U.S. as they navigate changing ideas about gender roles. I resonate with the idea that we are "drowning in information, while starving for wisdom," as E. O. Wilson put it. And I don't see a way out of this trap as things continue to get worse with climate disaster and economic woes continuing unabated. Humans tend to show their best and their worst in moments of crisis.

**ID:** You have recently argued that the vocabulary of QAnon outlived the movement itself and now surfaces in official government communication. What does a dead conspiracy theory leave behind that a living one does not?
**MH:** I would argue that conspiracy theories never really die. One of the incredible things about QAnon is its capaciousness and durability. It absorbed all other American conspiracy theories into itself. So, when we talk about the existence of the "deep state," which could be entirely plausible, we are already in QAnon territory. The theory has captured anti-establishment discourse so effectively that people may be espousing QAnon talking points without even knowing it. And with the continued scandal of the Jeffrey Epstein cover-up, it will likely

continue to attract new believers for years to come. Every time the Trump administration uses QAnon ideas in their official posts, online conspiracy theorists get very excited. Eventually it will finally fizzle out, but I worry about what comes next.

**ID:** Information literacy is the standard institutional answer to disinformation, and you have written about where it falls short. If teaching people to evaluate sources is not sufficient, what is the honest alternative? And how much can a university actually supply?
**MH:** One thing that always frustrates me when I give talks about conspiracy theories is that people will say we just need more information literacy. Information literacy is a wonderful discipline with an array of techniques and methods which are foundational to how we think about information, and I'm not dismissing information literacy in practice. But I am skeptical that information literacy *by itself* is effective against conspiracy theorists, and I am especially skeptical of the frameworks provided by the Association of College and Research Libraries. As I argue in the article you referenced, "Information Literacy in the Age of Internet Conspiracism," which is available online, that framework is in desperate need of an update for the post-2016 information landscape.

This seems especially necessary given that Steve Bannon, chief strategist for Donald Trump in his first administration, understood well the role of digital platforms and spaces for controlling information. His strategy was to flood the zone with disinformation to distract people. We still need information literacy very much, but we need to develop dynamic new frameworks explicitly for the post-2016, post-QAnon information environments in which we are drowning now. And ACRL does not seem to be especially interested in revising those frameworks. Their new update as of 2026 is basically to repurpose the old framework with some new language about artificial intelligence, and I felt there was still insufficient consideration of conspiracy theories, disinformation, or information warfare, which are the most salient information problems of our time.

**ID:** Anonymity online is usually described as a mask. Is there a case for reading it the other way, as disclosure rather than concealment?
**MH:** Anonymity is a complicated phenomenon. On the one hand, it provides a space for trolling and bad behavior. On the other hand, it can protect vulnerable people who want to avoid toxic online behaviors that so many people experience. I think we need to protect anonymity, which is why I oppose the notion of the "real name internet." Instead, we need to develop tools to help people think about anonymity as an identity itself. I have been working on a project that explores anonymity as a form of identity politics on the internet, a space for rethinking identity and how people perform online. And I believe anonymity is important for protecting individuals, even as it exposes what many people truly believe. When someone spews hateful nonsense from behind an anonymous avatar, they reveal something fundamental about their own character, their values and beliefs. As much as I hate to see that stuff, I believe it is important to know what people really think.

**ID:** Much of your evidence comes from platforms that are hostile, deceptive, and populated in part by automated accounts. How do you handle the evidentiary problem of not knowing whether your subject is a person?
**MH:** My approach is to consider the discourse happening online and the reception it receives. In that regard, a post by a bot could be very interesting if it gets attention. Furthermore, I have been following some of these accounts for a while, so I know what kinds of content they tend to disseminate. Having said that, a fascinating phenomenon occurred recently on X.com (formerly Twitter). They changed the platform interface so that accounts would also show

metadata indicating the location of the account owner's original IP address, and many of the more vitriolic and toxic accounts perpetuating "America First" content were not from America. More recently, Ukraine destroyed a Russian bot farm and far-right traffic on social media noticeably diminished. These are great examples of how ideologies are being cultivated by foreign adversaries of the United States as a way of sowing social discord. As a nation, America needs to develop extensive pedagogical resources and programs to help citizens navigate social media and identify these efforts to influence our ideas, beliefs, and values.

## Artificial Intelligence, Labor, and the Classroom

**ID:** Where does the boundary fall between a task that can be handed to a machine and one that cannot, when the machine is capable of imitating both convincingly?
**MH:** This is a very prominent question right now, one which a DH/DS space is uniquely poised to explore. In fact, the Digital Scholarship Hub just hosted a conversation about the role of the scholar in the age of AI, so it is very top of mind for those of us in this field. On the one hand, I'm old enough to remember the hand-wringing about massive open online courses, which were supposed to mark the end of in-person learning at universities and colleges. What happened to all that hype? The COVID pandemic pushed all of us online, and we quickly learned that in-person learning is still necessary for learning. So, the rhetoric changed. On the other hand, AI is causing massive disruptions to former ways of thinking and working and being in the world.

In my teaching, I have begun exploring what knowledge means. What is uniquely human about thinking, and how can we redesign our teaching to showcase those skills? And what we are starting to see is that the flexibility and nuance of humanistic modes of thinking are surprisingly durable and attractive in an age where machines can do many tasks moderately well. If we no longer need to write essays, for example, how do we help students develop the thought processes that writing essays helped to develop? What would that look like? How can we avoid offloading all thought and creativity onto machines while also avoiding the hand-wringing that comes with each new technology?

This is not to say that there are not significant challenges facing us in the age of AI. I think there will be massive disruptions to the ways in which we live now, but I'm far more worried about the climate or political radicalization or the future of labor and capitalism than I am about AI on its own. We need to have a serious global dialogue about how we view one another and what it means to be human. I think that such a conversation is long overdue, and I hope AI gets it started.

**ID:** A language model can produce a fluent, confident account of a novel it has not read in any sense a reader would recognize. Describe precisely what is missing. Is the difference epistemological, phenomenological, or something else again?
**MH:** Something happens to us when we read. Reading is one of the rare moments in life when we are alone with a text, when we are thinking in concert with dialogue and setting and characters and events that exist only on the page and in our minds. I think that this is an amazing thing. We are transformed by reading in ways that an LLM can never be. It reminds me of when I talk to someone about a book and they ask me what it's about. How do I characterize my experience of sitting in my chair and enjoying the unique flavor of this combination of words, the associations and metaphors and beautiful and tragic moments. I'm reading Ray Bradbury's novel *Something Wicked This Way Comes* right now, and I feel such a deep and bittersweet resonance with this book because of my gender and nationality and age and experience and all

the rest. And each of us has an enormous repository of such books to explore. That is a wonderful thing.

And the same is true of non-fiction books. I tell my students that working through a book of philosophy or history or theory is training our brains *how* to think. And I try to encourage them to take that seriously and not outsource that thinking to AI.

**ID:** Students are told that the difficulty of writing is the point, while every product marketed to them removes that difficulty. What argument has actually worked on a nineteen-year-old, in your experience?
**MH:** I don't think I've had much success here, but I will say that many of my students get it. I don't think they are all captured by AI. Students are curious, thoughtful, and smart. Do they always do the reading I assign? No. But they are trying. And I think that we need to continue to push the narrative that reading and writing is a workout for your brain, that we need people who can navigate nuance and shades of gray, who can puzzle through complex problems without resorting to a reductive list of bullet points. AI can do that, but we can hold a problem up and try to work through it in so many ways. And if we want to be instrumental about it, this skill will actually be marketable too. We don't need more coders. AI can code. We need more thinkers who can work through the social and cultural aspects of that code.

**ID:** Forecasts point to entry-level white-collar work as the sector most exposed to automation. Does that weaken the case for a humanities degree or strengthen it?
**MH:** I don't really know what will happen. Capitalism is entering a phase in which the only growth industry left is AI, and we don't know what will happen when that bubble bursts. Efforts to regulate AI seem doomed to failure when the international order is based on competition and resource extraction. The United States and China are currently locked in an adversarial struggle for AI supremacy, for example, which will have unforeseen downstream effects on the global political order. I also worry that we don't know what to do with labor markets that can be replaced by AI. There are many, many jobs that are part of the so-called "gig economy," which will likely disappear. What will happen to those people? How will they survive in a hostile and unaffordable world? Tech billionaires keep telling us that AI will allow us all to work less, but I think this is purely utopian and disingenuous. If these tech billionaires really wanted to help society, they would commit to our shared social contract by paying the same taxes as everyone else.

I also think the plight of higher education is tied to the travails of capitalism. We transformed higher education into a job-readiness training program, leaving very little room for what I believe should be the role of higher education: gaining knowledge and learning how to use it. Having said that, I do believe that some of the learning outcomes of a humanities education will be, and indeed, always have been, marketable. There is a reason that most industry leaders have education in the humanities and social sciences. But it is hard to make that case when an education is ridiculously expensive, and, if we want a healthy society, we need to make education free and accessible to everyone. There was a moment just after World War II when universal education was seen as a necessity for an educated populace, when education was connected to national security and prosperity. I guarantee the humanities would be more popular if we could remove the unbelievable costs of that education. It's amazing to realize that a student could have received a free education at the University of California, Berkeley until Ronald Reagan became governor of California and eliminated that opportunity. Neoliberalism has wrecked higher education in ways that continue to impact students, and making education free would also help fight misinformation, disinformation, and conspiracy theories.

**ID:** Data centers consume water and power, and they are increasingly built where the political cost of building them is lowest. How should a humanist raise that question without sliding into moralizing that changes nothing?
**MH:** Humanists need to do research on this topic so as to communicate the challenges and engage the community on this topic. Data centers are going to be a huge problem for communities and ecologies, and we will need thought leaders and intellectuals who can engage in that conversation with facts and data rather than vibes. My Associate Director is currently engaged in research on data centers and government policy, and I am always impressed by the reasoned and thoughtful work she is doing.

Humanists certainly have a place at the table in these conversations. Environmental humanities has long been one such vibrant multidisciplinary area of research that could take up this project as well, but such engagement will require collaborations with scientists and policymakers and industry leaders. I am also increasingly interested in the narratives we tell about AI and data centers. I am currently working on a book project investigating how conspiracy theories are capturing the narrative terrain of climate discourse. And as we develop the Digital Scholarship Hub, we look forward to hosting such research and policy collaborations so we can support healthy communities and ecologies.

**ID:** Researchers can now train small models locally rather than renting capacity from a handful of firms. Is that a genuine alternative to platform dependence or a marginal gesture?
**MH:** I think a lot of people are becoming interested in what a small, locally hosted LLM can offer. I don't know if the idea will take off, but we at the Digital Scholarship Hub are very interested in it. This semester is focused on the theme of "Artificial Realities," and we are exploring all manner of artificialities. We have invited a group from San Francisco who have developed their own language model based entirely on English text from the 1930s, which raises some fascinating possibilities for historical thinking and research (as well as about the role of AI in that work) and we are hosting a workshop on building small, historical training data for developing other LLMs. This will be an exciting event for thinking about how library collections might be leveraged for interesting projects like this.

## Language, Geography, and the Uneven Digital

**ID:** Optical character recognition and handwritten text recognition for Arabic have improved substantially in recent years. What becomes methodologically possible for North African archives that was not possible before, and what will still not be possible?
**MH:** I think that one of the exciting aspects of new AI tools and resources is the possibility of expanding our tools to work with languages that were, for a long time, ignored in the rush to build digital tools. We've reached a point where some of the limitations of the past are no longer as pertinent, and we can explore new possibilities. DS/DH, as a field, has long been a space where scholars have identified and diagnosed the limitations of tools for multilingual analysis, and I think the capabilities have expanded greatly. I cannot wait to see what exciting research will emerge now with the development of new tools and models for research on North African materials. It's going to be a fruitful time for research in this space.

Methods will need to be developed for working with these archives, and this will require digitization and access, both of which are not free. Projects such as HathiTrust have done some fantastic work to digitize materials from around the world, and the UW–Madison Libraries are engaged in such work. My hope is that the possibilities for working with these manuscripts will inspire researchers and libraries to begin digitizing and OCR-ing their holdings for scholars

around the world, and that large DH organizations will support such work through financial support.

**ID:** Multilingual digital humanities is usually defended on grounds of inclusion. Is there a stronger argument to be made, one about method rather than fairness?
**MH:** To me, the question is about the scholarly record and about knowledge. It is tempting to see the current infrastructure as somehow representative of human knowledge and forget that many of the digital objects and archives we can currently analyze with DS/DH are managed, curated, preserved, and digitized by institutions. Many of those institutions are educational, but some are private corporations with their own commitments and interests. We are also witnessing a potential shift in how we think of online knowledge. With the appearance of massive LLMs, online materials could easily be seen as fodder for the AI rather than as a record of human knowledge. For me, the major question is what is not currently available? What is missing from the available scholarly record? And how can we incentivize making those materials available?

**ID:** You have worked with Moroccan colleagues over several years. What would you warn a research laboratory here against when it begins building digital infrastructure on limited funding? Where does the money get wasted?
**MH:** Funding is always an issue. I think there are several things I would emphasize. One is to focus on the specific needs of the researchers and students at your particular institution. There is no point in building a DS/DH lab focused on 3D printing if everyone is working on digitizing texts and analyzing them. And this takes some time because the faculty and students may not even know what their interests will be yet. I suggest starting small. Host a few workshops, like the ones I did when I visited your lab in Tétouan. Identify which methods and tools your faculty and students want to use and work from there to develop the infrastructure to make those resources available.

**ID:** Partnerships between a well-funded American center and a North African laboratory can quietly become extractive, with data traveling in one direction and credit in the other. What distinguishes a reciprocal collaboration from a polite version of that arrangement?
**MH:** This is a good question. I think that a good collaboration should always be reciprocal and treat each partner as vital and equal. This is true in personal collaborations as well as institutional partnerships. And while we all speak of "collaboration," especially in Digital Humanities and digital scholarship spaces, the truth is that it is not necessarily a given that each partner knows *how* to collaborate effectively. We don't really have a developed set of best practices for what a healthy collaboration might look like, and each partner may have completely different expectations of what the collaboration should be.

I think this is why formal partnerships between institutions rely on the "memorandum of understanding" as a model for clarifying what each partner contributes and expects. Here at UW–Madison, we have just finalized a formal collaboration with Stellenbosch University in South Africa, and we have been very deliberate in identifying expectations, possible project partnerships, and expectations for all parties involved. Such a process feels unnecessarily formal in some cases, but I think it is an essential tool to ensure that the collaboration is healthy and productive for each party.

## Teaching, Practice, and What Comes Next

**ID:** You teach conspiracy theories to undergraduates, some of whom will arrive already persuaded. How do you keep such a course from becoming either a debunking exercise or a cabinet of curiosities?
**MH:** Research on conspiracy theories has shown that debunking exercises don't really work. When I first started teaching in this space, I worried about this a lot because I didn't want the course to be about trying to debunk conspiracy theories, which doesn't really work, but I also didn't want these theories to be a source of ridicule or entertainment at the expense of the individuals who may hold these beliefs. I almost always begin my course by asking students how many of them have friends or family members who believe in conspiracy theories, and it is a useful reminder that conspiracy theorists are just people we know and care about. I also focus the course on building literacy about conspiracy beliefs and how to think about them, rather than simply showcasing them as absurdities.

Having said that, there is invariably a bit of humor and fun in exploring conspiracy theories. Some theories get very weird, especially around celebrities such as Taylor Swift, which students seem to find amusing. But some conspiracy theories are horrible and challenging, such as Great Replacement theories about migrants, so it is a real challenge to avoid traumatizing students or convincing them of conspiracy theories accidentally while also taking the subject seriously. So, I spend a lot of time looking at discourse and asking students to work through the rhetorical and ideological dimensions of conspiracy beliefs. I also require students to engage directly with primary texts, which I carefully curate, because I want them to see how these conspiracy theories develop as cultural artifacts and rhetorical objects, and I think this helps contextualize them within a broader history. One student described my course as an "inoculation" against conspiracy theories, which I loved.

**ID:** Data disappears when it becomes politically inconvenient. If you could guarantee the survival of one endangered body of data, what would it be, and who should be responsible for it?
**MH:** I would preserve climate change data, which many librarians and scientists have actually been doing. We are facing an existential crisis caused by a complete disregard for the environment, and much of the data that have been collected over the past few decades are at serious risk of disappearing due to political conspiracy theories about the climate hoax. Fortunately, there have been some incredible "data rescue" efforts led by digital humanists, librarians, and researchers to back up that data, preserving it hopefully for a future in which we take climate science as seriously as we should have long, long ago.

**ID:** What are you working on now that you are not yet ready to defend in print?
**MH:** I'm currently working on a new edited collection with a colleague, which we have titled *Paranoid Planet: Conspiracy Theories and the Environmental Humanities*, and we will be soliciting papers very soon. This volume asks how narratives about climate change, which the environmental humanities have long praised as an important component of public climate literacy, have been co-opted by online conspiracy narratives that acknowledge climate change only as the product of weather-control technologies and other fantastical tech.

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# *Generative AI and the Future of the Humanities: Reading, Writing, Teaching, Labor*, by Dana J. Gavin. 1st ed., Palgrave Macmillan, 2025. viii + 116 pp., ISBN: 978-3-032-06533-9.

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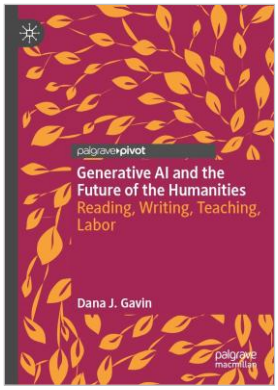
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## Book Review

# *Generative AI and the Future of the Humanities: Reading, Writing, Teaching, Labor*, by Dana J. Gavin. 1st ed., Palgrave Macmillan, 2025. viii + 116 pp., ISBN: 978-3-032-06533-9.

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Generative AI entered the composition classroom as a fait accompli, and a torrential downpour of academic and non-academic commentary followed soon after with the same urgency: reactive and only slowly theoretical. Dana J. Gavin recalls that the initial response to generative AI was pure alarm: "The College Essay Is Dead," *The Atlantic* reported just over a week after ChatGPT was publicly released. This was quickly followed by a backlash of "toxic positivity" (5). Subsequent books written in reaction to this crisis have organized themselves along disciplinary lines and targeted audiences. For example, Naomi Baron's *Who Wrote This?* (2023) presents a linguistic approach to the crisis through cognition and literacy. Similarly, Shannon Vallor's *The AI Mirror* (2024) offers a philosophical account of the crisis as a challenge to human capacity for moral decision-making and rational thought. John Warner's *More Than Words* (2025) is intended for the general reader who seeks to learn about the changes composition is undergoing because of AI. In contrast, the integrationist wing of composition studies can find a common point of reference in *TextGenEd* (2023), an open-access collection edited by Annette Vee, Tim Laquintano, and Carly Schnitzler. Gavin writes from yet another position, that of the writing center. Her *Generative AI and the Future of the Humanities* offers a perspective similar to Warner's but adds a historian's viewpoint. The author serves as Director of the Writing Center at Dutchess Community College and has taught first-year composition at four institutions (18). Her dissertation research concerned the nineteenth-century steam-powered printing press (2). She has also studied Victorian fiction such as *The Moonstone* and the Sherlock Holmes stories (29), all ventures that afford her an exceptionally broad scope when viewing a phenomenon that has been continuously described as unprecedented. Gavin's contribution therefore falls squarely within the domain of composition and rhetoric as opposed to linguistics or philosophy. Her book is the result of that dual formation, and while that particular disciplinary address is one of the project's strengths, it is also one of its limitations.

Gavin describes her goals as follows: "to raise questions, offer suggestions, and ultimately argue for action rather than passivity" (1). Gavin argues throughout her six-chapter book that generative AI is less a novel disaster than an accelerator of what she calls "a mass illiteracy event" (56) that has been occurring for decades, due in part to the failure of the humanities to articulate the value of what they teach. Two figures organize Gavin's book. The first figure is pollution. Gavin uses the smoke-tainted wine of California's 2017 wildfires (4) as her metaphor for an art form poisoned from outside; she returns to this theme throughout the "polluted assemblage of knowledge" that generative AI represents (13), in the dual senses of pollution as desecration and pollution as contamination (14), and in the "slop" and "rot" of the subsequent chapters. The second figure is the Luddite. Using economic and policy scholarship on the Luddites, Gavin transcends the rudimentary understanding of the Luddites as technophobic

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anti-modernists and reclaims them as skilled artisans protecting the quality of their craft from low-cost, low-effort "cut-up stockings" (7). Gavin makes the analogy directly applicable to machine-generated text: "slop poisons the well for everyone" (79).

Chapter 1 establishes these conceptual frameworks; Chapter 2 delves into writing and memory; Chapter 3 examines reading, trust, and the material costs of using generative AI; Chapter 4 turns to labor and what she refers to as "incapacitating technocapitalism" (13); Chapter 5 discusses pedagogy and the plagiarism panic; and Chapter 6 proposes coalition building.

The steam press anchors Gavin's historical position. By drawing upon Jane Bennett's new-materialist *Vibrant Matter* (2010) and Marshall McLuhan's *Understanding Media* (1964), Gavin views both the nineteenth-century steam-powered press and large language models as "vibrant assemblages of human and non-human materials" (10). The frame enables Gavin to view John Walter's covert installation of steam-driven presses at *The Times* and the threat of violence from the press workers (9-10) as a structurally rehearsed version of today's standoff among developers, educators, and displaced expertise without reducing the two moments to equivalent positions. The account is brief, about three pages (8-10), but it is critical to an understanding of Gavin's methodological approach as she expands the assemblage framework into authorship in Chapter 2. Her main target is the "lone genius," the Romantic writer who operates "alone in a room" (30). Gavin suggests writers are always community-based, shaped by teachers, editors, previous readings, and physical instruments. Writers, she asserts, invoking Donne, are never "an island" (31), and therefore citation should be employed as "explicit transparency with respect to our information assemblages" (32) instead of a proprietary boundary. The author disputes the often aestheticized mythology of the solitary writer, not individual ability: "The focus for me is the 'lone' part of the myth, not the 'genius' part" (30). The chapter also introduces sustained attention to disability, from assistive technology designed to help students with dysgraphia (22) to Friedrich Kittler's description of how Nietzsche turned to the Malling-Hansen writing ball when his sight began to fail (27-28). Accounts of writing technology continue in subsequent sections focused on hiring software (42-44) and accessible pedagogy (97). For a writing center director, the practical implications of the book are clear: the argument shifts plagiarism anxiety away from seeing it as a matter of individual dishonesty and toward viewing it as a symptom of an ideology of sole proprietorship.

The third chapter is the longest and conducts the book's most extensive synthesis. After an introductory reading of Conan Doyle's "The Adventure of the Copper Beeches" (37-39), the chapter examines AI as a product—Super Bowl advertising, a multiplicity of transparency regulations, and HireVue's explainability statement (40-44). The chapter then focuses on the cost of materials: examining data-center power consumption using Jevons's paradox, including the examples of Meta's proposed Louisiana data center and Ireland's strained grid (44-51); and the labor behind model training—from Kenyan workers earning less than $2 an hour to reduce toxicity in ChatGPT (53), to underage data-taggers hired from Pakistan to the Philippines (54). Only then does the chapter reach its epistemic core. Gavin argues that reading relies upon a "two-way trust street" between the reader and the author (55), where trust enables a reader to enjoy watching Holmes break a substitution cipher, or recalling that the Enigma was broken by Polish and British cryptographers (55). Using Emily Bender and her co-authors' "On the Dangers of Stochastic Parrots" (2021) as the chapter's sharpest analytical instrument, Gavin explains that a language model combines words into phrases "without any reference to meaning," resulting in a "stochastic parrot." Therefore, according to this line of reasoning, all comprehension derived from it is "an illusion arising from our singular human understanding of language" (qtd. in Gavin 55). Gavin follows this with a reading of Frederick Douglass's

*Narrative* (1845) and Maryanne Wolf's *Reader, Come Home* (2018), arguing that literacy can be understood as a form of liberation rather than a functionally instrumental skill. "What he most dreaded, that I most desired," Douglass writes concerning his enslaver's fear of his literacy (qtd. in Gavin 59), and Gavin worries that generative AI arrives before many readers have become the "expert readers" this level of trust requires (61). The chapter concludes by returning to Bennett and to Sarah K. Burriss and Kevin Leander's "Critical Posthumanist Literacy" (2024), in a section of the book (64-67) to which I return below.

However, an issue arises from Gavin's omission regarding existing theoretical positions. Gavin's case against the solitary author revisits debates that have already been worked through. This topic has been explored at length in two bodies of literature. First, in literary theory, Roland Barthes's "The Death of the Author" (1967) argued that a text's meaning is produced during the reading activity itself rather than being guaranteed by an "Author-God," and Michel Foucault's "What Is an Author?" (1969) posited that the author is a historical construction ("author-function") rather than a natural fact of written works. Neither piece appears in Gavin's reference lists or anywhere in the book's chapters. Second, Gavin fails to cite a substantial body of scholarship developed within her discipline (composition studies) that challenged the notion of solitary authorship during the late twentieth century. These include Linda Brodkey's "Modernism and the Scene(s) of Writing" (1987), which critiques modernist images of writers who create alone in a garret; Karen Burke LeFevre's *Invention as a Social Act* (1987); Lisa Ede and Andrea Lunsford's *Singular Texts/Plural Authors* (1990); and Rebecca Moore Howard's *Standing in the Shadow of Giants* (1999), which addresses plagiarism and patchwriting, among other works. Not one of them is cited in the book. While Gavin references Kittler's media theory effectively (27-28), she fails to provide the reader with any account of why she is taking an assemblage-theoretical approach via Bennett and McLuhan instead of drawing on the apparatuses established by her own field to dissolve notions of solitary authorship. As it stands, the claim reads like a rediscovery to anyone trained in literary studies or composition studies.

The Barthes omission matters most in Chapter 3, where the question of authorial intention becomes structural. The assumption of an intending author is central to Gavin's understanding of reading as trust. Gavin states that this is sustained by "a belief that the author of the text is trying, in good faith, to put forward something coherent" (12) in addition to "a bone-deep trust that someone is trying to tell me something" (63). Additionally, Bender and her co-authors point out that comprehension is an illusion if one party to the communication has no intention to mean anything (55). This is precisely what Barthes's essay claims is dead with his relocation of meaning to the reader; in other words, the book dissolves the solitary author in Chapter 2 and calls it back as the guarantor of meaning in Chapter 3. While these two positions are not strictly contradictory, since a writer embedded in communal assemblages could still have intentions, the book commits itself to an intentionalist theory of meaning. Literary studies have been contesting this for decades, and Gavin provides no defense of this position. Since she argues in Chapter 3 that generative AI is "untrustworthy" (37) based upon an intentionalist theory of meaning, the gap in perspective is not merely academic, and the omission is more than a theoretical nicety.

A related concern arises when Gavin turns to Burriss and Leander. Gavin agrees that placing generative AI in the writing assemblage allows us to "think about 'writers' as confederations rather than individuals" and trace texts to "human–non-human assemblages rather than singular human authors" (66). However, she resists "treating generative AI as a singular entity with discrete agency of its own"; she prefers instead to "break down the assemblages within the assemblage of generative AI" (66). This disaggregation is entirely consistent with Bennett's philosophy. The difficulty lies in the justification she gives for the remaining asymmetry between generative AI and human agents. She opts out of treating generative AI "with the same

wholeness as the human being" because "generative AI is not an approximation of a discrete unit in the way a human comes closer to manifesting" (65-66). In other words, she makes an ontological assertion that is presented rather than argued. The rationale she develops elsewhere in the chapter for this asymmetrical treatment is political-economic: a chatbot appears to be a complete unit but conceals scraped texts, underpaid moderators, and data centers (44-54). For this reason, *Vibrant Matter* is not a suitable source for the ontological statement since Bennett's project is to refuse clear distinctions between human and nonhuman actants. Foucault's author-function, which Gavin never uses, could easily have supplied the distinction Gavin's prose keeps reaching for. Had she applied this concept, she could have granted generative AI a role in the writing assemblage but denied it proper authorship. It would also have allowed her to ground the denial of authorship in the social and legal practices of attribution that inform her political-economy argument instead of grounding it in which entities are more nearly whole.

Chapters 4 and 5 turn Gavin's focus outward to the university at large and to the ways "technocapitalism" affects it. To Luis Suarez-Villa's definition of "technocapitalism" in *Globalization and Technocapitalism* (2012) as the fusion of corporate power and technology (76), Gavin adds a qualifier of her own to define the concept further: "incapacitating technocapitalism," or technology used "for the enrichment of the few that also has a useful numbing effect" (13), based upon McLuhan's interpretation of Narcissus as narcosis. Her question—"Who benefits from a populace that can no longer read and write effectively?" (76)—leads to the chapter's culminating claim that an illiterate public is easier to control. Her most incisive labor example is not the most obvious one. A UCLA medievalist had ChatGPT generate course material as well as breakout session content for her teaching assistants. The true cost was borne by the graduate students who were denied the opportunity to engage in the formative labor of creating them (78). Gavin is similarly critical of AI-generated feedback and recommendation letters: a high school teacher advocating for using AI to give instant feedback on over 140 students' drafts is, according to Gavin, an argument for smaller ratios (83); and letters drafted by AI can end up having "generative AI 'talk' to generative AI" (84). Gavin presents her darkest case study of incapacitating technocapitalism through the co-optation of the NaNoWriMo program. Originally a grassroots writing project, the organization had by 2024 a leadership that dismissed criticism of AI use as classist and ableist, despite a resigning board member pointing out that an AI-powered writing tool had become a sponsor (76-77). The chapter's most crucial section is "Communicating Value" (79-88), in which Gavin turns on her own discipline. Fields that "authentically believed in the necessity of the skills developed through their practice," she argues, "would not have permitted the casualization and de-professionalization of the profession" (80). Her solution for auditing humanistic skill development in the workplace and reporting those findings to the public (79, 81) is perhaps the clearest expression of the book's central premise, though more blueprint than edifice.

In Chapter 5, Gavin shifts her attention to the relationship between teachers and students. Gavin examines detection software, from Turnitin's huge databases of stored student papers (95) to modern AI-based detection tools that are "presented as entirely reliable," while their own terms clearly indicate that they are "in no way foolproof" (96). What is distinct about Gavin's position vis-à-vis both surveillance technologies and AI is that she rejects each with equal vigor. Gavin views the retreat to blue books and pencils along with the abandonment of Universal Design for Learning as a pedagogy of "domination through penalty" (97), and she explicitly rejects "forcing students to hand write essays in class" (102). Instead, she suggests making students' "metacommentary the primary assessment object, rather than the final draft" (101). Of the book's specific suggestions, this is probably the most exportable to other educators

and administrators. The conjunction of anti-AI and anti-surveillance positions lends Gavin's perspective a distinctive edge.

The book's remaining limitations are chiefly a matter of evidence. First, the frame of reference for Luddism is narrower than its central position warrants; Gavin's use of this frame (6-7) is primarily based upon Gary M. Anderson and Robert D. Tollison's "Luddism as Cartel Enforcement" (1986); this public-choice economics piece uses the cartel frame in a way that does not fit well with Gavin's heroic view of the Luddites. Moreover, she does not mention the labor-history tradition that has reclaimed the Luddites, from E. J. Hobsbawm and E. P. Thompson to Brian Merchant's *Blood in the Machine* (2023). Second, Gavin's empirical base is uneven. She uses survey and agency data when possible—for instance, the PIAAC and NAEP literacy results (56-57), the International Energy Agency's projections (45-47), Alexandra Sasha Luccioni and her co-authors on rebound effects (51)—but many of the facts supporting her political-economy arguments rely on journalism, corporate reports, newsletters, and podcasts; and some of these facts and figures reach the reader at several removes. For example, the claim that training a single model can produce "more than 626,000 pounds of carbon dioxide equivalent" appears via a *Forbes* column reporting *MIT Technology Review* (11), although the original source was a 2019 study cited by Gavin elsewhere through Bender and her co-authors (44). This is understandable in a book written from inside an ongoing controversy; however, many of its factual elements will date in a way its historical and educational elements will not.

Third, Gavin's use of the Douglass passage relies on a comparison that bears too much weight. Although the legal and violent repression of literacy in chattel slavery and the underfunded and algorithmically distracted degradation of literacy education now are each real, they do not exist on a single continuum. Gavin later recognizes this distinction—"we do not have the same kind of threat to literacy as Frederick Douglass faced as an enslaved man" (111)—although the acknowledgment occurs approximately fifty pages after the comparison has done its rhetorical work, and the passage that uses Douglass the most (59-60) does not include it. The book also shows signs of rushed editing, including the erroneous spelling of Maryanne Wolf's name as "Wolfe." The slip is minor, but a second edition should correct it.

The book's hybridity of genres constitutes both its appeal and its primary structural limitation. Gavin writes as memoirist and polemicist as much as scholar. The majority of her chapter titles are directly extracted from 1 Corinthians, Conan Doyle, Agatha Christie, Dante, and Robert Frost, and the chapters vary greatly in focus. For instance, Chapter 3 ranges from Louisiana and Irish data-center strain to effective altruism and Peter Singer's "drowning child" to Jevons's paradox before concluding with trust and literacy. To a sympathetic reader, this will appear to be richly detailed; however, to one looking for a consistent, sustained argument, it may seem digressive. The book concludes similarly. Chapter 6 rewords Frost's "A Servant to Servants," whose speaker admits that she "can see no way out but through" (qtd. in Gavin 105); Gavin changes the word "out" to "forward." She states: "This is why I rather wantonly reworded Frost's beautiful poetry, to change the word 'out' to 'forward.' I do not believe there is an 'out' here" (107). Gavin offers tangible, if modest, examples of coalition building. These include unionizing, summer round tables with K-12 educators, pending state legislation, and even European and Australasian car safety assessors pushing back against touchscreens in favor of physical controls, offered as an unlikely precedent for walking back bad design (107, 110-12). Her use of a personal register grants the book accessibility as well as pedagogical authority; however, it also means that claims are asserted rather than developed across the chapters into a cumulative case.

*Generative AI and the Future of the Humanities* is ultimately a document that captures the AI discourse's present moment, written from the front line with genuine expertise. The book will likely be most valuable for writing center professionals, composition and rhetoric scholars,

and humanities faculty members who seek a usable framework as well as concrete classroom strategies. Scholars who want to theorize authorship or the ethics of AI, by contrast, will need a more systematic treatment. Gavin's work is strongest when she is grounded in her own institution-based roles: the writing center, the first-year composition classroom, the union negotiation table. Composition studies is where Gavin has authority to speak, but she does not draw on the theory of social authorship that composition studies developed decades earlier; therefore, her contribution to the theory of authorship she alludes to remains an opportunity rather than a resolution. Gavin ends with an imperative—"Be bold and go deep, because others will follow" (113)—and the book's truest achievement lies in modeling this confidence even if the book's theoretical foundation has yet to catch up to its conviction.

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# *Intelligence artificielle et apprentissage: Fondements, concepts et applications*, by Sarah Chardonnens. De Boeck Supérieur, 2026. 336 pp., ISBN: 978-2-8073-7188-0.

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# Book Review

## *Intelligence artificielle et apprentissage: Fondements, concepts et applications*, by Sarah Chardonnens. De Boeck Supérieur, 2026. 336 pp., ISBN: 978-2-8073-7188-0.

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Sarah Chardonnens published *Intelligence artificielle et apprentissage: Fondements, concepts et applications* (Artificial Intelligence and Learning: Foundations, Concepts, and Applications) with De Boeck Supérieur in 2026. A doctor of educational sciences, she is a professor at the Haute École Pédagogique de Fribourg and the University of Fribourg in Switzerland and has focused on research and teacher training since 2019 (325). The book examines the effects of artificial intelligence on education. Its main purpose is to explain how AI can support learning without replacing the student's intellectual effort.

The book is not simply a guide to digital tools, nor does it present AI as a perfect solution to educational problems. Chardonnens promises "principles, not prescriptions," and warns that readers will not find "a catalog of applications, sorted by subject or by level," because such a catalog would soon be obsolete (18, 20; my trans.). She argues instead that AI should remain a learning aid and should not do the intellectual work for the student.

Chardonnens writes for secondary and higher-education teachers, adult trainers, and instructional designers, and she sends readers with management, coordination, IT, or legal responsibilities to chapter 11 on governance (19, 21). Its central question is how AI can be used without weakening the learner's abilities. In the author's words, the question is not "which tool to choose?" but "what do we want to teach, to whom, and at what cognitive and motivational cost?" (18; my trans.).

The question matters because AI produces answers very quickly. It can write a text, summarize a document, or explain a difficult concept. Speed, however, does not always lead to learning, and a student may obtain a correct answer without understanding it. Hence the book's refusal "to confuse production and learning, speed and understanding, assistance and autonomy" (18; my trans.).

Chardonnens adopts a balanced position. She neither recommends banning AI nor supports its unlimited use. For her, AI is "neither a condition nor a taboo" but "an environment variable" (227; my trans.). Its value depends on the way it is used and on the learning objective the teacher defines.

## Human Intelligence and Artificial Intelligence

The first part of the book presents the main theoretical ideas, beginning with the distinction between human intelligence and artificial intelligence (51-70).

Human beings learn through experience by connecting new information to previous knowledge, and their emotions, memories, and relationships also shape that learning. Human

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learning is therefore a complex process that involves reasoning, feeling, remembering, and interacting with others.

Artificial intelligence works differently. It processes large amounts of data, identifies patterns, and produces results through statistical calculation. Such a system "learns" in the computational sense, by optimizing a mathematical function, but it "does not understand in the human sense: no intentions, no intrinsic meaning, no lived experience" (55; my trans.). It can generate a clear and convincing answer without understanding that answer as a human being would.

The distinction is essential, because a well-written answer can still be incorrect. Fluent language does not guarantee truth, so students must learn to check information, compare sources, and use their own judgment.

Two later chapters examine the processes involved in learning, namely attention, memory, motivation, emotions, and sleep, all of which affect the learner's progress (71-90, 123-32).

Learning is more than receiving information. Students must select and organize it, connect it to what they already know, and restate it in their own words. Finally, they must be able to use it in a new situation.

Effort plays an important role in this process. Mistakes are useful too, since they help students identify difficulties and correct their reasoning; error is a normal part of learning.

AI can sometimes reduce this necessary effort. When it immediately provides a complete answer, the student may skip important stages of reflection, which is why the author recommends using it carefully.

## The SYNAPSE Model

The second part presents the SYNAPSE model, the book's main contribution. It organizes learning into four phases: "reception and activation," "adaptation and adjustment," "observation and self-regulation," and "consolidation and storage." The name stands for the English labels the book gives these phases: Sensory Input, Network Adaptation, Participation, and Storage & Embodiment (19).

Chardonnens built the model from a systematic literature review conducted to PRISMA standards, which narrowed 1,371 publications to 301 articles coded with MAXQDA, and from three exploratory qualitative studies carried out between 2023 and 2025 in a university, a secondary school, and an initial teacher-education program (147-49).

Motivation sits at the center of the model and influences every phase (141). It helps students begin a task and sustain their effort, and it also supports memorization.

The four phases are connected. Learners can return to an earlier stage, change their strategy, or reactivate previous knowledge, so learning appears as a dynamic process rather than a hierarchical sequence (139).

### *Reception and Activation*

The first phase concerns the beginning of learning. Students must direct their attention toward the task and activate their previous knowledge, which makes new information easier to understand (151).

AI can support this phase in several ways. It can open a lesson with a question, or it can generate an image, a simulation, or a personalized example whose relevance the class then discusses (164-65). Such uses may stimulate curiosity.

The teacher, however, must keep a clear objective in view. An attractive activity is not always educational, and capturing attention is not enough. In the age of AI, Chardonnens writes, the

danger is not only distraction but an activation "by proxy," in which the machine captures attention and supplies answers before curiosity, questions, and hypotheses have emerged in the learner (166; my trans.).

### *Adaptation and Adjustment*

The second phase concerns the transformation of knowledge, and the author calls it "the beating heart of the SYNAPSE model" (183; my trans.). Faced with a difficulty, the student searches for a solution, develops ideas, tests them, and sometimes makes mistakes that lead to a better understanding.

In this phase, error has a positive function. It shows what the student has understood and helps the teacher provide suitable support.

AI can adapt exercises to a learner's errors and offer counterexamples and explanatory feedback (173, 178-79). This assistance must remain limited, however, because help that comes too quickly can remove the effort that learning requires.

Her answer is a simple rule, an "imposed delay" before AI is used: students first sketch a solution on their own, then compare it with the AI's answer and discuss what the tool added, what they keep, and what they change (183; my trans.). This approach protects their intellectual activity and reduces their dependence on technology.

### *Observation and Self-Regulation*

The third phase concerns the ability to observe one's own work. Learners must plan their actions, identify their mistakes, and evaluate their methods (187).

This ability, known as metacognition, allows students to understand how they learn. It also strengthens their independence and makes them more responsible for their progress.

AI can support this process by asking reflective questions, commenting on a method, or helping students monitor their progress.

The author recommends a sequence she sums up as "reflection first, comparison afterward": students reason on their own, then compare their approach with the one an AI proposes, and finally explain what they retain from the comparison (197-99; my trans.). AI must not become an unquestionable authority. The final judgment must remain human.

### *Consolidation and Storage*

The final phase concerns long-term memory. New knowledge is fragile at first, so it must be reviewed several times and used in different situations (203-04).

The book emphasizes spaced repetition and active recall. Active recall requires learners to retrieve information without immediately consulting their notes, and this method strengthens memory.

Sleep also contributes to the consolidation of knowledge, and regular practice remains necessary. Learning therefore requires time and repeated effort.

Because AI can create quizzes, organize reminders, and provide varied exercises, it can become a useful revision tool. Chardonnens also reviews recent work on "cognitive offloading" and on what researchers at MIT have called "cognitive debt," and she concludes that AI can strengthen memory when it serves active retrieval but can weaken it when it entirely replaces the learner's own cognitive processes (207). The remedy is to keep learners active: they produce their own answers and explain ideas in their own words. Technology should strengthen mental activity, not replace it.

## From Theory to Practice

The third part of the book is more practical. It shows how to plan teaching with SYNAPSE (235-52), what AI literacy, governance, and regulatory compliance require of teachers and institutions (253-62), how to educate critical citizens (263-70), how to put the model to work in class (271-88), and how to train teachers in a reasoned use of AI (289-302).

Several simple routines serve to develop critical thinking. One, "think first, compare afterward," asks students to produce something of their own before they look at an example, a model answer, or an AI output. Another, "Pause–Check–Decide," has them restate what the tool claims, verify at least one point, and then write in two lines whether they accept, reject, or qualify it, and why (273-75; my trans.).

Chapter 13 also supplies assessment rubrics and a short template for declaring the use of AI, to be attached to certain assignments, which allows students to explain how they used the technology (279-83). Such transparency encourages responsible use. Downloadable supplements on the publisher's website, among them SYNAPSE checklists and a "trust but verify" protocol, complement the text (8), and a glossary defines the main terms (313-24).

The examples cover mathematics, languages, science, arts and music, and physical education, along with an interdisciplinary project (283-88). This variety shows that the model can be adapted to different educational settings.

AI should not be added to a lesson without a clear purpose. Its use belongs in the lesson plan: only after making their pedagogical choices do teachers decide whether AI is forbidden, allowed, or required for a task, and on what conditions (272).

## The Main Contributions of the Book

The book's first strength is its educational approach. According to the author, the originality of the model lies in a deliberate choice "to begin with the learner's internal trajectory, and not with technology" (19; my trans.), so education remains at the center of the discussion.

The model, as Chardonnens frames it, does not merely describe "what AI can do" but asks "what education must preserve" in the face of automation (139; my trans.). This change of perspective keeps teachers from following technological trends without reflection. The same feature, such as automated feedback, a dashboard, or a conversational agent, can strengthen or weaken learning depending on the phase in which it intervenes and on how it is built into the lesson (19).

The second strength is the SYNAPSE model, which brings together several dimensions of learning, including attention, motivation, memory, and metacognition. It gives teachers a clear framework for analyzing learning activities and identifying students' needs. Its value also extends beyond digital education, since the author offers it as a common language for analyzing a teaching sequence "with or without AI" (19; my trans.), whether a traditional lesson or a group project.

The third contribution concerns ethics, with discussions of bias in AI systems, data protection, transparency, and fairness (91-122, 253-62). Students do not all have equal access to digital tools or the same digital skills, and Chardonnens warns that AI designed without vigilance can widen the digital divide (103). Schools have to make sure that AI does not deepen existing inequalities.

Institutional responsibility receives similar attention. High-stakes decisions require human supervision (283), teachers remain responsible for pedagogical decisions and assessment, and AI "can never be the sole basis of an academic judgment" (258; my trans.).

Finally, the book practices what it recommends. In a Post Scriptum placed after the conclusion, Chardonnens names the AI tools she used while writing, among them Perplexity, SciSpace, and NotebookLM, and the purposes they served, from testing analogies and proposing counterexamples to summarizing articles. She adds that she accepted no reference without checking its authors, dates, and DOI (307).

## Limitations

The empirical claims call for more caution than the introduction suggests. The introduction presents the book and the model as resting on "a solid empirical base" of field studies conducted "on various continents" (19; my trans.). Chapter 5, however, describes its three exploratory studies in a few paragraphs, without sample sizes and without naming the institutions or countries involved, and presents them as offering "first information for the empirical validation" of the model (148-49; my trans.). For now, SYNAPSE is best read as what its author calls "a heuristic and reflective tool" (137; my trans.) rather than as a validated model.

Chapter 11, whose title carries the year 2025, surveys the European AI Act and the GDPR, the Swiss, Canadian, British, and American frameworks, and international references from UNESCO and the OECD (253-62). The survey makes the chapter concrete, but it will date quickly, and it says nothing about African legal frameworks, so Moroccan readers, for instance, will have to transpose its guidance to their own data-protection rules.

## Conclusion

*Intelligence artificielle et apprentissage* is a useful and well-documented book that offers a balanced reflection on artificial intelligence in education. Its main argument is convincing: AI does not automatically produce learning. Used well, AI should preserve the student's attention and effort, develop the ability to check information, and strengthen independence and critical thinking.

The book does not ask readers to choose between teachers and machines. It defines their different roles instead: AI may provide assistance, while teachers remain responsible for objectives, methods, and assessment.

Chardonnens's vision of education is human-centered: education does not stop at producing correct answers but teaches students to reason, verify information, defend ideas, and correct mistakes. The SYNAPSE model offers teachers a relevant method and can help students use AI responsibly, even if its empirical grounding still needs to be consolidated. The book's final message is clear: AI "does not replace education; it shifts what education must prioritize" (303; my trans.).

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