A Pedagogical Framework for Integrating Generative AI into Interactive Learning Environments

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Abstract

Educational practices have been positively impacted by Generative Artificial Intelligence (AI) and Large Language Models (LLMs) such as ChatGPT. Unlike traditional systems and learning platforms, ChatGPT engages users in conversations, provides tailored feedback, and creates new knowledge in virtually any area. This paper provides a detailed model for educational practice using ChatGPT and other generative AI systems. The model attempts to address, in an equitable manner, the three most challenging aspects of educational practice: pedagogical concerns, technological availability, and ethical peripherals. The model enhances students' engagement, promotes the development of their higher-order thinking skills, and is designed to improve learning outcomes through personalization. This paper discusses a conceptual model for adaptive generative tutoring and provides technical illustrations, tables, and formulae to describe the process. The use of generative AI in STEM problem solving and language learning is primary, but the challenges of academic honesty, bias, and data privacy are also addressed. The current paper provides a potential framework for the thoughtful and purposeful use of ChatGPT in educational settings and makes a valuable contribution to the discourse on the intersection of educational technology and the ethics of AI in teaching.

Keywords: Generative AI, Large Language Models, ChatGPT, Interactive Learning.

Introduction

Thanks to technological advancements, education has seen the addition of new tools that leverage various forms of Artificial Intelligence (AI). These tools range from automated grading systems to intelligent tutoring systems (Gambo et al. 2025). However, the tool that is perhaps most significant in terms of its impact is generative artificial intelligence, specifically Large Language Models (LLMs). LLMs can generate responses to user prompts that feel human. Users can have multi-turn conversations in which the assistant demonstrates understanding of previously discussed topics. The assistant can also use its ability to synthesize new information to create explanations of varying complexity.

Background and Motivation

Most previous e-learning systems used inflexible models that could not answer questions or provide explanations outside their predefined parameters, giving feedback and information based

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solely on the models and algorithms that programmed them (Almohammadi, 2025). There may have been some limited use cases where these systems were effective, but they are severely lacking in creativity, flexibility, and personalization. In contrast, ChatGPT can interact with a user in a way that enables complex dialogue. It can ask questions, provide information, and guide the user to answers in a manner appropriate to the user's level of understanding. Educational stakeholders, such as teachers, administrators, and policymakers, anticipate that Generative AI tools, such as ChatGPT, can serve as a "co-teacher" to assist in the instructional process (Joshi, 2025). A teacher may ask ChatGPT to create practice exercises based on a student's areas of weakness, while outside of class, students use ChatGPT to explain concepts that were unclear during class. However, the use of these tools presents several challenges, including reliability, ethical considerations, and pedagogical concerns. The use of ChatGPT in education, with no restrictions, may create more challenges than it was designed to address.

Research Problem

In addition to crafting personalized learning experiences, providing instantaneous feedback, and delivering real-time answers, Generative AI can enhance learning in other ways. However, its responses may not be accurate, unbiased, or aligned with the curriculum's intended goals. There is a risk that students may inappropriately rely on ChatGPT, which may unreasonably diminish their ability to think critically, or may use it inappropriately, which could constitute academic dishonesty (Nwozor, 2025). Teachers may not have the necessary background or expertise to assess the AI-generated products (Huang et al., 2025). Institutions must grapple with implementing AI systems that comply with privacy and accreditation regulations. The main focus of this research is to investigate the challenges of integrating ChatGPT and other generative AIs to enhance learning quality, protect the integrity of the pedagogical process, and ensure ethical responsibility.

Objectives

This paper has the following objectives:

1. Assess the present state of AI in education, specifically focusing on generative AI.
2. Suggest a multi-dimensional pedagogy, technology, and ethics framework.
3. Present a model of adaptive generative tutoring, technology, and ethics framework.
4. Provide STEM and language learning examples.
5. Assess the challenges and risks of integration.

Literature Review

AI in education is not novel (Aiken & Epstein, 2000); however, the entry of Generative AI signified a drastic shift away from previous methods. To define the contextual relevance of ChatGPT, this section examines the literature on the development of Intelligent Tutoring Systems (ITS), adaptive learning systems, and, most recently, Generative AI in education.

Intelligent Tutoring Systems (ITS)

The initial phase of AI in education concentrated on Intelligent Tutoring Systems (ITS). The goal of the ITS was to provide a similar experience to that of a human tutor by using algorithms and a structured knowledge representation (Nussbaum, 2021). There are typically four fundamental components:

- *Domain Model:* Knowledge representation of the subject.
- *Student Model:* The learner's knowledge and progression state.

- *Tutoring Model:* Teaching methodologies.
- *User Interface:* Medium of interaction.

As examples of Intelligent Tutoring Systems (ITS), Cognitive Tutors for math (Anderson et al., 1995) and AutoTutor for natural language dialogue (Graesser et al., 2001) come to mind. While ITS demonstrated measurable gains in student performance, it has always faced scalability and adaptability challenges. Because they relied too heavily on rule-based logic, they struggled with open-ended questions and were unable to create anything beyond their pre-programmed knowledge.

Adaptive Learning Systems

The most recent developments include adaptive learning platforms such as ALEKS, Knewton, and Smart Sparrow, which use machine learning to create personalized learning pathways. Such platforms use a student's mastery of certain concepts and adjust content delivery based on probabilistic models of predicted mastery. Adaptive learning has been shown to improve learning retention and reduce the time spent learning (Pane et al., 2014), but these systems are assessment-driven and fall short in enabling natural conversation with the system. They are great at predicting the next lesson, but they do not explain why in a humanistic manner.

Chatbots and Conversational Agents

Educational chatbots that predate ChatGPT provided basic conversational capabilities, performed administrative tasks, and provided navigational support through course FAQs. Examples include Jill Watson (implemented at Georgia Tech using IBM Watson) and chatbots integrated into learning management systems (LMS) (Venkatesh, 2000). While chatbots provided some administrative relief, they lacked advanced contextual reasoning and generation. They operated on intent recognition, typically pre-programmed responses, and did not generate responses from context.

Generative AI and ChatGPT in Education

Large Language Models (LLMs) are rapidly changing the world computationally. With each LLM version, including the most recent, GPT-4, systems become more generative and able to build new content rather than just pull from existing content. One example, ChatGPT, has proven to enhance education by helping explain obscure concepts in easy language, creating examples, quizzes, and study guides, role-playing in Socratic dialogues to nurture analytical thinking, and giving constructive comments on essays, programming, and problem-solving. In early studies (Kasneci et al, 2023; Rudolph et al, 2023), ChatGPT has been and still is able to perform the functions and roles of a writing coach, coding assistant, and study partner. Still, generating plausible, inaccurate answers, reinforcing biases, and ethical issues such as plagiarism and cheating on assessments are valid concerns about ChatGPT. The key differences in the use of each platform (ITS, adaptive, and ChatGPT-based systems) are summarized in Table 1.

Table 1: Comparative Features of Educational AI Systems

Feature	Intelligent Tutoring Systems (ITS)	Adaptive Learning Systems	Generative AI (ChatGPT)
Content Generation	Pre-programmed, static	Limited (item banks)	Dynamic, generative
Dialogic Interaction	Limited scripted dialogue	Minimal	Natural conversation
Adaptivity	Rule-based	Probabilistic	Prompt-based + contextual
Transparency	High (explainable logic)	Medium (black-box ML)	Low (opaque neural nets)
Engagement Potential	Moderate	Moderate	High (interactive, creative)
Risks	Narrow scope	Lack of flexibility	Bias, misinformation, plagiarism

Gaps in Existing Research

Adaptive systems and prior systems (ITS) offered a balanced mix of structure and reliability along with a flexible, human-like reasoning void. Generative AI provides new opportunities and new risks:

- *Reliability Gap:* Differently from ITS systems, ChatGPT provides answers that may seem true, but are actually false (Kim et al., 2025).
- *Pedagogical Gap:* Misalignment between use case and theory (e.g., Bloom's, constructivism) is observed in most current applications (Devassy et al., 2025).
- *Ethical Gap:* Governance frameworks that address plagiarism, data privacy, and bias in generative AI are minimal or nonexistent (Pathan & Shah, 2025).

Research Justification

Considering these gaps, it is imperative to provide a structured framework to capture the strengths of ChatGPT (e.g., adaptivity, creativity, dialogic interplay) and contain the risks. This review of literature illustrates the demand for a framework with multiple dimensions and for the fusion of pedagogy, technology, and ethics, which this paper calls for in the following sections (Hummel, 2025).

Theoretical Framework

The successful merging of ChatGPT and Generative AI into educational practice isn't as simple as garnering enthusiasm. Here, I need to build a framework. With this in mind, I focus on the intersection of pedagogy, socio-technical design, and AI ethics to build a geo-ethical framework. This framework is based on three interrelated conceptual pillars: Pedagogical Integration (P), Technological Infrastructure (T), and Ethical Governance (E).

Pedagogical Integration (P)

The centerpiece of this framework is pedagogy. Deploying ChatGPT in education means consideration of the following learning theories:

- *Constructivism:* This theory rests on the notion that learners build knowledge more successfully when they actively engage in the process. Here, ChatGPT offers the possibility of being a “cognitive partner” who actively engages in conversations with learners, rather than simply providing answers.

- *Bloom’s Taxonomy:* Different Generative AIs can be designed to engage users at varying levels of the cognitive processes, ranging from simply recalling facts to evaluating and creating, which are higher-order skills.
- *Formative Assessment:* The principle of scaffolding student learning is supported by the feedback Loop. Instant feedback is a feature offered by ChatGPT, and as such, supports the need for formative assessments.

As such, pedagogical integration, in the case of ChatGPT, means using the tool sparingly, and creating boundaries so that critical thinking, problem solving, and creativity are fostered and developed.

Technological Infrastructure (T)

The second pillar concerns the technical integration, and infrastructures that support safe and effective integration. This includes:

- *Prompt Engineering:* Designing inputs that elicit accurate and curriculum-aligned outputs.
- *Explainability and Validation:* Pairing ChatGPT with knowledge verification modules to detect inaccuracies.
- *Scalability and Accessibility:* Deploying ChatGPT via secure APIs integrated into Learning Management Systems (LMS), ensuring equal access across institutions.
- *Feedback Loops:* Leveraging reinforcement learning from human feedback (RLHF) to continuously refine system outputs in real educational contexts (Chaudhari, 2025).

  This pillar emphasizes the role of technical design in maintaining reliability, usability, and security.

Ethical Governance (E)

Incorporating an ethical dimension means ensuring that the integrity of the education system is maintained, in the adoption of generative AI. Main principles are:

- *Fairness:* Mitigating the occurrence of bias in generated content (e.g. gender or cultural stereotypes).
- *Transparency:* Students should be made aware that AI is being utilized as a support during evaluative and learning processes.
- *Privacy:* Student information should be kept secure, and regulations pertaining to it (FERPA, GDPR) should be observed.
- *Academic Integrity:* Measures should be put in place that guard against plagiarism, and other forms of ghost writing or AI writing on assessments.

  Without strong governance, generative AI risks damaging trust and credibility in education (Zhang & Reusch, 2025).

Conceptual Model

Figure 1: Triangular relationship Among pedagogy, Technology, and Ethics

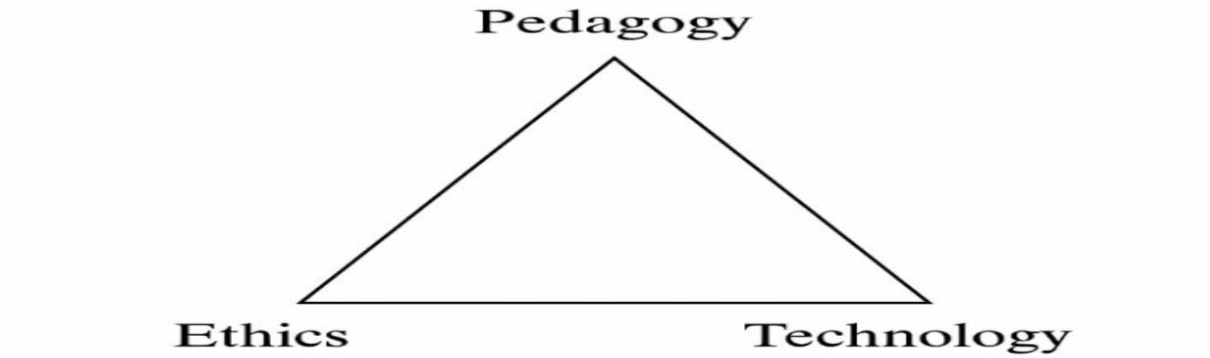


Figure 1 illustrates the framework, depicting the triangular relationship between pedagogy, technology, and ethics.
Effective AI Integration (EAI), situated at the triangle's center, occurs when all these foundational pillars function in a balanced, interdependent manner. The equilibrium is disrupted when one pillar is missing, resulting in incomplete, or even harmful, implementation. The dynamic relationship between pedagogy, technology, and ethics drives the AI in education phenomenon. Pedagogy focused on objectives informs the contextual use of AI, while technology provides the means and support for the instructional frameworks. Integration is also governed by ethics, providing a foundation of equity, accessibility, transparency, and responsible design. The combination of these factors provides the integrated governance of the AI in education phenomenon. The integration of the factors provides the accountable and sustainable use of AI in education.

Mathematical Expression of the Framework

The three pillars can be formalized as a function of effective AI integration (EAI):
$EAI = f(P, T, E)$ Where:

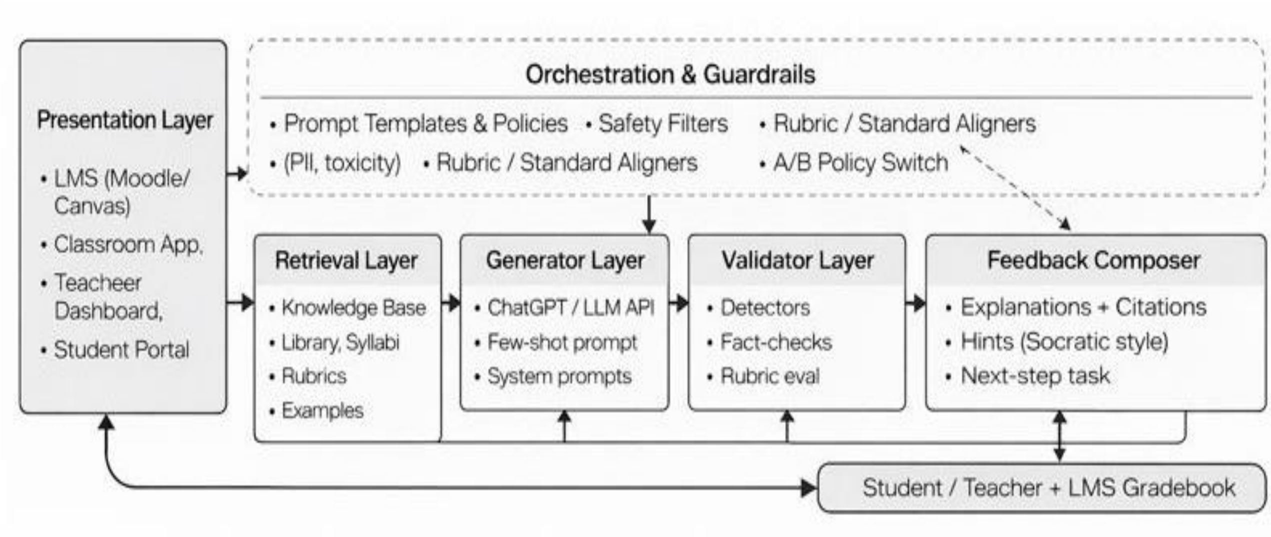
- P = Pedagogical alignment with learning theories and instructional design
- T = Technological readiness and infrastructure reliability
- E = Ethical governance and compliance mechanisms

Each variable can be weighted according to institutional priorities:
$EAI = \alpha P + \beta T + \gamma E with \alpha + \beta + \gamma = 1$
Here, coefficients (α, β, γ) reflect the relative importance of each pillar. For instance, a university prioritizing ethics might assign $\gamma=0.5$, while a technology-focused pilot program may assign greater weight to T.

Proposed Framework

This section operationalizes the theory (P–T–E) into a deployable framework that is designed for ease of adoption by institutions. Reference architecture, data and control flows, tutoring algorithm with assessment logic, and governance controls are included. Reference architecture is shown in Figure 2.

Figure 2: Reference Architecture



Key Concepts of the Reference Architecture

Separation of Concerns: Each component has its own unique functionality. This is done to enhance reliability and robustness. Each component has its own distinct purpose. The retrieval component focuses on collecting authoritative sources, representative samples, and standard writing rubrics from trusted sources. The generation component uses large language models (Plaat et al., 2025). Multi-step reasoning with large language models, a survey. ACM Computing Surveys.) to create clear and cohesive explanations and other instructional materials from the information that has been retrieved. The final component, validation, is responsible for ensuring that the generated outputs are factually correct, aligned to the standards, and overall, the integrity of the outputs through systematic fact checking. This is done through rubric-based validation.

Policy-First Orchestration: Pre-generation and post-generation steps of the pipeline have multiple layers of policy, governance, and compliance for oversight and control. The compliance layers of the pipeline ensure that every output is aligned to operational ethics, pedagogy, and other institutional restrictions. This is done through blocking and filtering for safety, constant alignment checking for standards, and telemetry monitoring for accountability and adaptive feedback.

Feedback as a Primary Output: The system treats feedback not as an additional element, but rather as a primary artifact of feedback. The system, instead of providing simple answers, constructs feedback which contains explanation, context using hints in the manner of Socratic dialogues, and provides tailored to-do lists for learner-educator pairs actions to be taken.

Data and Control Flows

Here we describe the system's start-to-finish data and control flows, as seen in Table 2, focusing on how the system transforms inputs into validated learning artifacts on modular components. Each step provides for the inputs' used imperfections and the system's output imperfections, as in ambiguity, hallucination, or the leakage of private data, and describes each step's corresponding and targeted adjustment. Together, these flows enable traceability, reliability, and adherence to policy throughout the learning pipeline.

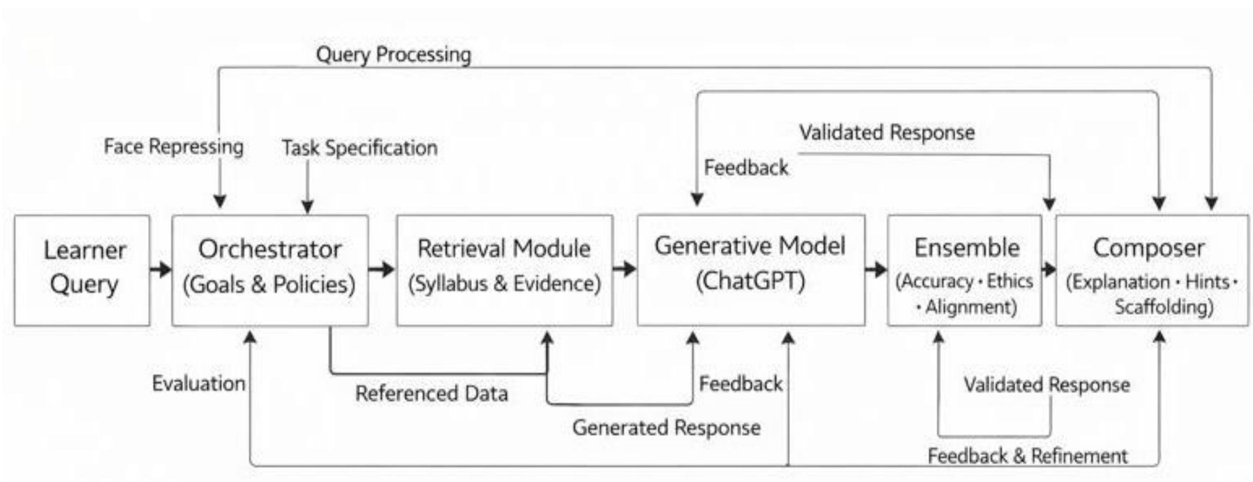
Table 2: High-level flows and artifacts

Step	Input → Output	Component	Primary Risks	Controls
1	Prompt, goal → Routed request	Orchestrator	Ambiguous goals	Goal schema; role/context templates
2	Request → Evidence set	Retrieval	Outdated sources	Time filters; syllabus whitelist
3	Evidence, prompt → Draft	Generator	Hallucination	Evidence-anchored prompts; max-claim rule
4	Draft → Scores, flags	Validator	False negatives	Multi-check ensemble; confidence thresholds
5	Scores, draft → Feedback pack	Composer	Cognitive overload	Chunking; progressive disclosure
6	Feedback → LMS events	Telemetry	Privacy leakage	Pseudonymization; minimal logging

Adaptive Generative Tutoring (AGT) Algorithm

This section describes the AGT system architecture and AGT algorithm as shown in Figure 3, which presents the architecture of the AGT system. It depicts how pedagogical goals, policy parameters, retrieval, generation, validation, and feedback integration are managed in a system for closed-loop adaptive tutoring.

Figure 3: Adaptive Generative Tutoring (AGT) System Architecture



Let a learner profile be (L= (^n, h, c)) with mastery vector (^n), history (h) (recent attempts), and cognitive load estimate (c). Let items map to skills via a matrix (Q{0,1}^{mn}) which states how relevant each of the n skills is to each of the m instructional items. Algorithm 1 in table 3 demonstrates the complete operational flow of the Adaptive Generative Tutoring (AGT) system (Garcia, 2025).

Table 3: Algorithm 1, Adaptive Generative Tutoring Framework

Input: Query q, Syllabus S, Learner profile L, Q-matrix Q, Retriever R, Generator G, Validator V

Output: Feedback pack F={E,H,N,s}, Explanation, Hints, Next task, confidence Score

```
g ← goal(q, S)                    # learning objective
EVD ← R(g, S, K)                  #retrieve evidence
p ← prompt(q, g, EVD, L)          # build prompt
ŷ ← G(p, M)                       # generate draft
s ← V(ŷ, EVD, rubric(g))          # validate draft
while s < τ and t < T do          # self-correct
    p ← refine(p, V.signals)
    ŷ ← G(p)
    s ← V(ŷ, EVD, rubric(g))
Δθ ← update(L, ŷ, Q)              # learner model update
N ← next_task(Δθ, g, L.c)         # adaptive task
H ← hints(g, L, ŷ)                # Socratic hints
E ← explain(ŷ)                    # explanation
F ← {E, H, N, s}                  # feedback pack
return F
```

Validator Ensemble

This section describes the validator ensemble as a collection of distinct verification modules that examine correctness, pedagogy alignment, and safety. The consistency checker assesses evidence consistency via snippet overlap and entity role alignment. The rubric checker assesses alignment with the intended learning outcomes, separating higher-order thinking from simple recall. The safety checker examines the outputs to identify any present PII, toxicity, and banned help. The uncertainty scorer assesses the reliability of a response based on the presence of lexical hedge, self-contradictory statements, and the scope of evidence coverage. Table 4 summarizes some signals from the validator ensemble.

Table 4: Example validator signals

Signal	Description	Action
Low evidence coverage	<60% claims supported by retrieval	Force cite + regenerate
Outcome misalignment	Draft misses target Bloom level	Re-prompt with level cues
High entropy answer	Diffuse, contradictory steps	Ask clarifying question
PII detected	Personal data present	Redact + refuse

Feedback Composer (student-facing)

Feedback directed to students is grouped into “packs” that are sequential, to help cognitive load and provide a path for formative learning. Each individual pack includes an explanation, generally given as a worked or annotated example, then Socratic-style reasoning hints that don’t provide answers, followed by a task that is either more difficult or of an adjacent concept, then finally, a confidence score between [0,1] with a short reason for the score. This particular configuration promotes the same level of consistency, transparency, and scaffolding in the automation of feedback.

Roles and Responsibilities

The clear demarcation of system roles is intended for pedagogical coherence, accountability, and governance. Teachers select content that corresponds with the syllabus, validate cue questions, and manage the confirmation of prompts; effectiveness is ascertained with respect to alignment scores and the prompt feedback time. The AI facilitator is responsible for the monitoring of telemetry, the adjustment of the decision escalation thresholds, and the evaluation of adaptive policies in the context of practice-based studies; the most desired level of success is the improvement of the knowledge of the student and the decrease in the time to resolve the alerts. The administrator is responsible for the enforcement of the policy concerning the system's privacy, auditing, and access restrictions, and their evaluation is based on the provided metrics regarding legislative adherence and the operational availability of the system. Students are responsible for engaging meaningfully with the feedback provided, reflecting on the outcome of the activity, and the demonstration of academic honesty, which is evaluated based on the mastery level of content and the pattern of attempts. In Table 5, the roles, responsibilities, and performance metrics in the operational model are delineated.

Table 5: Operating Model Roles and Associated KPIs

Role	Responsibilities	KPIs
Instructor	Curate syllabus sources; approve prompts; review validator flags	Alignment score; time-to-feedback
AI Facilitator	Monitor telemetry; tune thresholds; A/B policies	Learning gains; flag resolution time
Administrator	Policy & privacy; audit logs; access control	Compliance incidents; uptime
Student	Use feedback; reflect; academic honesty	Mastery gains; attempt cadence

System Deployment and Constraint Analysis

At the start, deployment should be limited to one course at a time, retrieval should be from the syllabus exclusively, and weekly outcomes need to be clearly delineated. Performance should be evaluated based on mastery pre- and post-testing, the categorization of errors, and the amount of time spent on the task. With improvements in the quality of content, there should be tightening of the thresholds (τ), more sophisticated unsupported claim, and more rigorous citation control to be relaxed. Scaling should continue with LMS and gradebook integration, institutional SSO, and privacy-by-design logging. System effectiveness is limited by the currency of the teaching materials and coverage of the retrieval. Rubrics are specific to the context, and re-tuning is required for cross-course transfer. The architecture continues to be pliable to tool-based reasoning, including code running for computation and data analytics, by explicit orchestration-level tool routing.

Case Applications

This time, we will analyze the AGT Framework, focusing on its design and potential for deployment, as proven in a STEM teaching example (Chamo & Broza, 2025). This example will illustrate how ChatGPT can improve classroom practices in formative assessment and how it can help maintain curricular and cognitive fit.

Instructional Context and Procedure

The example occurred in a secondary school physics classroom focusing on Newton's laws of Motion. During one of the formative assessment exercises, students had the opportunity to engage with the system by entering a conceptual question. For example, one question posed to the system was, "Explain Newton's Second Law with an example." Relaying this query to the AGT Framework, the system generated a response that, in part, combines formal and contextual representations (i.e., F = ma), and, in part, to explain that the net force (N) acting on an object is equal to the product (N) of its mass (m) and acceleration (a), and then exemplified in a scenario where a 1000 kg vehicle is accelerating at 2 m s2, and therefore the net force is 2000N.

Evaluation and Adaptive Output

The first step after the generation of the response is to obtain an evaluation. This process analyzes the response to confirm whether it is aligned with the curriculum and rubric on the level 'apply' of Bloom's Taxonomy. Additionally, an evaluation of the response's confidence score is conducted. The response achieved a confidence score of 0.84, surpassing the threshold. After passing the evaluation step, the system output a structured instruction containing a sample, a reflective question "How would the required force change if the car's mass were doubled?" and a corresponding practice question relating to mass and acceleration. This practice was designed to foster transfer of learning on different concepts and strengthen flexible thinking.

Pedagogical Implications

Interactions on the instruction reveal that the combination of explanation, reflective question, and practice activity is designed to enable engagement with the fundamental cognitive processes that underpin the design of the AGT. Allowing the use of generative AI coupled with the layers of the framework to provide validation and the scaffolding structure helps to steer the use of ChatGPT to serve a pedagogical purpose design in STEM. This example demonstrates how the framework harnesses the positive aspects of AI while limiting the potential negative aspects of unfiltered AI and the cognitive gap.

Language Learning Application

This scenario looks at the integration of the Adaptive Generative Tutoring (AGT) framework within an English as a Second Language (ESL) environment, specifically targeting students' progression at the B1 to B2 levels of the Common European Framework of Reference for Languages (CEFR) (Cummings & Anderson, 2025). The scenario demonstrates how graduate AI supports communicative competence within the given framework.

Instructional Context and Procedure

An ESL classroom served as the instructional context, and learners were building their vocabulary and discourse around workplace communication. During guided practice, one learner prompted, "help me practice English idioms about work." The AGT framework, upon receiving the learner's request, began the work of generating a list of workplace idioms including, "burning the midnight oil" and "back to the drawing board," and constructed contextual example sentences for each idiom to demonstrate how to use them.

Evaluation and Adaptive Output

After capturing the data, the next step in the framework involved processing data through the evaluation layer. This entails cross-referencing the data in the evaluation layer with the course syllabus to determine coverage of the targeted vocabulary, rudimentary evaluation to check alignment with CEFR B2, especially the descriptors pertaining to the use of abstract and figurative language, and self-confidence scoring. The capture provided a self-confidence score of 0.79, which, while positive, warranted an instructor's review due to the score being above the threshold and the high likelihood of varying exposure to the system's idiomatic expressions. After the data passed through the evaluation layer, the system provided an adaptive instructional response, which included some instructional boundaries, a usage example, and a reflection question: \"Can you think of a time when you had to ‘burn the midnight oil’? “\" Additionally, the system provided a role-play activity in which students are expected to use the idioms in mock business discussions.

Pedagogical Implications

The learner responses indicate active language use, as opposed to mere memorization, occurs when the explanation, reflection and practice components are integrated together. Since idiomatic expressions are meaningful, the AGT framework is in harmony with the principles of communicative language teaching and promotes the teaching of pragmatics. This particular case exemplifies the framework’s ability to fit the output of generative AI to specified proficiency levels without losing instructional and pedagogical consistency. A comparative use of the adaptive generative tutoring framework across STEM and Language Learning is presented in Table 6.

Table 6: AGT Framework Application in STEM and Language Learning

Step	STEM Example (Physics)	Language Example (ESL)	Shared Mechanism
Input	“Explain Newton’s Second Law”	“Practice idioms about work”	Student query
Generation	Formula (F = ma), example	Idioms + contextual use	ChatGPT response
Validation	Physics rubric, unit consistency	Vocabulary rubric, CEFR alignment	Validator checks
Output	Worked example + practice question	Idiom definition + role-play task	Feedback Composer
Pedagogical Outcome	Conceptual application	Communicative fluency	Adaptive Tutoring

Challenges and Risks

The pedagogically rich potential ChatGPT and generative AI possess in teaching and learning, is accompanied with considerable technical, pedagogical, ethical and institutional challenges. These challenges include generation of inaccurate and hallucinatory content which may mislead the learner, academic dishonesty in the form of plagiarism and AI assisted ghostwriting, learning dependency which may diminish critical thinking and cognition because of reliance on automated feedback, and bias, resulting in the cultural, linguistic, or gender inequities of bias being perpetuated. Moreover, there are challenges with privacy and data security in relation to the handling of students’ data with respect to the GDPR and FERPA regulations (Parks, 2017). Lastly, the insufficient institutional readiness which is characterized by inadequate faculty training, unclear governance, and stalled policy making may lead to suboptimal implementation of the tools. Implementing systematic mitigation strategies such as human oversight, AI-informed assessment design, structured feedback, bias audits, privacy-preserving frameworks, and continuous institutional capacity building, can address these challenges. Major risk categories and strategies are shown in Table 7.

Table 7: Risk Categories and Mitigation Strategies

Category	Risk	Mitigation
Accuracy	Hallucinations	Retrieval validation; instructor oversight
Integrity	Plagiarism, ghostwriting	AI-aware assessments; detection tools
Cognition	Overreliance, overload	Progressive feedback; reflective tasks
Bias	Cultural stereotypes	Bias audits; diverse datasets
Privacy	Data leakage	Pseudonymization; GDPR/FERPA compliance
Institutions	Lack of readiness	Training, governance, pilot adoption

ChatGPT can be beneficial or harmful to education, depending on how it is used. Institutions that overlook risks may compromise academic integrity. In contrast, institutions that address risks through responsible frameworks and pedagogy can optimize the use of ChatGPT and achieve considerable educational value.

Conclusion

The introduction of generative artificial intelligence, especially of large language models such as ChatGPT, disrupts the design and implementation of educational technologies. This study posits that the educational value of such systems lies not in their ability to generate, but in how frameworks, pedagogy, technology, and ethics are applied to integrate them. The paper is designed to offer a response to this challenge in the form of a Pedagogical–Technological–Ethical (P–T–E) framework and demonstrate its operationalization through the Adaptive Generative Tutoring (AGT) algorithm. The educational theory underpinning this framework is that generative AI may create meaningful learning experiences through constructive, formative, and cognitive scaffolding. Examples of STEM and language learning show that structured feedback, Socratic questioning, and adaptive task sequencing can facilitate understanding and communication skills and reduce the risk of surface learning or cognitive over-reliance. From a techno-pedagogical perspective, the most important findings suggest that the reliability and instructional coherence of generative AI systems result from their architecture rather than from the sophistication of the model. The most advanced educational models combine retrieval-augmented generation, validator ensembles, and confidence scores to mitigate the most significant and widely recognized limitations of large language models: unhinged creativity and unaligned results. This approach to educational governance is more sophisticated than informal or unauthorized uses of technology. From an ethical standpoint, the proposed model contributes to the discourse by incorporating, at the operational level, the design principles of academic integrity, privacy, justice, and accountability. By delineating the roles of constituents and establishing governance mechanisms, the study advocates for a design logic of ethical accountability as a primary imperative rather than a secondary one, thereby facilitating long-term institutional adoption of the model.

Although the proposed framework is integrated responsibly and offers a guiding model, the study is still primarily illustrative and conceptual. Future studies should evaluate empirical learning outcomes within and across fields, the learner's longitudinal impact, and the framework's footprint across different types of institutions. As a final observation, this paper argues that the educational potential of generative AI is more influenced by its design than by its sophistication. Generative AI is more likely to serve as a constructive educational partner rather than a disruptive educational substitute when integrated into a pedagogically sound, technologically appropriate, and ethically responsible framework. This study marks the beginning of the possibility of employing generative AI in education, and it maintains the values of learning, integrity, and equity.

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