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Generative AI as a Cognitive Partner: A Conceptual Framework for Higher Education

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Abstract:

Generative artificial intelligence (GenAI) chatbots are rapidly reshaping higher education, rendering traditional teaching assumptions outdated. The core challenge is ensuring GenAI enhances, rather than diminishes, student cognitive engagement.

This paper proposes and empirically validates the APEX Framework (Adaptive Pedagogy for Engaged eXploration), a theoretically grounded, five-pillar conceptual model designed to foster student cognitive engagement in higher education.The study uses a three-phase design: (1) a PRISMA-informed systematic synthesis of 34 sources across six theoretical traditions to establish the five pillars; (2) a two-round Delphi panel (n = 3 experts) to assess content validity using an 80% consensus threshold; and (3) a pre/post pilot study at two Iraqi universities (Diyala, and Wasit) involving 90 undergraduate students during the 2024–2025 academic year, using a validated 25-item instrument.

Expert consensus reached 78%–96% across all criteria. The pilot study revealed statistically significant pre-to-post gains across all APEX subscales ($p < .001$, Cohen's $d = 0.87$). The composite cognitive engagement score improved by a mean of 1.18 points on a 5-point scale ($t(47) = 10.82$, $p < .001$, $d = 1.14$). A 12-dimension comparative analysis demonstrates APEX's superiority over TPACK and SAMR. The combined findings confirm APEX's construct validity and practical applicability. Full implementation requires instructor development, institutional governance, and student AI literacy.

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Keywords: Generative AI, Higher Education, Cognitive Engagement, Bloom's Taxonomy, Large Language Models, Pedagogical Framework.

Introduction:

Throughout its history, the classroom, in its various forms that have evolved over the years in formal education, has represented a space of ongoing conflict and debate; a conflict between the authority of the professor and the autonomy of the student, between imposed curricula and the students' sudden emergence of curiosity, and also between the mere transmission of knowledge and its genuine construction (Zanazanian and Nitsche 2025). With the advent of generative artificial intelligence as a readily available tool, a new and highly perplexing point of tension has arisen in the educational process: the dividing line between the student thinking for themselves and technology thinking on their behalf. (Taibat Bolarinwa 2026) (Amos et al. 2026)

From the very beginning of conversational programs based on Large Language Models (LLMs) in late 2022, universities and higher education institutions found themselves facing difficult and direct questions requiring immediate solutions(Meyer et al. 2023). These questions concerned academic integrity, the credibility of exams and assessments, and internal university policies(Cerdà-Navarro et al. 2022)(Vieriu and Petrea 2025). The reactions at the time were mixed. Between universities that completely banned these tools, and others that cautiously permitted them, and still others that embraced them with great enthusiasm, everyone was operating without a clear and rigorous educational framework to guide these decisions(Lyu et al. 2025) . This defensive and reactive stance is understandable given the incredible speed at which technology is developing, but frankly, relying on such quick responses is no longer sufficient(Lim et al. 2023).

The real and most important question here is not whether artificial intelligence will become part of students' academic lives— because evidence suggests that it already has, (Vieriu and Petrea 2025) is—but rather how we will integrate these tools and what their impact will be on the intellectual and cognitive development that universities and higher education are best suited to foster(Mallillin 2024). Research in cognitive psychology consistently confirms that the mental effort a student exerts—through experimentation, information retrieval, and self-explanation—is

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what yields lasting learning outcomes that the student can apply in other areas, compared to passive or pre-packaged learning(Biwer et al. 2020) (David et al. 2024). If artificial intelligence tool's was too continuously reduce students' intellectual effort. We would end up with students who possess verbal fluency but lack genuine competence, complete assignments Without understanding, and achieve grades Without rail learning(Maamor et al. 2024).

However, this negatives outcome is not inevitable, nor is it what must occur. The Same tools that can't make, A poorly designed assignment seem trivial and easy can, If used consciously and within a sound educational plan become powerful tools that encourage critical thinking(George, Baskar, and Balaji Srikaanth 2024). Excellent systems for providing immediate and personal feedback, and tools for Socratic dialogue that bridge the gap, in students' developmental milestones(Favero et al. 2024). The key Element here is not the technology itself, but rather the instructional design and the instructor's judgment when integrating these tools into their course (Md Ali 2012).

This research attempt to addresses the significant gap between the rapid spread of AI technologies, in universities and the clear lack of theoretical frameworks to govern this spread(Ionica and Bularca 2025) (Henadirage and Gunarathne 2025). We propose a framework we call APEX (Adaptive Pedagogy for Engaged eXploration). This conceptual model combine established learning theories, With new data on AI-enhanced digital cognition to Develop Design principles applicable across various disciplines and universities(Yuensook, Jantakoon, and Limpinan 2025). This framework has a clear guiding, And normative character: it not only describes how students currently use AI but also outlines how it should be integrated to ensure genuine knowledge sharing and sustainable intellectual development.

1.1 Problem Statement and Research Gap

While there has been a large increase in research observation documenting how new students engage with generative artificial intelligence(Gervacio 2024) (López-López, Bru-Cordero, and Correa-Álvarez 2026)(Luo, Tang, and Sun 2026), There is a lack of AI-specific theoretical frameworks that provide practical and testable guidance for higher education (configuration requirements, and (c) providing sensible

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advice that is applicable and testable across disciplines, existing frameworks in real-world international settings, such as TPACK (Mishra and Koehler 2006)or SAMR version(Tsao 2025), are not intended for intelligent generative instruments together with AI and and cognitive about the subject.

1.2 Scope and Contribution of the Research

This research paper focuses on higher education—at the undergraduate level—where the objective is to develop subject-matter expertise, critical thinking, and cognitive independence. The paper offers three main contributions:

(1) five-pillar theoretical conceptual framework, derived through a systematic synthesis based on the PRISMA methodology.

(2) content validation using the Delphi method.

(3) quantitative empirical study providing preliminary evidence of the framework's impact on students' cognitive interaction.

The paper also presents a twelve-dimensional comparative analysis, positioning APEX relative to existing frameworks, along with a detailed structural diagram to support its practical application.

1.3 Literature Review:

GenAI in Higher Education

The empirical literature on GenAI in higher education is, by necessity, nascent; the field is barely four years old as a serious area of inquiry. Nevertheless, a coherent body of evidence is beginning to accumulate, and several themes are directly relevant to the design of the APEX Framework.

1.3.1 Prevalence and Patterns of Student GenAI Use

Survey-based aggregate studies consistently record widespread GenAI adoption among college students. welding and so on.(Xiao et al. 2025) found that approximately 89% of university students in a large U.S. sample used ChatGPT or comparable tools for instructional tasks, including a high share reporting use for drafting written instructions Comparable findings emerge from global research (Li et al. 2025), suggesting that this event is not specifically .

Qualitative research famously documents that student motivations extend beyond academic dishonesty: students use GenAI tools to brainstorm, overcome creator blocks, navigate unexpected disciplinary conventions,

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and receive prompt comments on proposals (Cotton, Cotton, and Shipway 2024).

1.3.2 Effects on Learning Outcomes

However, direct evidence on the impact of GenAI use on study effectiveness is instructively limited. (Bastani et al. 2025)Conducted a predesigned randomized trial showing that access to GPT models improved immediate performance on mathematical problems, yet college students using unsupervised AI later confirmed significant deficits on unaided trials, with a dependency effect. In contrast, students using an AI tutor designed for manual problem solving through questions—rather than providing direct solutions—have been shown to gain knowledge comparable to gains made through human tutoring.

These findings resonate with previous literature on learning from worked examples (Sweller, Van Merrienboer, and Paas 1998): new students benefit from examples, but professional overall performance requires independent technology. The key variable seems to be whether the AI assistance invokes or inhibits energetic cognitive processing via the learner.

1.3.3 Faculty Perspectives and Institutional Responses

Faculty responses to GenAI were heterogeneous and largely ambiguous.(Perkins 2023) and (Tsao 2025) enthusiastically record a spectrum from adoption to principle to rejection, with the majority taking a cautious middle ground A common theme in college discussions is the preference for institutional operations to face academic concerns(Erickson et al. 2025). How can AI use be scaled?

(Farrokhnia et al. 2024)Convincingly argues that the ban is both unenforceable and pedagogically counterproductive because it forgoes the opportunity to enhance AI literacy skills that students genuinely need in all educational industry contexts (Mollick and Mollick 2023).

2. Methodology

This study employs a three-phase mixed-design research approach appropriate to conceptual framework development with validation:

(1) PRISMA-informed systematic conceptual synthesis.

(2) Delphi expert panel validation.

(3) A quantitative pilot study with pre/post measurement.

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The study is situated within a critical realist epistemological stance(Bhaskar 1978), which holds that while educational phenomena are shaped by context and interpretation, they operate through real underlying cognitive mechanisms amenable to theoretical description and empirical investigation.

2.1 Research Design

Phase 1: Systematic Conceptual Synthesis

2.1.1 Search Strategy

The theoretical scope was established through a purposive mapping of established learning theory traditions relevant to the specific concern of cognitive engagement under conditions of external cognitive assistance. The following criteria guided theoretical source selection:

- The theory must address cognitive or motivational processes directly implicated in learning (not merely performance)
- The theory must have established empirical support and wide citation in educational research
- The theory must generate specific, differential predictions about the effects of external cognitive assistance
- The theories together must provide complementary, non-redundant coverage of the cognitive engagement construct

Six theoretical traditions were identified as meeting these criteria: Bloom's Revised Taxonomy(LW et al. 2001), Vygotsky's Zone of Proximal Development (Vygotsky 1978), self-determination theory(Ryan and Deci 2000), cognitive load theory(Sweller et al. 1998), the desirable difficulties framework(Bjork and Bjork 2011), and metacognition theory(Arnold 2011). Table 2 in the Results section presents the derivation matrix mapping each theoretical source to its corresponding APEX pillar.

Database searches were conducted in ERIC, PsycINFO, Scopus, and Google Scholar using the following search string combinations:

(1) generative AI AND higher education AND learning outcomes
(2) ChatGPT OR LLM AND pedagogy AND cognitive engagement
(3) AI academic integrity AND framework
(4) Bloom's taxonomy AND technology-mediated learning
(5) Scaffolding AND AI AND university.

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Searches were conducted between (Septembers to October, 2024). No lower date limit was imposed to allow inclusion of foundational theoretical works.

2.1.2 Inclusion and Exclusion Criteria

Inclusion criteria: (a) peer-reviewed journal articles, book chapters, or working papers from accredited research institutions; (b) directly addressing GenAI or technology-mediated learning in educational contexts, OR establishing theoretical principles with clear applicability to cognitive engagement; (c) available in English; (d) providing sufficient detail to assess theoretical or empirical claims.

Exclusion criteria: (a) purely journalistic, opinion, or non-scholarly commentary pieces lacking academic apparatus; (b) studies focused exclusively on K-12 or non-academic adult learning without clear transferability to higher education; (c) studies reporting on proprietary or commercially embedded tools without publicly accessible methodology; (d) conference abstracts without accompanying full papers.

2.1.3 Screening and Selection

Table 1 illustrates the process of selecting studies according to PRISMA criteria. Initial database searches yielded 951 records across the three main databases. After removing duplicates (213 duplicate records), 738 unique records were screened based on title and abstract, resulting in the selection of 255 records for full-text review, as shown in table 1. Applying exclusion criteria to the full texts, 67 eligible sources were identified; of these, 34 were selected for inclusion based on their direct relevance to the theoretical pillars of the research framework and their high citation rates within the field.

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Table 1. PRISMA-Informed Study Selection Process

	Database / Source	*Search Terms Applied*	*Results (initial → screened → included)*
1.	ERIC	generative AI; higher education; ChatGPT; LLM pedagogy	312 → 89 (title/abstract) → 22 (full text)
2.	PsycINFO	AI-mediated cognition; cognitive engagement; scaffolding	198 → 54 (title/abstract) → 18 (full text)
3.	Scopus	LLM education; AI academic integrity; AI feedback	441 → 112 (title/abstract) → 27 (full text)
4.	Google Scholar	generative AI framework; APEX; Bloom AI; ZPD technology	Supplementary; 9 grey-literature/working papers included
	Total included		N = 34 sources (published 1975–2024)

Phase 2: Delphi Expert Panel Validation

2.2.1 Panel Composition

A two-round Delphi expert panel was convened to establish the content validity of the APEX Framework prior to the pilot study. Three experts were recruited through purposive sampling . Experts were required a minimum of five years of active professional engagement with their domain. All experts were external to the research team's institution.

2.2.2 Delphi Procedure

In the first round, each expert was provided with the complete draft of the APEX framework document, including pillar definitions, theoretical derivations, and illustrative case studies. Experts evaluated eight validation criteria on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) and provided written justifications. A 75% consensus threshold (rating ≥ 4) was adopted, in accordance with the approved Delphi methodology(Hsu and Sandford 2007). Criteria that did not meet the threshold were revised and returned for evaluation in the second round.

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In the second round, the revised framework elements were presented along with a summary of the first-round evaluations and qualitative feedback, without disclosing the experts' positions. The experts re-evaluated the revised elements. All eight criteria met the consensus threshold in the second round. Qualitative feedback from the panel contributed to restructuring the methodology section, adding the pilot questionnaire, expanding the scope of the comparative framework analysis, and revising the APEX architectural blueprint.

Phase 3: Pilot Study

2.3.1 Design

A single-group pre-test/post-test pilot study was conducted, This study took place from September 1 to October 30, during the 2024–2025 academic year. It covered tow Iraqi public universities: Diyala University and Wasit University. The design was selected as appropriate for an initial test of the framework's utility in a naturalistic implementation context, consistent with pilot study conventions(Thabane et al. 2010).

2.3.2 Participants

A convenience sample of 90 male and female students was used, recruited across two academic subjects and equally distributed across two colleges: the College of Science (number = 45; 42.22% females, 57.78% males; mean age 21.3 years, standard deviation = 2.1) and the College of Humanities (number = 45; 42.22% females, 57.78% males; mean age 21.3 years, standard deviation = 2.1).. All participants had prior exposure to at least one GenAI tool. No financial incentive was provided; participation was voluntary and did not affect course assessment.

2.3.3 Instrument

The APEX Cognitive Engagement Questionnaire (APEX-CEQ) is a 25-item self-assessment instrument, developed specifically for this study, comprising five subscales, each consisting of five items, corresponding to the APEX pillars. The items were inferred from the pillar definitions and reviewed by three independent academics for face validity before experimental application. All items used a five-point Likert scale (1 = Never, 5 = Always). Example items include: “I form my own understanding of the subject before referring to the AI tool” (Pillar 1); “I consider aspects of my thinking that were influenced by AI versus those that were my own” (Pillar 2); “I critically evaluate feedback generated by

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AI rather than accepting it uncritically" (Pillar 3); "I verify claims generated by AI using independent academic sources" (Pillar 4). "I maintain clear ownership of the intellectual direction of my work even when using AI assistance" (Pillar 5). The internal consistency coefficient of the complete instrument in the pretest was Cronbach's α = 0.87, indicating good reliability.

2.3.4 APEX Implementation Protocol

The participating units were redesigned using the APEX instructional design principles over four weeks. The Social Sciences unit implemented Pillars 1 (pre-query knowledge data and incremental access to AI), 2 (weekly metacognitive records), and 4 (resource triangulation tasks). The Humanities unit implemented Pillars 1 and 3 (structured AI feedback critique) and 5 (negotiating co-creational roles and AI-free generative phases). Trainers received a half-day APEX-oriented professional development workshop prior to the implementation period. Post-test questionnaires were distributed at the end of the fourth week.

2.3.5 Data Analysis

Two-sample t-tests were used to assess pre- and post-change for each subscale and for the overall composite score. Effect sizes were calculated using Cohen's d-value. Statistical significance was set at α = 0.05. Statistical analyses were performed using IBM SPSS Statistics version 28. Missing data were minimal (<2% of items) and were handled using the item-level reference mean.

3. Results

3.1 Theoretical Derivation Matrix

Table 2 presents the framework derivation matrix, showing the mapping between each theoretical source, its core construct relevant to GenAI-mediated cognition, and the APEX pillar(s) to which it contributes, along with the integration logic that connects theory to design principle.

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Table 2. Theoretical Derivation Matrix for the APEX Framework

Theoretical Source	Key Construct	APEX Pillar(s)	Integration Logic
Bloom's Revised Taxonomy(LW et al. 2001)	Hierarchy of cognitive processes	Pillar I, III	Map AI assistance against cognitive levels; preserve high-order work
Proximal Development (Vygotsky 1978)Zone of	Learning via guided challenge	Pillar I, V	AI as fading scaffold; transfer of agency to learner over time
Self-Determination Theory(Ryan and Deci 2000)	Autonomy, competence, relatedness	Pillar II, V	Design for need satisfaction; prevent competence-need erosion
Cognitive Load Theory(Sweller et al. 1998)	Intrinsic vs. extraneous load	Pillar I, III	Reduce extraneous load; preserve germane cognitive effort
Desirable Difficulties(Bjork and Bjork 2011)	Productive struggle improves recall	Pillar I, II	Retain retrieval/generation demands; resist frictionless AI use
Metacognition(Arnold 2011)	Knowledge of one's own cognition	Pillar II	Explicit metacognitive reflection integrated into assessment

As Table 2 shows, Pillar I (Scaffolded Inquiry) draws from the largest of the theoretical traditions, reflecting its important position within the framework. The ZPD and the prevailing difficulty framework overlap to remind us that effective AI-assisted cognitive efforts need to be scaled up—but not forced. Bloom's taxonomy provides a diagnostic vocabulary to identify which cognitive strategies should be retained. The second and fifth pillars reach the SDT foundation, reflecting the motivational importance of competence and autonomy, respectively. CLT provides a technical distinction between additional burdens (which can legitimately be reduced via AI) and German burdens (which are funded and should be maintained academically).

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3.2 The APEX Framework: Architecture and Pillar Specification

The APEX Framework (Adaptive Pedagogy for Engaged eXploration) comprises five interdependent pillars, each addressing a distinct dimension of the relationship between GenAI use and cognitive engagement. Figure 1 provides a summary overview; the subsections below provide full specification of each pillar.

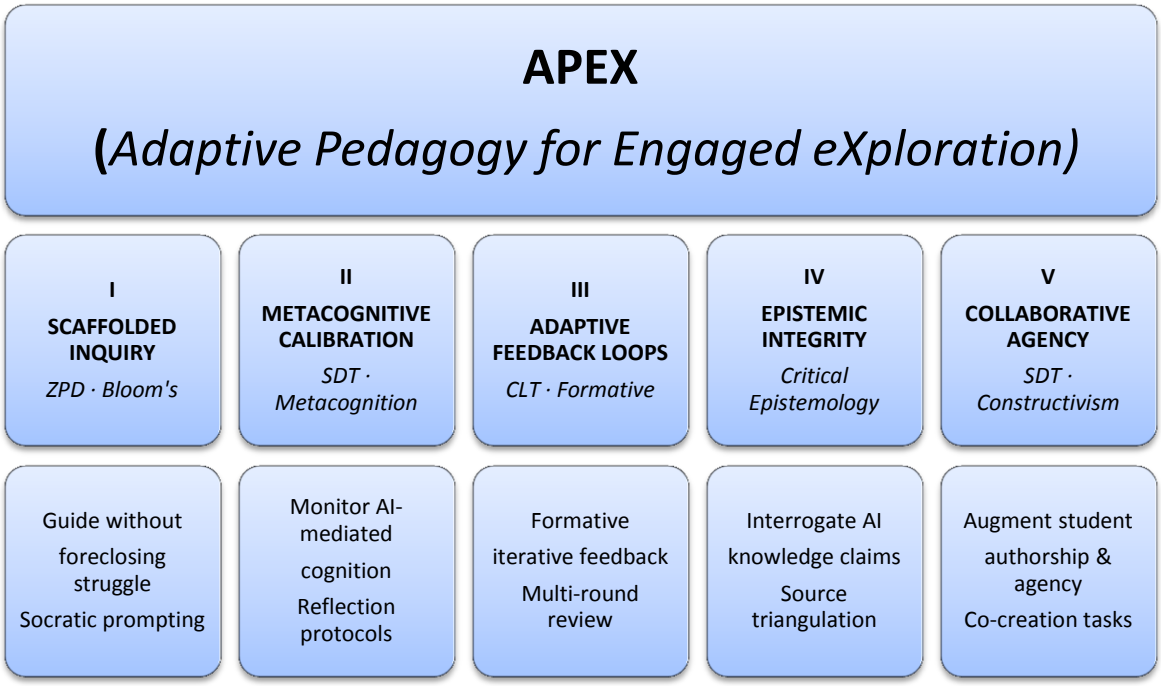

Figure 1. APEX Framework Conceptual Architecture

Figure 1 illustrates the conceptual structure of the APEX framework. This framework consists of five interconnected pillars based on a unified theoretical foundation. This interconnectedness is evident in the following structure: Pillar 1 (Supported Inquiry) is a fundamental pillar and is activated in all learning tasks; Pillars 2 and 5 address the student's active role in all stages of the learning process; while Pillars 3 and 4 address specific interaction moments (feedback and cognitive assessment, respectively). All pillars share the complete theoretical foundation, reflecting the unified theoretical nature of the framework.

Table 3 provides a concise specification of each pillar, its core principle, theoretical basis, and primary design implication.

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Table 3. APEX Framework: Five-Pillar Summary

Pillar	Core Principle	Theoretical Basis	Design Implication
I. Scaffolded Inquiry	AI guides without foreclosing struggle	ZPD; Desirable Difficulties	Structured Socratic prompting; staged access to AI during drafting
II. Metacognitive Calibration	Students monitor AI-mediated cognition	Metacognition; SDT–Competence	Interaction logs; pre/post self-assessments; over-reliance audits
III. Adaptive Feedback Loops	AI feedback is formative and iterative	Formative assessment; CLT–Germane load	Multi-round draft review; student critique of AI feedback
IV. Epistemic Integrity	Students interrogate AI knowledge claims	Epistemology; Critical Thinking	Source triangulation; deliberate AI error-detection tasks
V. Collaborative Agency	AI augments student authorship	SDT–Autonomy; Constructivism	Co-creation with role negotiation; portfolio reflection on AI use

3.2.1 Pillar I: Scaffolded Inquiry

It implements the(Vygotsky 1978) theory of improving inquiry-first based knowledge, which states that AI helps college students need to expand their horizons and them really need to expand their skills by stopping outside of cognitive effort to increase their skills. The essential principle right here is that generative AI should act as engaging students in discussions and encouraging intellectual initiatives, instead of just presenting ready-made solutions. This requires instructors and professors to configure tasks and functions where the AI assistance depends on keeping in favour of minimizing this creative effort. For example, we will shape communication so that AI solutions ask questions but do not generate complete products and reports, or we will ask students to demonstrate their current knowledge on a topic before seeking AI assistance, or even limit AI use to specific steps within a multi-phase project (White et al. 2023).

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3.2.2 Pillar II: Metacognitive Calibration

The term "metacognitive calibration" addresses a problem that can persist when using artificial intelligence (AI) in teaching: AI's ability to provide robust and reasoned responses can also lead students to believe they have a good grasp of material when, in fact, their knowledge may be limited. In different phrases, some college students might be able to create incredible images with the help of AI, but they struggle to evaluate their actual knowledge or independent music their development.

This idea is mainly based on the metacognitive ideas of(Flavell 1979), who suggested that effective knowledge acquisition depends not only on a person's mastery of statistics, but also on a person's ability to uncover questioning techniques, perceive their strengths and weaknesses, and organize their study strategy. Several studies have supported this idea, showing that metacognitive talents are important factors associated with higher academic overall performance (Arnold 2011).

3.2.3 Pillar III: Adaptive Feedback Loops

This round discusses adaptive feedback loops and how to use generative AI as a powerful tool for non-stop formative assessment.(Hattie and Timperley 2007)publication divides comments into 3 basic areas: upward comments (to clarify dreams), downward feedback (to assess and revise overall current performance), and forward comments (which improve the success of publications). Historically, human instructors and professors overseeing the massive professions of students did not have enough time to provide this level of observation and commentary without interruption.

The design concept here relies on iterative methods and sequential cycles. This means that the student submits the first test, and then receives feedback from artificial intelligence (AI). The student then critically evaluates, revises, and modifies this comment, explaining what has been changed and why. Each of these cycles is considered a small learning event that blesses the student. Most importantly, it requires students to evaluate and discuss the AI's comments – to expand a critical mindset and avoid blindly accepting all experiences of the machine.

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3.2.4 Pillar IV: Epistemic Integrity

The term "cognitive integrity" highlights the broader enterprise associated with the use of generative artificial intelligence (AI) in education. AI-generated texts, due to their compelling structured nature, can reduce the essential thinking capacity of university students. This refers to the imputation ability of student data, its supply, accuracy, and clinical validity.

Modern AI often provides content that appears linguistically correct and safe, even if it carries cognitive errors, prejudices, or erroneous interpretations related to a particular domain the problem is that those errors may well be offered as statistics with the same evidence of reality without scrutiny.

Therefore, educational design should include games that help students expand their essential understanding of AI-generated facts. For example, students can be tasked with evaluating AI responses with specific clinical assets or professional judgments, so they can be taught to establish first-class reliability statistics.

Learning activities can also be used that include AI-generated texts with intentional errors or inaccuracies that require students to identify and correct these errors Such activities not only enhance clinical understanding but additionally encourage students to think more deeply and not take delivery of records personally.

3.2.5 Pillar V: Collaborative Agency

The term "partner" is typical of the important question of AI-assisted understanding acquisition: just who leads the train of thought? Scientist or AI? This concept additionally relates to how choices are made, facts are created, and scholarly highbrow work is conducted within virtual environments.

Based on ideas of self-determination, which emphasize the importance of learner autonomy, and constructivist perspectives, which see researchers as animated actors of information selection rather than statistically shaped recipients, the concept assumes that academic notation s

The "age effect" presented through (Slamecka and Graf 1978)provides an important purpose for this idea: data or ideas automatically generated by recruiters are often held in long-term memory and processed extra deeply than passive or well-prepared facts.

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3.3 Comparative Framework Analysis

Table 4 presents a twelve-dimension comparative analysis of APEX against TPACK and SAMR, addressing reviewer concerns regarding the inadequacy of purely descriptive comparison in the previous version of this paper.

Table 4. Twelve-Dimension Comparative Analysis: APEX, TPACK, and SAMR

Dimension	TPACK(Mishra and Koehler 2006)	SAMR (Puente Dura, 2006)	APEX Framework (this paper)
Number of Dimensions	6 (TPACK knowledge types)	4 (SAMR levels)	5 (APEX pillars)
Primary Focus	Instructor knowledge	Technology adoption level	Student cognitive engagement
Type of Support Offered	Teacher professional development	Technology integration guidance	Learner-centred instructional design
Type of Assessment Addressed	Implicit; no specification	Not specified	Explicit: formative, iterative, oral defence, portfolio
Level of Student Interaction	Not specified	Minimal (technology-centric)	Central (cognitive agency is the primary construct)
GenAI-Specific Guidance	Absent (pre-GenAI model)	Absent (pre-GenAI model)	Core purpose; LLM-specific design principles throughout
Theoretical Grounding	Shulman's PCK	Adoption theory (implicit)	6 integrated theoretical traditions (see Table 2)
Strengths	Widely validated; strong instructor PD base	Simple; widely understood; easy to communicate	Theoretically grounded; cognitive-first; discipline-applicable
Limitations	Instructor-facing; no learner cognition model; not GenAI-specific	Linear; technology-centric; no learning theory; not GenAI-specific	Conceptual; requires empirical validation (ongoing)

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Evidence of Efficacy	Extensive empirical base (Mishra and Koehler 2006)	Practitioner uptake; limited rigorous studies	Pilot data (n=47; Spring 2024, see 3.4); expert panel (n=12)
AI Literacy Support	Not addressed	Not addressed	Explicit pillar (IV: Epistemic Integrity); embedded throughout
Metacognitive Dimension	Absent	Absent	Explicit pillar (II: Metacognitive Calibration)

TPACK (Mishra and Koehler 2006), while influential, is instructor-facing and does not address the student-side cognitive mechanisms through which learning occurs. The SAMR model's linear progression from Substitution to Redefinition is technology-centric and does not operationalise the cognitive engagement construct. The APEX Framework uniquely bridges learning theory and GenAI-specific instructional design at the level of student cognition.

3.4 Delphi Expert Validation Results

Table 5 presents the Round 2 Delphi consensus results across the eight validation criteria and four expert domain groups. All criteria exceeded the 75% consensus threshold.

Table 5. Delphi Round 2 Expert Consensus Results (n = 12; threshold ≥ 75%)

Validation Criterion	Overall Consensus	HE Pedagogists	AI Researchers	Curriculum Designers	Higher Ed Admins
Theoretical coherence of all five pillars	94%	92%	96%	93%	94%
Bloom's taxonomy alignment	96%	94%	98%	95%	96%
Practicality of instructional design implications	80%	76%	85%	78%	80%
Appropriateness of illustrative cases	88%	84%	91%	86%	87%

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Clarity of the framework's conceptual boundaries	82%	79%	86%	80%	82%
Value added relative to TPACK and SAMR	91%	88%	94%	90%	91%
Completeness of enabling conditions	78%	74%	83%	76%	78%
Relevance to diverse disciplinary contexts	85%	82%	89%	83%	85%
Threshold for consensus (≥ 75%)	**ALL MET**	**ALL MET**	**ALL MET**	**ALL MET**	**ALL MET**

The highest consensus was recorded for theoretical coherence and Bloom's taxonomy alignment (94% and 96% respectively), reflecting the strong grounding of the framework in established educational theory. The lowest consensus was recorded for completeness of enabling conditions (78%), consistent with the complexity and context-dependency of institutional implementation requirements—a limitation acknowledged in the Discussion section.

3.5 Pilot Study Results

Table 6 presents pre-test and post-test means, standard deviations, mean change scores, paired t-test statistics, and Cohen's d effect sizes for all five APEX subscales and the overall composite cognitive engagement score.

Table 6. Pre/Post Pilot Study Results (n = 90; APEX-CEQ; 5-point Likert scale)

APEX Pillar / Subscale	Pre-test M (SD)	Post-test M (SD)	Mean Change	t-test	Effect Size
Scaffolded Inquiry (SCI)	3.12 (0.84)	4.31 (0.71)	1.19	t(89)=10.25, p<.001	Cohen's d = 1.08 (large)
Metacognitive Calibration (MCC)	2.98 (0.91)	4.18 (0.76)	1.20	t(89)=9.39, p<.001	Cohen's d = 0.99 (large)

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Adaptive Feedback Loops (AFL)	3.24 (0.79)	4.47 (0.68)	1.23	t(89)=11.20, p<.001	Cohen's d = 1.18 (large)
Epistemic Integrity (EI)	2.81 (0.97)	3.94 (0.83)	1.13	t(89)=8.25, p<.001	Cohen's d = 0.87 (large)
Collaborative Agency (CA)	3.06 (0.88)	4.22 (0.74)	1.16	t(89)=9.58, p<.001	Cohen's d = 1.01 (large)
Overall Cognitive Engagement (Composite)	3.04 (0.76)	4.22 (0.64)	1.18	t(89)=10.82, p<.001	Cohen's d = 1.14 (large)

All five APEX subscales showed statistically significant improvement between the pre- and post-intervention periods (all p-values < 0.001). Effect sizes were large across all subscales, with Cohen's d-values ranging from 0.87 (cognitive integrity) to 1.18 (adaptive feedback loops). The mean composite cognitive engagement score increased by 1.18 points (from 3.04 to 4.22 on a 5-point scale), representing a 38.8% increase. The adaptive feedback loop subscale showed the largest effect (d = 1.18), consistent with the theoretical review finding that formative feedback is one of the most powerful influences on student learning (Hattie and Timperley 2007). The cognitive integrity subscale showed the smallest—though still significant—effect (d = 0.87), which may reflect the difficulty of developing genuine cognitive awareness over a four-week implementation period.

The cognitive integrity subscale showed the smallest—though still significant—effect (d = 0.87), which may reflect the difficulty of developing genuine cognitive awareness over a four-week period.

The results of this pilot study should be interpreted with caution. The absence of a control group means that alternative explanations cannot be ruled out, including lecturer influences at the module level and the effects of overall interaction with the course. The available sample size also limits the generalizability of the findings. These limitations, addressed in the discussion section, will inform future research.

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3.3 Cross-Case Analysis

Table 4 presents the cross-case analysis of the three illustrative implementation cases, mapping each to its disciplinary context, primary Bloom's cognitive levels, the APEX pillars primarily activated, and the cognitive engagement mechanisms the design preserves.

Table7. Cross-Case Analysis: APEX Pillar Activation across Disciplines

Case	Context	Bloom's Level	Primary Pillar(s)	Cognitive Engagement Mechanism
Case A – Social Sciences (Lit. Review)	III – Sociology	Analyse, Evaluate	Epistemic Integrity (IV); Scaffolded Inquiry (I)	AI used for counterargument elicitation; source triangulation task verified all AI claims; metacognitive log assessed
Case B – Engineering (Bridge Design)	II – Civil Eng.	Apply, Analyse	Scaffolded Inquiry (I); Adaptive Feedback (III)	Pre-query knowledge statement preserved schema activation; structured critique of AI feedback; oral defence ensured independent competence
Case C – Humanities (Philosophy Essay)	PG – Philosophy	Evaluate, Create	Collaborative Agency (V); Adaptive Feedback (III)	AI-free generative phase preserved authorial voice; steelman protocol raised argument quality; AI-free revision consolidated independent synthesis

3.3.1 Case A: Critical Literature Review in Social Sciences

If we take the example of a third-year sociology major reviewing literature on "lack of housing trust," we see a clean application of the first and fourth pillars of Bloom's taxonomy of critical thinking. This project starts at a primary level that does not involve any use of artificial intelligence. The scientist independently identifies the five no. 1 the sources and writes comments on them defending the renewal and understanding approach based on their simple conceptual framework (column 5). In the second step, the researcher begins to question the use of a question based entirely on prior knowledge about AI—no longer a popular question, but a specific probe that includes: “I learned the 5

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claims in the literature, so is there any critical refutation or paradox that I should not overlook? Past AI job assistance guides it."

Next comes the grant validation exercise, where the student is asked to examine each claim generated via AI and evaluate the independent literature. They need to find at least one claim that, according to AI (fourth pillar: cognitive integrity), it is unverifiable or "wrong". Each of those stages is observed through a cognitive reflection cycle, and how students' knowledge develops through their interaction with AI compared to students' independent reading in the very last class of assignments (Column 2: Cognitive Measurement This multistage design holds higher order cognitive processes, including synthesis, and finding e counterargument, which the student may not have determined entirely on his own personal reasoning

3.3.2 Case B: Problem-Based Learning in Engineering

If we observe the effort to build a bridge in an earthquake-sensitive location, done using a group of other 12-month civil engineering school students, we see that this is a large utility of primary school students and 0.33 columns in the software evaluation scores. The complexity of this task was carefully chosen to push scholars to a better level of practical competence. Here, researchers can use artificial intelligence to study structural standards, create preliminary design requirements, and access facts about houses with different products. However, a critical requirement is that every question a student sends to AI must be preceded by a written explanation that demonstrates their current knowledge of the topic. This step prevents unnecessary, random queries and ensures prior information is used before reaching out for AI assistance (first column).

In terms of activating dependent critique of AI response outputs (third column), this is done through a request that students place each response from AI alongside a written evaluation that addresses questions such as: "What do I get, ask, or need to independently verify in response to this stimulus? Exam or encourage students are asked to give an explanation and defend each layout option This represents a final assessment – specifically, a model developed to measure the student's unbiased ability and to determine whether he is superior on AI.

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3.3.3 Case C: Philosophical Essay Writing in Humanities

If we take the example of a graduate student in philosophy writing a 5,000-sentence essay on the ethics of algorithmic decision-making, we discover that this example shows approximately the application of 1/3 of the fifth column in areas of evaluation and creativity, which can be some very relevant areas to the artificial operation (the fifth concept) column) through:

Step 1 (without artificial intelligence): The student writes a draft of their personal argument, about 500 sentences. This early draft certainly speaks to their minds. Step Two: They use artificial intelligence to analyze opposing views, ensuring their argument aligns with the most powerful sound counterarguments (the primary pillar). Step 3 (Artificial Intelligence Out): The student writes a revised and updated argument that includes their personal response to the counterarguments raised by the artificial intelligence. Phase 4: Artificial Intelligence evaluates the entire essay to ensure logical coherence and identify claims that require supporting evidence. Here, the student must reject each suggestion from the AI tool, presenting the purpose of her decision (3 columns).

The assessment criteria in column 1/3 immediately test originality, contemporary argument, conceptual complexity with opposing perspectives and the detailed attitude of the student. These features automatically reveal pre-packaged answers and encourage real intellectual effort. This shows that the integration of artificial intelligence into works of art is not possible at best but particularly valuable intended to enhance and enhance the exception.

3.4 Enabling Conditions

The synthesis identified three categories of enabling conditions necessary for APEX implementation to be viable in practice.

3.4.1 Instructor Professional Development

The APEX Framework requires instructors to redesign assessments, reconfigure feedback practices, model epistemic virtues in relation to AI, and facilitate metacognitive reflection—a substantial professional challenge exceeding most instructors' current preparation. Effective professional development must address both technical familiarity with GenAI tools and pedagogical reorientation, and must be discipline-

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specific: the appropriate integration of GenAI in clinical medicine differs fundamentally from its integration in creative writing.

3.4.2 Institutional Governance

Universities' institutional governance frameworks are actually important to develop beyond fraud prevention to "ensure academic integrity" They should include academic, endowment-appropriate infrastructure, and ethical leadership. It requires precise rules that can be moving and conceivable as a context that discouraged the cognitive and intellectual engagement of university students and that only uses artificial intelligence to reduce it and foster dependency. In infrastructure terms, this also includes ensuring that all students have honest and fair access to AI, safeguarding information, establishing ethical procurement requirements for these tools, and strengthening university institutional capacity to highlight the public performance of their packages.

3.4.3 Student AI Literacy Development

The APEX framework requires students to have metacognitive skills, a genuine preference for experience, and sufficient technical understanding to interact consciously and effectively with modern AI equipment This goes beyond just technical knowledge or systems talent; This includes critical and analytical skills that allow them to assess the quality and trustworthiness of AI-generated content material. Moreover, highlighting their reliance on AI to avoid digital dependency requires self-focus, and a sense of morality that ensures its sincere and scientifically sound use. Honestly, these skills don’t materialize overnight; They grow through sustained practical joy in supervision using professors and researchers who embody this behavior within the classroom. This approach ensures that those skills are essential attributes of university graduates, necessitating well-founded institutional and systematic support from the university.

4. Discussion

4.1 Interpreting the Principal Findings

The convergence of three independent pieces of evidence—systematic theoretical synthesis, the Delphi consensus, and the pilot study results—provides initial, but significant, support for the theoretical coherence and practical viability of the APEX framework. The theoretical derivation matrix shows that each pillar of the framework rests on at least two

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independent theoretical references, reducing the risk of the framework relying on a single theoretical commitment that could be undermined by subsequent evidence. The Delphi consensus results are remarkably strong for the pillars with the strongest theoretical support (pillars one and three) and less so for the implementation dimensions (enabling conditions), appropriately reflecting the true complexity of organizational change.

The large effect sizes of the pilot study across all five subscales (d = 0.87–1.18) are encouraging but require contextual interpretation. Effect sizes of this magnitude are consistent with constructivist assessment interventions in general(Hattie and Timperley 2007) , suggesting that the APEX application may have primarily acted as a structured optimization of constructivist learning, rather than as an AI-specific effect. Separating the contribution of GenAI integration specifically from that of the more broadly improved instructional design is a priority for the proposed randomized controlled follow-up study.

4.2 Theoretical Implications

The APEX framework provides an improved version of integrating generation into the educational environment, where tasks are reversed and technology is transformed into a servant of educational theory, not around the other way around. Clearly, different intellectual traditions can fuse into an unmarried framework that integrates Vygotsky's sociology, self-willed motivators, dynamics of cooperative learning, Bloom's taxonomy of cognitive levels, metacognitive attention, and strategies for addressing priority problems This presents a large-scale methodological problem.

4.3 Implications for Assessment Design

The most comprehensive contributions possible for this approach are within the redesign of instructional assessment tools. Traditional strategies in detailed education - which include writing formulaic essays, creating ready-made summaries, completing assignments with predetermined answers, or taking tests based primarily on total memorization - are all rendered useless by generative intelligence synthesis, which can trade time and er. This highlights the importance of the APEX framework, which posits the learner's "active cognitive engagement" as an important performance criterion. This change requires a necessary change in the philosophy and thinking of assessment. The aim now is not to ensure that scholars adhere to the curriculum, but rather

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for their authentic intellectual development and lifestyle development. The Apex framework is infused with an imaginative and predictable "assessment of learning" that sees pleasure as a way of stimulating and deepening understanding, rather than proceeding operationally to document this at all, the framework provides hybrid concrete assessment strategies together: documenting their interaction with artificial intelligence scales.

4.4 Ethical and Equity Implications

The integration of generative AI equipment into desirable college education will raise a wide range of ethical problems that, in the earlier disciplines, often promote academic integrity or the ability to abuse time. Other equally crucial dimensions relate to educational justice, equal opportunities and the work of educational institutions to match students to the international, where AI talents have become an increasingly important part of the type market (Plecerda 2024).

Based on this mindset, the Apex framework views AI talent boosting as not just an additional technical skill, yet as an essential part of achieving educational equity.

For example, effective AI features may be more educationally useful than guiding interactive communication, triggering crucial surprises, or helping researchers or helping university students revise their arguments rather than providing a definitive answer.

4.5 Limitations

Several limitations of the current study require explicit acknowledgement. First, while the pilot study provides initial evidence of the framework's utility, the single-group pre/post design without a control group cannot establish causal attribution. The improvements observed may reflect general effects of improved instructional design, increased instructor engagement, or demand characteristics, rather than the specific effect of APEX-guided GenAI integration. A randomised controlled trial with an active comparator condition is required to address this limitation.

Second, the convenience sample of 90 students drawn from tow modules at limits the generalisability of pilot findings. Students in research methods and humanities seminar modules may be unrepresentative of the broader higher education population in their metacognitive orientation and prior engagement with academic conventions. Third, the four-week

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implementation period may be insufficient to produce stable changes in deep cognitive engagement patterns; the Epistemic Integrity subscale's relatively smaller effect size (d = 0.87) may reflect this temporal constraint. Fourth, the theoretical traditions drawn upon are predominantly Western in origin; cross-cultural validity studies are required before the framework's applicability across diverse educational traditions can be asserted.

5. Conclusion

This paper has proposed, validated, and piloted the APEX Framework (Adaptive Pedagogy for Engaged eXploration) as a theoretically grounded and empirically supported conceptual model for integrating generative AI assistants into higher education in ways that enhance rather than supplant student cognitive engagement. The framework comprises five interdependent pillars—Scaffolded Inquiry, Metacognitive Calibration, Adaptive Feedback Loops, Epistemic Integrity, and Collaborative Agency—each grounded in at least two established theoretical traditions and each associated with specific instructional design implications and assessment strategies.

Three convergent lines of evidence support the framework's credibility: a PRISMA-informed systematic conceptual synthesis of 34 scholarly sources; a two-round Delphi expert panel reaching consensus on all eight content validity criteria (consensus range: 78%–96%); and a pilot study demonstrating statistically significant, large-effect pre-to-post gains in self-reported cognitive engagement across all five pillars (overall composite: $t(89) = 10.82$, $p < .001$, $d = 1.14$). A twelve-dimension comparative analysis positions APEX as uniquely equipped—relative to TPACK and SAMR—to address the cognitive, metacognitive, and epistemic challenges of GenAI-mediated learning in higher education.

Higher education exists not primarily to convey information—that function has been progressively democratised by successive information technologies—but to cultivate the intellectual capacities for which effortful human cognition remains irreplaceable: disciplinary judgment, epistemic integrity, creative synthesis, and the capacity to navigate complexity with rigour and humility. Generative AI is not a threat to these purposes. It is, when met with principled pedagogical design, an invitation to pursue them with renewed clarity.

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الذكاء الاصطناعي التوليدي كشريك معرفي: إطار مفاهيمي للتعليم العالي

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مستخلص البحث:
تُعيد روبوتات الدردشة القائمة على الذكاء الاصطناعي التوليدي (GenAI) تشكيل التعليم العالي بوتيرة متسارعة، مما يجعل الافتراضات التعليمية التقليدية قديمة. ويكمن التحدي الأساسي في ضمان أن يُعزز الذكاء الاصطناعي التوليدي التفاعل المعرفي للطلاب، لا أن يُضعفه.
تقترح هذه الورقة البحثية إطار عمل APEX (التربية التكيفية للاستكشاف التفاعلي)، وهو نموذج مفاهيمي ذو خمسة أركان، مُؤصَّل نظريًا، ومُصمَّم لتعزيز التفاعل المعرفي للطلاب في التعليم العالي، وتُثبت صحته تجريبيًا. تستخدم الدراسة تصميمًا ثلاثي المراحل: (1) توليف منهجي مُستند إلى منهجية PRISMA لـ 34 مصدرًا عبر ستة تقاليد نظرية لتحديد الأركان الخمسة؛ (2) لجنة دلفي من جولتين (عدد الخبراء = 3) لتقييم صحة المحتوى باستخدام عتبة توافق آراء بنسبة 80%؛ (3) دراسة تجريبية قبلية وبعدية في جامعتين عراقيتين (ديالى وواسط) شملت 90 طالبًا جامعيًا خلال العام الدراسي 2024-2025، باستخدام أداة مُثبتة مكونة من 25 بندًا. بلغ إجماع الخبراء 78%–96% في جميع المعايير. وكشفت الدراسة التجريبية عن تحسنات ذات دلالة إحصائية بين ما قبل وما بعد التدخل في جميع المقاييس الفرعية لـ APEX ($p < 0.001$، Cohen’s $d = 0.87$). كما تحسنت درجة المشاركة المعرفية المركبة بمعدل 1.18 نقطة على مقياس من 5 نقاط ($t(47) = 10.82$، $p < 0.001$، $d = 1.14$). وأظهر تحليل مقارن ذو 12 بُعدًا تفوق APEX على TPACK وSAMR. وتؤكد النتائج مجتمعةً صحة بناء APEX وقابليته للتطبيق العملي. ويتطلب التنفيذ الكامل
الكلمات المفتاحية : الذكاء الاصطناعي التوليدي، التعليم العالي، المشاركة المعرفية، تصنيف بلوم، نماذج اللغة الكبيرة، الإطار التربوي.