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Full Length Article

A Research Analysis Of Intelligent Tutoring Systems Based On Generative Artificial Intelligence And Adaptive Learning Approaches

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ABSTRACT
The integration of Generative Artificial Intelligence (GenAI) into Intelligent Tutoring Systems (ITS) has opened a transformative pathway for personalized, adaptive education. This study examines how GenAI-powered ITS influence learning outcomes across educational levels, focusing on cognitive performance improvement and embedded adaptive mechanisms. The research objectives are: (1) to evaluate GenAI-ITS effectiveness on student learning outcomes, and (2) to analyze adaptive learning mechanisms embedded within GenAI-driven platforms. A secondary research design was employed, synthesizing meta-analyses, randomized controlled trials, and systematic reviews published between 2016 and 2025. The hypothesis posits that GenAI-integrated ITS yield significantly superior academic outcomes compared to conventional instruction. Findings from five verified data tables reveal effect sizes ranging from $d = 0.66$ to $g = 0.76$, statistically significant pre/post-test gains ($p < 0.001$) in problem-solving and critical thinking, and GenAI academic adoption exceeding 60% among higher education students globally in 2023–2024. The study affirms that adaptive feedback, LLM-based interactivity, and personalized learning pathways drive these outcomes, while underscoring ethical and equitable implementation imperatives for responsible deployment.

Keywords: *Intelligent Tutoring Systems, Generative Artificial Intelligence, Adaptive Learning, Large Language Models, Personalized Education*

1. INTRODUCTION

The convergence of artificial intelligence and education has reached a defining inflection point with the proliferation of Generative Artificial Intelligence (GenAI). Since the public release of ChatGPT by OpenAI in November 2022, large language models (LLMs) have moved from research environments into everyday academic practice, fundamentally altering how students access instructional support and engage with educational content (Batsaikhan & Correia, 2024). Intelligent Tutoring Systems (ITS), which have existed in early forms since the late 1960s, are now being reimagined through integration with LLMs such as GPT-4, Google Gemini, and Anthropic's Claude producing systems capable of real-time dialogue, dynamic content generation, adaptive feedback, and personalized learning pathway construction that were previously unachievable within traditional rule-based architectures (Maity et al., 2024). Traditional classroom instruction operates under persistent structural constraints: fixed pacing, limited teacher-to-student ratios, and negligible individualization. ITS addresses these pedagogical gaps by deploying AI algorithms that monitor individual learner progress, identify knowledge deficiencies, and dynamically adapt instructional content (Karran et al., 2025). The GenAI enhancement of ITS extends this capability further by enabling Socratic-style conversational interactions that simulate expert one-on-one tutoring at scale (Dai et al., 2024). Crucially, these systems now generate customized questions, provide context-aware scaffolding, supply real-time error correction, and calibrate content difficulty functions that were entirely beyond the reach of earlier rule-based ITS architectures.

Empirical evidence strongly validates the effectiveness of ITS technologies. The foundational meta-analysis by Kulik and Fletcher (2016), synthesizing findings from 50 controlled evaluations, determined that ITS raised student test scores by 0.66 standard deviations above conventional levels effectively lifting performance from the 50th to the 75th percentile. More recent research confirms that this advantage strengthens with GenAI integration: a meta-analysis of 35 experimental studies found a moderately large positive effect of ChatGPT-based instruction ($g = 0.67$) on student learning outcomes across cognitive and non-cognitive domains. Furthermore, a rigorous randomized controlled trial conducted at Harvard University during Fall 2023 demonstrated that students using a pedagogically-designed AI tutor achieved significantly greater learning gains in less time than peers in active classroom settings, simultaneously reporting higher engagement and motivation (Kestin et al., 2025). Collectively, these findings indicate that GenAI-ITS integration constitutes not merely a technological upgrade but a fundamental pedagogical transformation. By synthesizing evidence from controlled experiments, meta-analyses, and large-scale institutional surveys, this research evaluates the effectiveness of GenAI-powered ITS and analyzes the adaptive mechanisms responsible for their documented educational gains with the aim of producing evidence-based insights for researchers, educators, and policymakers navigating this rapidly evolving domain.

2. LITERATURE REVIEW

Scholarly inquiry into ITS spans over five decades. Early systems such as SCHOLAR (1970) and BIP established the foundational principle that computers could adapt instruction to individual learners. By the 1990s, cognitive tutors grounded in Anderson's ACT-R theory exemplified by Carnegie Learning's Cognitive Tutor for algebra demonstrated measurable learning gains in real classroom settings. The landmark meta-analysis by Kulik and Fletcher (2016) synthesized 50 controlled evaluations and confirmed a median effect size of $d = 0.66$, positioning ITS significantly above both computer-assisted instruction ($d = 0.31$) and conventional human tutoring ($d = 0.40$) establishing the empirical credibility of ITS as a scalable instructional technology. Ma et al. (2014) extended this evidence base through a meta-analysis of 107 studies, confirming a mean effect size of $g = 0.76$ across diverse educational levels and subject domains, reinforcing the generalizability of ITS benefits irrespective of learner age or discipline. More recently, Wang et al. (2024) published a comprehensive meta-analysis of AI-enabled adaptive learning systems spanning 2010 to 2022, involving 47 studies, and yielded an overall effect size of $g = 0.70$ consistent with a medium-to-large pedagogical impact sustained across technological generations.

The emergence of GenAI has substantially restructured ITS research priorities and capabilities. Batsaikhan and Correia (2024) conducted a systematic review identifying five dominant themes in ITS evolution from 2018 to 2023: AI integration, personalized and adaptive learning, learning analytics, inclusion and equity, and STEM disciplines. Their review documented that students receiving personalized instruction through AI-powered ITS demonstrated higher engagement, improved academic performance, and greater knowledge retention than peers in conventional classrooms. Dwivedi et al. (2023) offered a multidisciplinary analysis of ChatGPT's implications for research and practice, acknowledging its transformative potential while identifying substantive ethical risks including algorithmic bias, misinformation propagation, and academic integrity threats that accompany GenAI adoption in educational contexts. Bettayeb (2024) presented a systematic literature review of ChatGPT's educational integration across studies published between 2022 and 2023, confirming benefits including personalized assistance, enhanced learning experiences, and improved information accessibility, while highlighting accuracy and over-reliance as central challenges. Lo et al. (2024) systematically examined ChatGPT's influence on student engagement, emphasizing that structured integration within purpose-built ITS platforms rather than open-ended chatbot interactions consistently maximizes engagement and learning outcomes. Dai et al. (2024) demonstrated GPT-4's potential within a modular ITS framework through the Socratic Playground for Learning (SPL), a pilot with 30 undergraduates, yielding significant gains in vocabulary, grammar, and sentence construction alongside high engagement and adaptivity scores. Kestin et al. (2025) provided rigorous RCT-level evidence through a Harvard-based experiment where an AI tutor designed on evidence-based pedagogical principles outperformed active classroom learning in both knowledge gains and student motivation. Mousavinasab et al. (2021) offered a comprehensive synthesis cataloguing student modeling, domain modeling, and feedback mechanisms as the three core pillars of effective ITS design pillars that GenAI now reinforces through dynamic, LLM-powered implementation. Contrino et al. (2024) evaluated CogBooks, a real-world adaptive learning platform, across biology and physics courses, finding performance improvements and reduced dropout rates, affirming that adaptive platforms produce measurable real-world educational gains beyond controlled experimental settings.

3. OBJECTIVES

1. To evaluate the effectiveness of GenAI-integrated Intelligent Tutoring Systems on student learning outcomes, including cognitive skill development and academic performance across educational levels and subject domains.
2. To analyze the adaptive learning mechanisms including real-time feedback generation, personalized learning pathways, and LLM-based interactivity embedded within contemporary GenAI-powered ITS platforms and their relationship to observed outcome improvements.

4. METHODOLOGY

This study adopts a secondary research design based on systematic analysis of published empirical literature. The research approach is quantitative-descriptive, drawing upon meta-analyses, randomized controlled trials, quasi-experimental studies, and large-scale survey data pertaining to GenAI-powered ITS and adaptive learning systems published between 2016 and 2025. Sources were retrieved from Google Scholar, PubMed Central, ERIC, Scopus, and IEEE Xplore using keyword combinations including "Intelligent Tutoring Systems," "Generative AI in Education," "Adaptive Learning," "LLMs in Education," "ChatGPT learning outcomes," and "AI-powered personalized learning." Inclusion criteria required studies to: (a) involve controlled or experimental comparisons of ITS with traditional instruction; (b) report quantifiable outcomes such as effect sizes, pre/post-test scores, or engagement metrics; and (c) be published in peer-reviewed journals or indexed conference proceedings between 2016 and 2025. Studies lacking empirical data, duplicates, and those outside the specified publication window were excluded. The analytical sample comprised 20 peer-reviewed studies and reports, including five meta-analyses collectively covering more than 250 primary studies and over 35,000 student participants across K-12 and higher education contexts in North America, Europe, and Asia. Data were extracted and organized into five comparative tables covering: pre/post cognitive performance under ITS intervention, effect sizes across meta-analyses, GenAI adoption rates among students, cross-domain ITS effectiveness, and student engagement and motivation metrics. Statistical values including Hedges' g, Cohen's d, paired-sample t-statistics, ANCOVA F-values, and mean differences were extracted directly from source studies without modification. This approach ensures transparency, reproducibility, and alignment with PRISMA-guided systematic review protocols.

5. RESULTS

Table 1: Pre-test vs. Post-test Cognitive Performance Under ITS Intervention in Mathematics (N = 300)

Cognitive Skill	Pre-test M (SD)	Post-test M (SD)	t-value	df	p-value
Problem-Solving	65.4 (8.2)	72.8 (7.9)	4.67	299	< 0.001
Critical Thinking	68.9 (7.5)	74.3 (7.1)	3.82	299	< 0.001
Logical Reasoning	63.2 (9.1)	70.1 (8.4)	3.45	299	0.001
Cronbach's Alpha (α)	0.80	—	—	—	—
ANCOVA (Problem-Solving)	F(1, 298) = 10.21	—	—	—	< 0.001

Source: Khasawneh (2024) as reported in Karran et al. (2025)

Table 1 presents pre-test and post-test performance data from a study of 300 high school mathematics students using an ITS over eight weeks (Karran et al., 2025). Paired t-tests revealed statistically significant gains across all three cognitive domains: problem-solving (Δ = 7.4 points, $p < 0.001$), critical thinking (Δ = 5.4 points, $p < 0.001$), and logical reasoning (Δ = 6.9 points, $p = 0.001$). ANCOVA analysis confirmed the ITS intervention's independent effect after controlling for pre-test scores ($F(1, 298) = 10.21$, $p < 0.001$), with Cronbach's α = 0.80 confirming instrument reliability, validating the statistical robustness of the observed cognitive gains.

Table 2: Effect Sizes Across Major ITS and GenAI Meta-Analyses

Study	Year	N Studies	Effect Size (d/g)	Comparison
Kulik & Fletcher	2016	50	d = 0.66	ITS vs. conventional instruction
Ma et al.	2014	107	g = 0.76	ITS vs. no/minimal tutoring
Wang et al.	2024	47	g = 0.70	AI adaptive systems vs. control
Castillo & Gidra	2024	22	d = 0.67	PAL vs. conventional (reading)

Sources: Kulik & Fletcher (2016); Ma et al. (2014); Wang et al. (2024); Castillo & Gidra (2024)

Table 2 consolidates effect sizes from five high-impact meta-analyses spanning ITS and GenAI-based educational technologies. All values fall consistently within the medium-to-large range (d/g = 0.66 to 0.76), affirming persistent effectiveness across five decades of ITS research. Kulik and Fletcher's (2016) landmark d = 0.66 establishes a robust baseline that subsequent GenAI-integrated studies maintain and approach. Castillo and Gidra (2024) demonstrate comparable gains in specialized domains such as reading literacy, evidencing cross-disciplinary generalizability.

Table 3: Student GenAI Adoption Rates in Higher Education (2023–2025)

Source	Sample	Year	GenAI Adoption	Nature of Use
25 Chinese Universities (Guo et al.)	72,615 undergrads	2023–24	>60%	Academic use > daily use

DEC Global AI Survey / HKUST	680 students	2023–24	96%	44% weekly; 23% daily
Arum et al. (UCI, USA)	Multi-cohort	2023	Widespread	Task-specific academic
Bettayeb (Global Lit. Review)	Multi-study	2022–23	Growing majority	Study enhancement
Chen et al. (China, longitudinal)	323 undergrads	2024	Positive engagement	Motivation and self-efficacy

Sources: Arum et al. (2025); Bettayeb (2024); Wang et al. (2025)

Table 3 presents GenAI adoption patterns across five institutional and global datasets. Adoption rates range from over 60% at large Chinese universities to 96% at HKUST (Hong Kong), confirming that GenAI usage has crossed a structural majority threshold in higher education globally (Arum et al., 2025). Academic-purpose use systematically exceeds casual daily use, indicating purposive, learning-oriented adoption rather than mere recreational engagement. Bettayeb's (2024) review confirms a global pattern of study enhancement as the primary motivator for adoption, with Wang et al. (2025) documenting that GenAI interaction quality positively mediates learning motivation and creative self-efficacy among undergraduate learners.

Table 4: Cross-Domain ITS Effectiveness (2016–2025)

Subject Domain	Source	N	Research Design	Outcome
Mathematics (High School)	Karran et al., 2025	300	Paired t-test + ANCOVA	Sig. improvement ($p < 0.001$)
Physics (University)	Kestin et al., 2025	233	RCT (Harvard, Fall 2023)	AI tutor > active classroom
English Language (SPL-GPT4)	Dai et al., 2024	30	Pilot pre/post	Sig. vocabulary/grammar gains
Reading Literacy (K-12)	Castillo & Gidra, 2024	22 studies	Meta-analysis ($d = 0.67$)	Med.–large positive effect
Spoken Fluency	Mousavinasab et al., 2021	Review	Fluency assessment	50% improvement (3 months)

Sources: Karran et al. (2025); Kestin et al. (2025); Dai et al. (2024); Castillo & Gidra (2024); Mousavinasab et al. (2021)

Table 4 documents GenAI and ITS effectiveness across five distinct subject domains. Statistically significant and practically meaningful gains are observed in mathematics (Karran et al., 2025), physics (Kestin et al., 2025), English language acquisition (Dai et al., 2024), reading literacy (Castillo & Gidra, 2024), and spoken fluency (Mousavinasab et al., 2021). The Harvard RCT (Kestin et al., 2025) provides the highest methodological rigor, demonstrating that a pedagogically-structured AI tutor surpasses established active-learning pedagogies even in a physics context. The 50% fluency improvement in language learning systems (Mousavinasab et al., 2021) illustrates GenAI's particular aptitude for high-frequency feedback environments.

Table 5: Student Engagement and Motivational Outcomes in GenAI-ITS Contexts

Metric	Conventional Setting	GenAI-ITS Setting	Source
Engagement (student self-report)	Moderate	Significantly higher	Kestin et al., 2025
Satisfaction Score (1–5 scale)	3.2	4.4	Dai et al., 2024
Learning Motivation	Baseline	Positively mediated	Wang et al., 2025
Creative Self-Efficacy	Baseline	Significantly increased	Wang et al., 2025
Behavioral Intention to Continue	Moderate	High (usefulness + ease)	Alshammari & Babu, 2025

Sources: Kestin et al. (2025); Dai et al. (2024); Wang et al. (2025); Alshammari & Babu (2025)

Table 5 presents comparative engagement and motivational indicators across five metrics. Students using GenAI-ITS reported substantially higher satisfaction scores (4.4 vs. 3.2 on a 5-point scale; Dai et al., 2024) and increased motivation relative to conventional instruction. Wang et al. (2025) confirmed through a two-wave longitudinal survey of 323 Chinese undergraduates that GenAI interaction quality and output quality positively mediated both learning motivation and creative self-efficacy. Alshammari and Babu (2025) found that perceived usefulness and ease of use strongly predicted students' behavioral intention to continue ChatGPT adoption in higher education indicating sustainable engagement trajectories beyond novelty-driven initial use.

6. DISCUSSION

The findings of this study provide convergent, multi-source empirical support for both research objectives. Concerning the first objective evaluating GenAI-ITS effectiveness on learning outcomes—the evidence from Tables 1 and 2 is unambiguous. The statistically significant pre/post cognitive gains in Table 1 (problem-solving $\Delta = 7.4$ points, $p < 0.001$; critical thinking $\Delta = 5.4$ points, $p < 0.001$; logical reasoning $\Delta = 6.9$ points, $p = 0.001$) confirm that ITS-mediated instruction produces measurable and robust academic improvements (Karran et al., 2025). When contextualized against the meta-analytic landscape of Table 2 where effect sizes consistently range from $d = 0.66$ to $g = 0.76$ across decades of independent ITS research these single-study gains align precisely with established effectiveness benchmarks (Kulik & Fletcher, 2016; Ma et al., 2014). The stability of these effect sizes across five independent meta-analyses, spanning different disciplines, technology generations, and geographic contexts, constitutes compelling evidence of cross-contextual generalizability. Furthermore, the finding from Wang et al. (2024) that AI-enabled adaptive systems sustain $g = 0.70$ across studies from 2010 to 2022 indicates that this advantage is not a novelty effect but a durable, instructional outcome linked to adaptive mechanism design.

Concerning the second objective analyzing adaptive learning mechanisms the evidence from Tables 3, 4, and 5 collectively illuminates the pathways through which GenAI transforms ITS from static tutoring architectures into dynamic, learner-responsive educational ecosystems. The high adoption rates in Table 3 (>60% across Chinese higher education; 96% at HKUST) confirm that GenAI tools are now central learning utilities, not peripheral supplements (Arum et al., 2025; Bettayeb, 2024). However, adoption rates alone do not determine learning outcomes. A critical distinction emerges from the literature: when GenAI is embedded within purposively designed ITS frameworks as demonstrated in the Socratic Playground for Learning (Dai et al., 2024) and the Harvard AI tutor (Kestin et al., 2025) outcomes are markedly superior to unguided chatbot interactions. This distinction aligns with Liang et al.'s (2023) mediation finding that GenAI improves learning achievement only when self-efficacy and cognitive engagement serve as active mediating mechanisms emphasizing that it is the design of the adaptive interaction, not the AI technology alone, that drives outcomes. The cross-domain data in Table 4 challenge the assumption that AI tutoring is effective primarily in algorithmically tractable domains such as mathematics. Comparable gains in physics, English language acquisition, reading literacy, and spoken fluency suggest that the generative flexibility of LLMs enables domain-agnostic adaptive tutoring. This is particularly significant for educational systems serving linguistically and culturally diverse learner populations such as those in India where access to qualified individual tutoring remains structurally constrained. The 50% spoken fluency improvement documented by Mousavinasab et al. (2021) and the significant vocabulary and grammar gains reported by Dai et al. (2024) illustrate how LLM-powered real-time feedback can replicate high-value, instructor-intensive activities at scale.

The engagement and motivation evidence in Table 5 adds an essential affective dimension. Satisfaction scores of 4.4 versus 3.2 (Dai et al., 2024), alongside heightened creative self-efficacy and sustained behavioral intention to continue use (Alshammari & Babu, 2025), indicate that GenAI-ITS not only generates short-term performance gains but sustains the motivational conditions necessary for longer-term learning persistence. These affective benefits are critical: conventional educational technology is frequently hampered by declining student engagement over extended use, making the sustained motivation reported in these studies a particularly notable finding. Nevertheless, substantive caveats must be acknowledged. Sajja et al. (2024) emphasized that AI-enabled intelligent assistants must incorporate pedagogically sound scaffolding to prevent shallow, surface-level engagement that mimics learning without producing it. Lo et al. (2024) highlighted that ChatGPT's engagement benefits diminish substantially when deployed without structured instructional frameworks. Dwivedi et al. (2023) raised systemic concerns about bias, misinformation, and critical thinking erosion through over-reliance, concerns that are amplified as adoption rates approach institutional universality. The ethical dimensions of data privacy, equitable access, and academic integrity represent unresolved challenges that institutional policy frameworks must address with urgency if GenAI-ITS are to deliver on their documented potential equitably and sustainably.

7. CONCLUSION

This research analysis confirms that Intelligent Tutoring Systems powered by Generative Artificial Intelligence and adaptive learning frameworks represent an empirically validated and pedagogically transformative approach to personalized education. Evidence drawn from five verified data tables spanning controlled experiments, meta-analyses, and large-scale institutional surveys from 2016 to 2025 substantiates statistically significant cognitive performance improvements, broad cross-domain effectiveness, high student adoption and engagement, and consistently positive effect sizes relative to conventional instruction. The study's central hypothesis that GenAI-integrated ITS yield superior academic outcomes compared to traditional instructional modalities is fully supported by converging multi-source evidence. Future researchers are encouraged to investigate long-term retention outcomes, equity-sensitive adaptive design, and multimodal GenAI integration in ITS. Policymakers and institutions must develop robust ethical governance, invest in teacher training for AI-complementary pedagogy, and build equitable access infrastructure to ensure the documented benefits of GenAI-enhanced tutoring extend meaningfully to all learner populations.

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