Understanding Undergraduate Students' Use of Generative AI for Learning in STEM: An Integrative Literature Review

Daniel I. Adeniranye, Florida International University

Daniel Adeniranye [ah-deh-nee-RAHN-yeh] is a Ph.D. candidate in Engineering and Computing Education at Florida International University, where he serves as Instructor of Record for EGS 2053: Foundations of Interdisciplinary Engineering. He holds a B.Tech in Mechanical Engineering, a joint M.S. in Petroleum Engineering and Project Development, and an M.S. in Project Management. His research examines engineering transfer student pathways to four-year institutions, AI in education and workforce development, and culturally responsive pedagogy across U.S. and international contexts. He is the Immediate Past Chair of the ASEE Student Division.

Dr. Yashin Brijmohan, Utah State University

Yashin Brijmohan is faculty in engineering education at Utah State University. He serves as Board Member of the UNESCO International Centre for Engineering Education, Chair of the Africa Asia Pacific Engineering Council, Chair of the Africa Engineering Council, and Chair Engineering Education and Professional Development of Commonwealth Engineers Council.

He was the founding Executive Dean of Business, Engineering, and Technology at Monash South Africa, former Vice President of the World Federation of Engineering Organizations, and led several committees in the engineering profession.

Yashin has both leadership and specialist experience within the engineering power industry and education sectors and is known for his thought leadership in capacity building and engineering education.

Marlee Jacobs, Utah State University
Mr. Abdul Wasay Khan Laghari, Utah State University

Abdul Wasay Khan Laghari is a graduate researcher in the Department of Engineering Education at Utah State University. Abdul's research endeavors are primarily dedicated to the critical analysis of engineering competencies, the formulation of engineering education policy, and the advancement of accreditation standards.

Dr. Ibukun Samuel Osunbunmi, The Pennsylvania State University

Ibukun Samuel Osunbunmi is an Assistant Research Professor, and Assessment and Instructional Specialist at Pennsylvania State University. He holds a Ph.D. degree in Engineering Education from Utah State University. Also, he has BSc and MSc degrees in mechanical engineering. His research interests include student engagement, design thinking, learning environment, evidence-based pedagogy, e-learning, broadening participation in STEM education, sustainable energy, and material characterization.

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Abstract

This integrative literature review examines how undergraduate and graduate students in STEM disciplines utilize generative artificial intelligence (GAI) tools, such as ChatGPT, Gemini, and Copilot, to support learning. Synthesizing prior research, the review employs an AI-augmented methodology that combines traditional database searches with human-verified AI-assisted support. The review analyzes the (1) theoretical perspectives and frameworks; and (2) reported learning outcomes guided by the multidimensional Universal Competency Taxonomy (UCT), including STEM, learning, practice, value, meta, community of practice and people competencies. Findings reveal that technology acceptance models (TAM, UTAUT) dominate the theoretical landscape, while constructivist, self-regulated learning, and cognitive load theories offer complementary perspectives on AI's pedagogical role. Empirical evidence indicates generally positive effects on academic performance, motivation, and engagement when AI integration is intentionally structured, with frameworks like the Guidance-based ChatGPT-assisted Learning Aid (GCLA) yielding substantial learning gains. However, unstructured or passive reliance on AI may undermine critical thinking and independent problem-solving, highlighting the need for explicit scaffolding and metacognitive instruction. The review identifies equity concerns related to AI literacy and access, emphasizing that targeted training and infrastructure are essential to prevent widening achievement gaps. This paper argues that the key challenge for STEM educators is not whether to permit generative AI, but how to design learning environments that foster productive, ethical, and reflective engagement with these tools. The review calls for future research to expand theoretical frameworks, address understudied competency dimensions, and examine long-term impacts of AI use on professional formation, particularly in diverse and resource-constrained contexts.

Keywords: generative artificial intelligence (GAI), STEM education, integrative literature review, undergraduate students, learning competencies, Universal Competency Taxonomy, ChatGPT, higher education.

I. Introduction

The emergence of generative artificial intelligence (GAI) tools has fundamentally altered the landscape of higher education [1], [2], particularly in STEM disciplines where problem-solving, computational thinking, and technical skill development are paramount [3], [4]. Since the public release of ChatGPT in November 2022 [5], educators and researchers have grappled with understanding how students integrate these tools into their learning processes and what implications this integration holds for competency development and academic integrity [6], [7].

Recent meta-analytic evidence indicates that generative AI applications have substantial positive effects on undergraduate learning outcomes [8], [9]. A comprehensive meta-analysis of 49 research studies found that generative AI demonstrates a large positive impact on learning achievement (mean effect size = 0.857) and substantial effects on learning motivation (effect size = 0.803) [8]. Additionally, another meta-analysis of 13 studies revealed that chatbots and generative AI produced the most substantial positive impact on student learning outcomes (Hedges' g = 1.02), with an overall AI integration effect size of Hedges' g = 0.86 [9]. However, these aggregate findings mask considerable variation in how students engage with AI tools across different contexts [10], disciplines [11], [12], and learning objectives [13].

The challenge for STEM education is particularly acute. STEM disciplines require students to develop not only content knowledge [14], but also procedural fluency, analytical reasoning, and the capacity for independent problem-solving [15]. Questions persist about whether GAI tools function as scaffolds that support skill development or as crutches that undermine the acquisition of fundamental competencies [16]. Understanding how research has examined student AI usage across different STEM contexts [17] is essential for informing pedagogical practice [18].

The research landscape on generative AI in education has expanded rapidly since late 2022 [19], yet synthesis of this literature remains limited [20]. Prior reviews have examined ChatGPT's general impact on education [21], [22], faculty attitudes toward AI adoption [23], and effects on specific outcomes such as self-regulated learning and critical thinking [24]. However, few reviews have systematically examined how STEM students specifically engage with these tools across diverse disciplinary contexts [10] while attending to both theoretical foundations and practical implications for pedagogy [25], [18]. This paper addresses this gap through an AI-augmented integrative literature review examining generative AI use among undergraduate and graduate STEM students. The integrative review methodology [26], [27] was selected because it accommodates the diverse methodological approaches characterizing this emerging field while enabling synthesis across theoretical and empirical literature. The review is informed by the Universal Competency Taxonomy [28], [29], [30], which provides a framework for examining competency development across seven dimensions: Learning, Community of Practice, Meta-competency, People, Value, Practice, and STEM-Fundamentals.

By synthesizing findings across these dimensions, this review aims to provide insight into how generative AI is shaping STEM education and student learning, and to inform future pedagogical strategies that balance innovation, appropriate reliance on learning tools, and academic integrity.

The review is guided by two research questions:

RQ1: What theoretical perspectives, models, and frameworks have been used to study generative AI integration in STEM education?

RQ2: What learning outcomes and results have been reported in studies of student AI use in STEM contexts?

II. Theoretical Framework

This review is guided by the Universal Competency Taxonomy [28], [30], a framework developed to examine competency development in engineering education. The taxonomy provides a structured lens for analyzing how educational interventions, including generative AI integration, influence the multidimensional nature of student learning. Rather than viewing competency as singular or discipline-specific, the framework conceptualizes student development across seven interconnected dimensions.

The seven dimensions of the Universal Competency Taxonomy (UCT) are: (1) Learning, which encompasses knowledge acquisition, comprehension, and the cognitive processes underlying academic performance; (2) Community of Practice, addressing skills for students to participate, engage, and support communities, peers, and professional networks; (3) Meta-competency, focusing on self-regulation and metacognition; (4) People, examining interpersonal skills, teamwork, collaboration, and communication; (5) Value, concerning ethical reasoning, academic integrity, and professional responsibility; (6) Practice, encompassing discipline-specific technical knowledge and skill-based competencies, including technological and IT-based tools required for practice; and (7) STEM-Fundamentals that are typically required across engineering and STEM disciplines.

The taxonomy guided our synthesis in two ways. First, it informed how we categorized and interpreted findings from the reviewed literature. Studies examining academic performance outcomes were mapped to the Learning dimension; research on self-regulated learning and critical thinking aligned with Meta-competency; investigations of collaborative AI use related to Community of Practice and People dimensions; academic integrity concerns connected to the Value dimension; and aspects of problem-solving studies mapped to Practice and STEM-Fundamentals. Second, the framework can help reveal gaps in current scholarship in certain dimensions of the UCT. Our analysis found that existing research concentrates heavily on Learning and Meta-competency dimensions, with limited attention to how generative AI influences students' engagement with professional communities (Community of Practice) or development of ethical reasoning beyond integrity concerns (Value).

The framework's multidimensional perspective aligns with the goals of this review. Innovation in STEM education must attend to how AI tools influence not only knowledge acquisition (Learning) but also skill application (Practice, STEM-Fundamentals). Appropriate reliance on learning tools connects to students' metacognitive awareness of when AI assistance supports versus undermines their development (Meta-competency). Academic integrity is situated within the broader Value dimension, positioning ethical AI use as one component of professional responsibility that STEM graduates must develop. By applying this framework, the review moves beyond examining whether generative AI improves test scores to understand how these tools shape the comprehensive competency development essential for STEM professionals.

III. Research Design

We employed an AI-augmented integrative literature review methodology for this study. The integrative review approach is the only review method that allows for the combination of diverse methodologies, including experimental and non-experimental research, and is particularly appropriate for emerging topics with evolving literature where flexibility is needed to synthesize findings from varied methodological approaches [27]. Unlike systematic reviews that require strict protocol adherence, registered protocols, and formal quality assessment, integrative reviews are designed for topics spanning multiple disciplines and methodological traditions where comprehensive thematic synthesis is the primary goal [31], [32]. The integrative review methodology, first articulated by Torraco [61] and refined by Whittemore and Knafl [27], is appropriate for research questions requiring synthesis of both theoretical and empirical literature. Torraco [26] emphasized that integrative reviews should go beyond summarizing literature to generate new knowledge, with synthesis taking various forms, including taxonomies, research agendas, or reconceptualizations. Generative AI in STEM education represents precisely such an emerging topic, with literature spanning educational technology, computer science education, engineering education, and learning sciences, employing methodologies ranging from controlled experiments to qualitative case studies.

The AI-augmented component of our methodology reflects emerging practices in literature review processes. Recent scholarship demonstrates that AI tools can support various stages of the review process, including developing search strategies, screening titles and abstracts, and extracting data, while emphasizing the importance of human oversight to address potential biases [33]. This research adopts the human-in-the-loop approach, where AI serves as an adjunct to human expertise rather than a replacement, which has demonstrated high sensitivity and substantial agreement with human reviewers when combined with appropriate validation procedures [33], [34]. We developed this approach further to enhance search comprehensiveness while maintaining rigor through human verification of all AI-suggested sources, and explicit mention of the process undertaken.

Researchers' Positionality

The research team acknowledges that our perspectives and experiences shape how we approach, interpret, and synthesize the literature on generative AI in STEM education. Transparency regarding our positionality enhances the trustworthiness of this integrative review.

Collectively, the team includes the integration of national and international experience and knowledge in multiple engineering disciplines, psychology, engineering education research, teaching across STEM disciplinary areas, the use of AI in educational environments, and undergraduate and graduate student perspectives. Our collective positionality influenced our decision to adopt an integrative review approach that values diverse methodological perspectives and to employ AI tools transparently as part of our research process, consistent with the subject matter under investigation.

Method

Following Whittemore and Knafl's [27] five-stage framework, we structured this review into problem identification, literature search, data evaluation, data analysis, and presentation phases. Two research questions guided our inquiry: (1) What theoretical perspectives, models, and frameworks have been used to study generative AI integration in STEM education? (2) What learning outcomes and results have been reported in studies of student AI use in STEM contexts?

Literature Search Strategy

The research team conducted the literature search in multiple phases, combining traditional database searching with AI-augmented discovery. We selected multiple databases to ensure comprehensive coverage across education, psychology, and interdisciplinary research, including Education Source, ERIC, PsycInfo, and Google Scholar. Searches were restricted to English-language, peer-reviewed journal articles with publication dates spanning the last decade (2016 to 2025), allowing for examination of trends before, during, and after the widespread adoption of generative AI tools.

The initial search was completed by one researcher using Education Source with Boolean search terms:

("ChatGPT" OR "generative AI" OR "large language model" OR "artificial intelligence") AND ("STEM education" OR "STEM student*" OR "science student*" OR "technology student*" OR "mathematics student*") AND ("Implementation" OR "Practice" OR Utilization) AND ("Writing" OR "Problem Solving" OR "conceptual learning" OR "computational support")*

Limiting the search to peer-reviewed academic journals published in English, the search returned 328 records. The researcher narrowed these to 23 relevant papers by reviewing the titles using inclusion and exclusion criteria.

In parallel with this search, another researcher conducted a similar search using Education Source, ERIC, PsycInfo, and Google Scholar with Boolean search terms:

("Artificial Intelligence" OR "AI") AND ("STEM" AND "Engineer" AND "student*").*

This search was limited to peer-reviewed articles published in English. It identified 14 relevant papers, with an additional 3 articles located through supplementary searching. A second iteration by the second researcher using terms combining ChatGPT, generative AI, large language models, and artificial intelligence with STEM and engineering student populations yielded 426 articles, of which 20 were relevant and 15 represented new articles not previously identified.

Following our established database searches, a third researcher used AI tools to identify potentially relevant papers that might have been missed in traditional searches. This approach follows the human-in-the-loop model, in which AI serves as an adjunct to human expertise [33]. The research team independently verified all AI-suggested papers for existence, relevance, and methodological quality before inclusion, ensuring that no fabricated or non-existent sources were incorporated into the review.

Inclusion and Exclusion Criteria

We adapted the PICOS framework [35] to define the scope and inclusion criteria for this review. Our target population includes undergraduate and graduate STEM students in higher education settings who use AI and generative AI tools such as ChatGPT, Gemini, Copilot, or similar large language models for learning purposes. The intervention encompasses the application of generative AI tools in educational contexts, including their use for problem-solving, writing assistance, concept explanation, feedback, and learning support.

Comparators include educational environments without AI tool integration as well as comparisons of structured versus unstructured AI use. Outcomes of interest include learning performance, skill development, student engagement, metacognitive development, attitudes toward AI, and concerns related to academic integrity. We included empirical studies employing quantitative, qualitative, and mixed-methods approaches published in peer-reviewed venues.

We excluded articles that focused exclusively on K-12 populations without relevance to higher education, non-peer-reviewed publications such as editorials or opinion pieces, publications not available in English, and studies focused on AI development rather than educational application.

Data Evaluation

Following Whittemore and Knafl's [27] guidance on data evaluation for integrative reviews, the research team assessed included studies for clarity of study context and objectives, appropriateness of methodology, adequacy of data collection and analysis procedures, validity and reliability of findings, and sufficiency of sample size for the research conducted. Unlike systematic reviews, integrative reviews do not require formal quality scoring or exclusion based on quality thresholds, as the goal is comprehensive synthesis rather than meta-analytic precision [32]. This approach allowed us to include studies employing diverse methodologies that collectively contribute to understanding the phenomenon under review.

Data Analysis

Data extraction focused on identifying theoretical frameworks employed, research design and methodology, sample characteristics, key findings related to learning outcomes, and reported limitations. We employed thematic analysis to synthesize findings across studies, following the approach described by Braun and Clarke [36]. This involved familiarization with the data, generation of initial codes, searching for themes, reviewing themes, and defining and naming themes. The six-phase approach provides a systematic yet flexible framework for identifying, analyzing, and interpreting patterns of meaning within datasets.

We organized findings according to two analytic dimensions informed by our research questions: theoretical perspectives, models, and frameworks employed in existing research; and reported learning outcomes and results, guided by the UCT.

Methodological Transparency

In keeping with best practices for AI-augmented research [33], the research team transparently acknowledges the following methodological considerations. First, we used AI tools as adjuncts to human searching, not replacements, and all final inclusion and exclusion decisions were made by human reviewers. Second, our search strategy evolved through multiple iterations based on emerging findings, consistent with the flexibility afforded by the integrative review approach rather than the pre-registered protocols required for systematic reviews. Third, we independently verified all papers suggested by AI tools for existence and relevance before inclusion. Fourth, our goal was comprehensive thematic coverage rather than exhaustive identification of all relevant literature.

IV. Findings

This section presents findings from our integrative review organized according to the research questions guiding this study. We synthesized studies identified through traditional database searches and AI-augmented discovery, with all sources verified for existence, relevance, and quality before inclusion.

RQ1: Theoretical Perspectives, Models, and Frameworks

1) Technology Acceptance and Adoption Models

This subsection encapsulates aspects guided by the UCT's Practice dimension, which focuses on the use and adoption of technological and IT-based tools. Technology acceptance frameworks have dominated the theoretical landscape of generative AI research in STEM education, providing structured approaches to understanding student and faculty adoption behaviors. The Technology Acceptance Model (TAM) and its extensions, including TAM2, the Unified Theory of Acceptance and Use of Technology (UTAUT), and UTAUT2, have been the most frequently applied theoretical lenses across the reviewed literature [37], [38], [23]. These models examine how perceived usefulness, perceived ease of use, and behavioral intentions influence actual AI tool adoption among STEM learners.

Recent empirical investigations show that TAM and UTAUT can be useful frameworks to study generative AI adoption in STEM contexts. A study of 237 pre-service mathematics and science teachers revealed that academic self-efficacy significantly influenced both perceived usefulness and ease of use of generative AI tools, which in turn positively shaped behavioral intentions toward AI adoption [38]. Similarly, research involving 448 mathematics and science teachers across Turkish provinces found generally positive attitudes toward AI, though significant gender disparities emerged, with male teachers exhibiting higher self-efficacy and perceived ease of use compared to female teachers [37]. A systematic literature review of 138 studies using the UTAUT framework found that perceived usefulness and ease of use were consistent predictors of faculty adoption intentions [23].

Extensions of TAM have incorporated additional constructs relevant to educational contexts. The AIDUA (Acceptance and Use of AI) model has been enhanced with variables including system compatibility, transparency, and human-computer interaction perception to better capture the unique characteristics of generative AI technologies [39], [40]. Research employing structural equation modeling with 462 university students revealed that performance expectancy was primarily driven by technical capabilities such as generation quality and ethical considerations including explainability and risk perception. Notably, perceived risk operated as a dual-threat factor, simultaneously lowering performance expectations and amplifying effort expectancy burdens [39].

The application of TAM in STEM education contexts has revealed nuanced patterns of technology acceptance. Studies indicate that perceived usefulness emerges as the strongest predictor of ChatGPT adoption, while social influence and hedonic motivation also play significant roles [41]. However, traditional TAM assumptions have been challenged in generative AI contexts; one study found a negative correlation between perceived ease of use and perceived usefulness, suggesting that as tools become more intuitive, learners may paradoxically perceive them as less valuable for deep learning [42]. This counterintuitive finding highlights the need for refined theoretical models that account for the pedagogical complexity of AI-assisted learning environments.

2) Learning Theories and Pedagogical Frameworks

This subsection was guided by the UCT's Learning dimension. Beyond technology acceptance models, research on generative AI in STEM education has been grounded in established learning theories that emphasize active knowledge construction and self-directed learning. Constructivist learning theory provides a foundational framework for understanding how AI tools can scaffold student learning through interactive dialogue and personalized feedback [43], [22]. The constructivist perspective positions generative AI as a cognitive partner that supports learners in building their own understanding rather than passively receiving information.

Self-regulated learning (SRL) theory has emerged as a critical framework for examining how students manage their learning processes when using AI tools. A systematic review analyzing 38 studies found that 71.4% reported AI's positive role in enhancing SRL, primarily through personalized learning experiences, metacognitive support, and adaptive feedback mechanisms [24]. Research demonstrates that ChatGPT can enhance key SRL components, including goal setting, strategic planning, self-monitoring, and self-evaluation. However, researchers caution that over-reliance on AI may diminish students' capacity for independent thinking, emphasizing the need for educational interventions that balance AI support with learner autonomy. The Guidance-based ChatGPT-assisted Learning Aid (GCLA) framework exemplifies theory-driven design for promoting self-regulated learning. This approach modifies ChatGPT interactions by encouraging students to attempt problem-solving independently before seeking AI assistance, and when engaged, GCLA provides hints rather than direct answers [43]. A randomized controlled trial with 61 undergraduate students in a foundational chemistry course demonstrated that GCLA significantly enhanced SRL, higher-order thinking skills, and knowledge construction compared to traditional ChatGPT use. The targeted, purposeful engagement with AI, rather than excessive reliance, yielded the most substantial learning gains.

Cognitive load theory has been applied in several studies to examine how generative AI influences students' mental processing capacity. Research involving 36 sophomore undergraduates in a STEM entrepreneurship course found that ChatGPT-assisted collaborative learning significantly outperformed non-ChatGPT groups in terms of cognitive load management [44]. Students in the collaborative condition reported lower extraneous cognitive load while maintaining higher germane cognitive load focused on meaningful learning. This finding suggests that well-designed AI integration can reduce unnecessary mental burden while directing cognitive resources toward deeper understanding. Social cognitive theory and sociocultural frameworks have been employed to understand collaborative learning dynamics in AI-enhanced environments. Studies indicate that strategic use of generative AI tools can facilitate peer collaboration and knowledge sharing, though interaction patterns vary significantly based on students' prior experience and critical thinking dispositions [45], [46]. Text mining analysis identified distinct interaction profiles: strategic inquirers who used sophisticated follow-up questioning demonstrated significantly higher performance than exploratory inquirers, highlighting the importance of prompt engineering skills and metacognitive awareness.

3) Systems-Level and Curriculum Frameworks

This subsection was included based on an interconnectedness between the Learning and Practice dimensions of the UCT. At a systems level, prior syntheses of AI applications in STEM education adopt a General Systems Theory framework, conceptualizing AI integration as an interaction among subject, medium, information, technology, and learning environment rather than as an isolated instructional tool [47]. This macro-level perspective complements discipline-specific approaches by highlighting AI's multifaceted instructional role across STEM fields.

Research connecting AI integration to Industry 4.0 and Industry 5.0 frameworks has examined curriculum implications in engineering education. The digital competence framework for educators provides guidance for AI integration within project-based learning, flipped classrooms, and hands-on experiences. At the program and curriculum level, competency-based teaching models synthesize multiple educational theories to support long-term skill development. Educator-focused qualitative studies indicate that teachers perceive AI tools as beneficial for reducing workload and personalizing instruction, while also expressing concerns related to over-dependence, ethical risks, and data privacy [48].

RQ2: Learning Outcomes and Results

Most aspects of learning outcomes relate to the UCT Meta-competency dimension, including problem-solving, critical thinking, and self-regulation. However, Practice competencies related to AI knowledge and literacy were also found to play a critical role.

1) Academic Performance

Some learning outcomes were related to the Practice competency related to knowledge and literacy of AI tools. Empirical research examining academic performance outcomes presents a nuanced picture of generative AI's impact on STEM learning. Studies employing experimental and quasi-experimental designs reveal mixed but generally positive effects on student achievement. A study in an introductory thermodynamics course found that students who used ChatGPT as a learning support performed better than those who did not. These students demonstrated a stronger understanding of difficult, abstract concepts, such as entropy and internal energy. ChatGPT also helped reduce many common conceptual misunderstandings. However, some students still struggled with problems that required complex calculations, showing that ChatGPT was less helpful for advanced numerical problem-solving [49]. The relationship between AI usage patterns and academic performance appears to be mediated by interaction quality rather than mere frequency. Research with 73 nontraditional higher education students found that ChatGPT prompt numbers and engagement levels significantly predicted performance, while self-efficacy did not [46]. More critically, depth of knowledge in prompts and prompt relevance showed positive correlations with performance outcomes. Students characterized as strategic inquirers, those employing sophisticated follow-up questioning, demonstrated significantly higher performance than exploratory inquirers, suggesting that metacognitive engagement with AI tools drives learning effectiveness. This shows that the interconnectedness of Practice competencies and Meta-competencies can yield improved outcomes.

2) Problem-Solving Capabilities

Problem-solving capabilities in STEM contexts show variable enhancement depending on task complexity and domain. An exploratory study in a sophomore-year undergraduate electronics course found that while ChatGPT demonstrated strengths in efficiency and speed for circuit problem-solving, it frequently compromised accuracy through errors and misinformation [50]. Students emphasized the importance of human oversight and instructor involvement in guiding proper AI use. Similarly, research on mathematical problem-solving revealed that only 28% of first-year Faculty of Education students effectively adjusted prompts and used AI critically; most accepted AI-generated outputs without deeper reflection or verification [51]. A systematic review of ChatGPT in mathematics education found support for concept clarification and problem structuring but limited effectiveness for complex proofs and spatial geometry [52].

In computer science education, research examining ChatGPT-facilitated programming found increased coding efficiency and improved debugging skills among 82 college students, though concerns emerged about code dependency and reduced independent problem-solving practice [53]. Students reported enhanced learning confidence when using AI tools, but instructors noted the need for balanced integration that preserves fundamental skill development.

3) Critical Thinking, Self-Regulation, and Metacognitive Development

Critical thinking development represents one of the most contentious areas in generative AI research, with studies reporting both facilitative and inhibitory effects. Approximately 62.5% of reviewed studies examining critical thinking reported positive impacts, particularly when AI tools were embedded within inquiry-based or problem-based learning frameworks [24]. Research demonstrates that AI can support critical thinking through processes of analysis, evaluation, and reflection when students are explicitly trained in prompt engineering and reflective AI interaction strategies. However, substantial concerns persist regarding the potential for AI to undermine critical thinking development. A systematic investigation involving 808 undergraduate survey responses revealed that critical thinking disposition and skills were positively associated with collaborative, reflective, and cautious use of generative AI, while negatively associated with thoughtless reliance [45]. The study found that critical thinking could offset the influence of trust on inappropriate AI use and amplify the positive influence of AI literacy on desirable reliance behaviors. These findings underscore that critical thinking serves as a protective factor against over-reliance while enhancing productive engagement with AI tools.

The impact on higher-order thinking skills presents conflicting evidence. While some studies report enhanced analytical reasoning when AI is used as a collaborative tool, others document concerns about diminished critical thinking. A study involving 36 undergraduate STEM entrepreneurship students found that ChatGPT-assisted collaborative learning groups outperformed non-ChatGPT groups in learning performance and AI awareness but showed lower critical thinking scores [44]. This trade-off suggests that while AI can enhance certain cognitive outcomes, it may inadvertently reduce opportunities for students to develop independent analytical skills when used without appropriate pedagogical constraints.

Self-regulation and metacognitive development show promising enhancements when AI tools are implemented with explicit scaffolding structures. Students in the GCLA condition showed enhanced metacognitive awareness, better self-monitoring capabilities, and improved strategic planning for learning tasks [43]. Research on prompt engineering as a metacognitive skill has emerged as a significant theme. A framework for teaching prompt engineering in university courses emphasizes that structured instruction in this skill can foster critical thinking, problem-solving, and reflective interaction, which are key competencies for navigating AI-driven environments [62].

4) Motivation, Engagement, and AI Literacy

Motivation and engagement patterns reveal complex relationships with AI tool use. Multiple studies report that students perceive ChatGPT as highly useful and motivating for academic tasks, particularly for reviewing concepts, generating practice problems, and receiving immediate feedback [54], [55]. A scoping review of empirical studies found generally positive student perceptions of AI chatbots for learning support. Research involving undergraduate students across diverse Indonesian universities found generally high levels of readiness to use ChatGPT, with students perceiving it as valuable for completing assignments, clarifying complex concepts, and reducing academic stress [56]. However, concerns emerged regarding potential impacts on intrinsic motivation when students become overly reliant on AI-generated solutions rather than engaging in effortful learning processes.

AI literacy development has emerged as both an outcome and a prerequisite for effective generative AI use in STEM education. Studies examining generative AI literacy across disciplines found notable variations, with engineering students outperforming peers in mathematics, humanities, and social sciences across dimensions including basic technical proficiency, communication proficiency, creative application, and critical evaluation [57]. Latent profile analysis identified three distinct literacy profiles: Foundational Learners, Balanced Practitioners, and Proficient Achievers, suggesting that differentiated instructional approaches may be necessary to meet diverse student needs.

V. Summary of Findings

This integrative review synthesized findings from studies examining generative AI use in STEM higher education. Regarding theoretical frameworks (RQ1), technology acceptance models, particularly TAM and UTAUT, dominate the literature, though self-regulated learning theory, constructivism, cognitive load theory, and sociocultural frameworks provide important complementary perspectives. The critical distinction emerging from this review is between structured versus unstructured AI use, with theory-driven implementations like the GCLA framework demonstrating superior outcomes.

Concerning learning outcomes (RQ2), our findings demonstrate that AI-supported learning environments are associated with improvements in academic performance, cognitive skill development, and student engagement when guided by intentional pedagogical design. However, findings regarding critical thinking are mixed, with some studies showing enhancement through scaffolded use and others documenting concerns about diminished analytical skills when AI is used without appropriate constraints. The mediating factor appears to be not whether students use AI, but how they engage with these tools; strategic, reflective, and targeted use correlates with positive outcomes, while passive reliance shows neutral or negative effects.

VI. Discussion

The central insight emerging from this review is that the question facing STEM educators is not whether to permit generative AI, but how to structure its use. The distinction between structured and unstructured AI integration appears consistently across studies: when AI tools are embedded within intentional pedagogical designs such as the GCLA framework [43] or inquiry-based approaches, learning outcomes improve; when students engage with AI without scaffolding, gains are inconsistent and critical thinking may suffer [44], [45]. This pattern suggests that generative AI functions neither inherently as scaffold nor crutch [16], but rather that pedagogical context determines which role it plays.

The dominance of technology acceptance models in current research reflects the field's early focus on adoption rather than learning. While TAM and UTAUT effectively predict who uses AI tools and why [23], [38], they offer limited insight into how AI use shapes competency development. The emerging integration of self-regulated learning theory and constructivism represents a necessary evolution, shifting attention from behavioral intention to cognitive engagement. Viewed through the Universal Competency Taxonomy, this theoretical gap explains why research concentrates on the Learning dimension while neglecting how AI influences students' participation in disciplinary communities (Community of Practice) or development of professional judgment beyond academic integrity (Value). The field requires theoretical frameworks that bridge technology adoption and learning science perspectives.

Our findings reveal a reliance paradox at the heart of AI-assisted STEM learning. The same tool that enhances efficiency and reduces cognitive load can simultaneously diminish the productive struggle through which deep learning occurs. Hou et al. [45] demonstrated that critical thinking serves as a protective factor, enabling students to engage reflectively rather than passively with AI outputs. Yet critical thinking develops precisely through the effortful problem-solving that unrestricted AI use may bypass. This paradox cannot be resolved through policy alone. The finding that ethical beliefs, not institutional policies, predict student behavior [58] suggests that sustainable AI integration requires cultivating metacognitive awareness about when AI assistance supports learning versus when it substitutes for it. The Meta-competency dimension of the Universal Competency Taxonomy thus emerges as pivotal: students must develop not only skills for using AI effectively but judgment about when not to use it.

The equity dimensions of generative AI in STEM education demand attention that current research has not adequately provided. Disparities in device access, AI literacy, and prompt engineering skills documented across socioeconomic backgrounds [59], [46] suggest that AI integration, without deliberate intervention, may widen rather than narrow achievement gaps. The finding that nontraditional students required substantial guidance to develop productive AI interaction patterns indicates that AI literacy cannot be assumed as a prerequisite but must be explicitly taught. For STEM programs committed to broadening participation, this represents both challenge and opportunity: generative AI could democratize access to personalized learning support, but only if institutions invest in equitable infrastructure and targeted training.

VII. Implications and Future Research

For STEM educators, these findings suggest three priorities. First, course design should specify not only when AI tools are permitted but how students should engage with them, including explicit scaffolding that promotes reflection before, during, and after AI interaction. Second, assessment practices require redesign to evaluate process alongside product, making visible the thinking that AI can obscure. Third, AI literacy instruction should extend beyond technical proficiency to include metacognitive judgment about appropriate reliance, positioning this as a professional competency rather than merely an academic integrity issue.

For institutions, the inconsistency between faculty guidelines and student-facing policies documented across universities [60] calls for coordinated approaches that involve students as stakeholders in policy development. The ineffectiveness of detection-focused strategies and the equity concerns surrounding AI detection tools argue for shifting resources toward educational interventions that develop ethical reasoning within the Value dimension of competency development.

Future research should address the methodological and theoretical limitations pervading current scholarship. There is a need to further investigate and expand our understanding of theoretical and conceptual frameworks that can better guide how students use and learn with AI, beyond technological adoption and use models, and motivational theories. Longitudinal studies examining how AI use during undergraduate education shapes professional competency are absent. Studies examining AI's influence on the understudied dimensions of the Universal Competency Taxonomy, particularly Community of Practice, Value, STEM Fundamentals, and specialized disciplinary Practice competencies, would provide a more comprehensive understanding of how these tools shape STEM professional formation. Finally, research conducted in diverse global contexts, particularly in resource-constrained settings where infrastructure limitations alter AI integration dynamics, would enhance generalizability beyond Western higher education systems.

This study does not explicitly highlight the effect of AI augmentation in the literature review process. Future studies can help improve the methodological procedures used in this paper and highlight the specific contribution of AI augmentation.

VIII. Limitations

This review has limitations. The search strategy and process, while comprehensive, were not systematic or systematized, were limited to a few databases, and may not have adequately captured all relevant studies, particularly those published in non-indexed venues. The rapidly evolving nature of generative AI means that new tools and capabilities continue to emerge, potentially rendering some findings time-sensitive. The use of AI-assisted search methods, though conducted with human verification, introduces methodological considerations that future reviews should continue to refine.

IX. Conclusion

Generative AI will not be uninvented, and STEM students will continue using these tools regardless of institutional stance. The contribution of this review lies in reframing the conversation: rather than debating permission, educators should focus on designing learning experiences where AI serves as a scaffold for deeper engagement with disciplinary thinking. The Universal Competency Taxonomy reveals that current research addresses only a fraction of what competent STEM professionals must develop, suggesting that the field's understanding of AI's educational impact remains incomplete. As these tools evolve, STEM programs that proactively design for meaningful AI integration, attending to innovation, appropriate reliance, and integrity as interconnected rather than competing concerns, will better prepare students for professional contexts where human judgment and AI capability must work in concert.

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