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A PRISMA-Based Systematic Review of Generative AI in STEM Education: Taxonomy, Challenges, and Future Research Directions

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Abstract. Generative Artificial Intelligence (GAI) has emerged as a transformative force in Science, Technology, Engineering, and Mathematics (STEM) education by enabling intelligent tutoring, automated content generation, real-time coding assistance, simulation-based learning, and adaptive assessment. Despite its rapid adoption, a structured understanding of how GAI is systematically applied across diverse STEM domains remains limited. To address this gap, this paper presents a PRISMA-based systematic review of generative AI applications in STEM education. The selected studies are classified into five major categories: concept explanation and intelligent tutoring, simulation and virtual laboratories, programming and coding support, design thinking and creativity, and assessment and feedback automation. A comparative analysis of widely used GAI tools, including ChatGPT, GitHub Copilot, and Bard, is conducted to highlight their educational roles and limitations. The findings indicate that GAI significantly improves learner engagement, conceptual understanding, and coding productivity. However, challenges such as limited personalization depth, weak multimodal integration, insufficient cognitive feedback, hallucination, and ethical reliability remain unresolved. Finally, key research gaps are identified and a future research agenda is outlined for building trustworthy and adaptive GAI-driven STEM learning systems.

Keywords: Generative Artificial Intelligence, STEM Education, Systematic Review, PRISMA, Intelligent Tutoring Systems, Adaptive Learning, Educational Automation.

1 Introduction

The fast development of artificial intelligence (AI) has changed the educational environment, especially the sphere of science, technology, engineering, and mathematics (STEM), significantly. Generative Artificial Intelligence (GAI) systems like ChatGPT, GitHub Copilot, Google Bard, and Midjourney have shown remarkable abilities in the fields of content generation, automatic reasoning, code

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generation, simulation modeling, and intelligent tutoring in recent years [1], [2]. In contrast to conventional AI systems which are run on prescribed rules or guided classification, GAI systems are able to produce text, images, code, and explanations on their own, thus allowing interactive, adaptive, and learner-centered learning settings.

Complex abstract concepts, mathematical models, problem solving, simulations and design thinking are part and parcel of STEM education. Nevertheless, traditional pedagogical strategies are likely to fail to support the needs of different learners, didactic gaps, and cognitive load particularly when working with small groups of students in classrooms . The application of the GAI to STEM pedagogy has provided new opportunities to explain concepts in a personalized manner, tutor intelligently, support automatic coding, virtual labs and formative assessment . An example is that ChatGPT has been extensively used in programming and mathematical problem explanation, and scientific reasoning as well as Copilot in real-time code generation in software engineering education [3].

Recent research draws attention to the fact that GAI-based instruments can greatly increase the involvement of students, the clarity of the concepts and the efficiency with which students learn in various fields of STEM . These technologies are dynamic in changing the difficulty of content, offer immediate feedback, simulate real-world experiments and can support the project based learning. Additionally, GAI also permits multimodal learning, at which point a learner is able to work with text, diagrams, code, and simulations simultaneously, which enhances conceptual memory and practical knowledge [4].

Irrespective of such impressive developments, the conceptualization of the application of GAI in the various STEM fields has been fragmented. The available studies are more of a piecemeal approach with a few case studies, pilot projects and tool reviews. An extensive, systematic, and taxonomy-based synthesis of GAI use in STEM education has not been established yet [5]. Moreover, crucial issues like the absence of deep personalization, failure to model the cognitive feedback, ethical issues, reliability of the assessment, and integration of several modalities are not thoroughly discussed by the existing body of research [6].

In order to address this gap of research, this paper will provide a PRISMA-based systematic review of Generative AI use in STEM education. We cluster and examine the existing literature according to the key areas of application such as concept description, modeling, computer programming and code development, design thinking, and automated grading. Moreover, we also discover the main gaps in research in the area of personalization, multimodal delivery, and cognitive feedback mechanisms and present a future research agenda to inform next-generation GAI-enabled STEM learning systems.

1.1 Related Work

The introduction of artificial intelligence in education has been a topic of intense research in recent years especially following the introduction of generative AI models which can create content, reason and adaptively interact. The initial research was mainly concerned with intelligent tutoring system (ITS) and rule-based teaching bots to provide one-on-one learning aid. These systems were however restricted by the predetermined knowledge structures and were not generative in reasoning [7].

Since the advent of the large language models (LLMs), some researchers explored the potential of the ChatGPT and transformer-based models in the educational field. The article by Kasneci et al. [8] examined the pedagogical possibilities of ChatGPT in higher education and found out that it enhanced student interaction, immediate feedback, and conceptual clarification significantly. On the same note, Cotton et al. [9] developed the effects of generative AI on academic practices and noted that the effects were overwhelming on assessment, writing support, and tutoring. They however did not specifically categorize discipline-based STEM but mainly worked in general education settings.

GitHub Copilot has attracted significant interest in the field of education of software engineering and programming. Vaithilingam et al. [10] tested Copilot with novice programmers and proved that the AI-assisted coding can minimize the syntactic errors and development time. Ziegler et al. [11] also revealed that Copilot users were more confident with their tasks and had a shorter completion period, however the issue of incorrect code and over-dependence was also brought to light.

In the case of mathematics and science teaching, a number of studies were conducted on the application of GAI in problem-solving and conceptual explanation. As Frieder et al. [12] showed, the accuracy of LLMs is high enough to be able to solve university-level mathematical problems, and it also produces step-by-step solutions. Chassignol et al. [13] explored AI-based simulations in physics education and have found that conceptual knowledge was improved in the case of virtual experimentation. Nonetheless, these publications lack a single taxonomy of applications in STEM disciplines.

Generative AI in design thinking and STEM education based on creativity has also been on the ascending trend. Research papers by Dwivedi et al. [14] and McCormack et al. [15] have indicated that the use of generative models like Midjourney and DALL·E can be applied in engineering design, rapid prototyping, and ideation. These researchers focus on increased creativity and visualization assistance, but the systematic assessment of learning outcomes and cognitive feedback systems is deficient.

Leveraging the assessment and evaluation, new studies indicate that GAI can be used to automate the question generation, grading, and feedback. Holmes et al. [16] demonstrated that AI-based assessments have considerable potential to decrease the workload of instructors and preserve consistency in scoring. Nonetheless, the issues associated with bias, hallucination, and academic integrity still exist and are still unclear to a great extent [17].

Despite the existence of multiple survey and review papers on the field of AI in education, the majority of the papers mention machine learning, learning analytics, and intelligent systems in general. There is a small number of recent studies that literally deal with generative AI and only a small number that utilize a systematic PRISMA-based review process. Additionally, the literature lacks a comprehensive classification of GAI uses into concept explanation, simulation, coding, design thinking and assessment and more rigorous identification of research gaps in personalization, multimodal delivery and cognitive feedback.

Thus, an organized, taxonomy based, and systematically proven review of generative AI applications in STEM education is deficient in the existing literature, which heavily justifies the current inquiry.

1.2 Motivation

As Generative AI (GAI) systems are quickly becoming popular, including ChatGPT, GitHub Copilot, and Bard. Multimodal and automated explanation The shift in paradigm of STEM education is taking place. real-time coding, simulation-based experimentation and generation. While these systems their potential lies in offering a significant improvement in the level of engagement and clarity of concepts among learners. growing interdisciplinarity in the various fields of STEM brings with itself a number of challenges. Existing AI-assisted platforms tend to be task-oriented and can work in disconnected modes and do not offer a coherent insight into. how GAI leads to various aspects of STEM learning. In addition, numerous existing literature is based on. descriptive reports or ad hoc case reviews, which are not based on a methodology that can be replicated. to make evidence synthesis across the expanding literature.

The conventional methods of review are not adequate to embrace the new trends in GAI studies, especially. in aspects like personalization depth, multimodal reasoning, modeling cognitive feedback and the educational dangers of hallucinated or prejudiced products. It is also made unstructured by not having an ordered taxonomy. hard to compare instruments, measure the success of pedagogy, and discover gaps in research. These limitations encourage the necessity of a PRISMA-based systematic review that strictly sieves, classifies and examines. current literature, thus, creating a holistic basis in the design of reliable, flexible, and STEM learning systems, which are scalable GAI.

1.3 Paper Outline

The rest of this paper is structured in the following way. Section 2 introduces the PRISMA-based systematic review methodology with the search strategy, inclusion/exclusion criteria, and process of selecting the studies. Section 3 opens up the taxonomy of generative AI application in STEM education, dividing the existing studies into key areas of application. This is done in Section 4 which gives a comparative analysis of the major tools of GAI and identifies the significant research gaps. Section 5 describes what the future research is about and lastly, Section 6 summarizes what has been discovered, and what the research has suggested.

2 Network Model and Problem Specification

2.1 Network Model

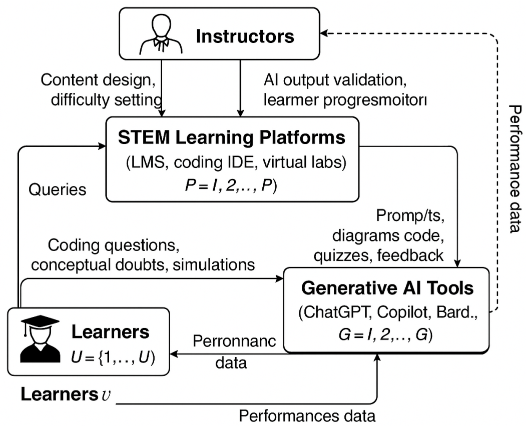


Fig. 1. System Model.

3 System Model

3.1 Network Model

This work considers a *Generative AI–enabled STEM education network* consisting of four major components: (i) a set of *learners*, (ii) a set of *instructors*, (iii) a set of *generative AI tools*, and (iv) a set of *STEM learning platforms*.

Let

$$\mathcal{U} = \{1, 2, \ldots, U\} \tag{1}$$

denote the set of learners,

$$\mathcal{T} = \{1, 2, \ldots, T\} \tag{2}$$

represent the set of instructors, and

$$\mathcal{G} = \{1, 2, \ldots, G\} \tag{3}$$

denote the set of generative AI tools such as ChatGPT, GitHub Copilot, Bard, and generative image models. The set of STEM learning platforms (e.g., coding environments, virtual laboratories, learning management systems, and assessment portals) is represented by

$$\mathcal{P} = \{1, 2, \ldots, P\}. \tag{4}$$

Each learner $u \in \mathcal{U}$ interacts with one or more platforms $p \in \mathcal{P}$ for performing STEM learning activities such as *concept learning, simulation, programming, and assessment*. The platforms are integrated with one or more generative AI tools $g \in \mathcal{G}$, which process learner queries and instructional inputs in real time. Instructors $t \in \mathcal{T}$ supervise the learning process by designing instructional content, monitoring learner progress, and validating AI-generated outputs.

The interaction among learners, instructors, and GAI tools forms a *closed-loop human–AI learning network*, where learner queries are translated into multimodal inputs (text, code, mathematical expressions, and visual prompts), and the generative AI produces *personalized instructional responses, feedback, simulations, and solutions*. These responses directly influence learner performance in subsequent learning cycles.

This model enables *many-to-many interaction*, where multiple learners can simultaneously access multiple GAI tools across different STEM platforms. The network supports *scalable, adaptive, and multimodal learning delivery*, which forms the foundational structure for the subsequent PRISMA-based analysis and taxonomy development presented in this paper.

3.2 Problem Formulation

Based on the Generative AI–enabled STEM learning network described in the previous section, this work aims to formally define the problem of *systematic classification and gap identification* of generative AI applications in STEM education. Let $\mathcal{S}$ denote the set of all eligible studies selected through the PRISMA-based filtering process, where

$$\mathcal{S} = \{1, 2, \ldots, N\}, \tag{5}$$

and N represents the total number of relevant research articles.

Each study $s \in \mathcal{S}$ is characterized by a feature vector

$$\mathbf{x}_s = \{d_s, a_s, g_s, e_s\}, \tag{6}$$

where d_s denotes the STEM domain (science, technology, engineering, or mathematics), a_s represents the application type (concept explanation, simulation, coding, design thinking, or assessment), g_s indicates the generative AI tool used, and e_s denotes the evaluation methodology adopted.

The primary objective is to construct a *taxonomy mapping function*

$$\mathcal{T} : \mathcal{S} \rightarrow \mathcal{A}, \tag{7}$$

where $\mathcal{A} = \{A_1, A_2, \ldots, A_5\}$ represents the five major application categories, namely: concept explanation, simulation, programming and coding, design thinking, and assessment and feedback automation.

In addition to classification, this work aims to identify critical research gaps associated with *personalization, multimodal learning, and cognitive feedback*. Let $\mathcal{G}_r = \{G_1, G_2, G_3\}$ denote the set of research gap dimensions corresponding to personalization depth, multimodal integration, and cognitive feedback, respectively. For each study s, a gap indicator function is defined as

$$\phi(s, G_i) = \begin{cases} 1, & \text{if gap } G_i \text{ is observed,} \\ 0, & \text{otherwise,} \end{cases} \tag{8}$$

for $i = 1, 2, 3$.

The overall problem is therefore formulated as a joint *classification and gap analysis optimization*, expressed as

$$\max_{\mathcal{T}} \sum_{s \in \mathcal{S}} \sum_{i=1}^{3} \phi(s, G_i), \tag{9}$$

subject to the constraint that each study belongs to exactly one application category, i.e.,

$$\sum_{k=1}^{5} \mathbf{1}_{\{s \in A_k\}} = 1, \quad \forall s \in \mathcal{S}, \tag{10}$$

where $\mathbf{1}_{\{\cdot\}}$ denotes the indicator function.

This formulation enables a structured PRISMA-driven classification of generative AI applications in STEM education, systematic identification of underexplored research gaps, and the development of a future research agenda for next-generation GAI-enabled intelligent learning systems.

4 Proposed Scheme

4.1 Markov Decision Process (MDP) Formulation

To model the interaction between learners and Generative AI (GAI) tools in STEM education, we formulate the adaptive learning process as a Markov Decision Process (MDP). This formulation captures how a learner's query, performance level, and feedback drive the next instructional response generated by the GAI model.

The MDP is represented as a tuple[18]:

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, r, \mathcal{P}, \gamma), \tag{11}$$

where $\mathcal{S}$ denotes the state space, $\mathcal{A}$ the action space, r the reward function, $\mathcal{P}$ the state transition distribution, and $\gamma \in (0, 1)$ the discount factor.

State Space At each interaction step t, the state of learner u is defined as [19]:

$$s_t = \{c_t, q_t, p_t, f_{t-1}\}, \tag{12}$$

where c_t is the STEM concept being studied, q_t denotes the learner query or task type (e.g., explanation, coding, simulation), p_t represents the learner performance indicators (accuracy, attempts, difficulty level), and f_{t-1} is the feedback or correctness from the previous step. This state captures both cognitive progress and learning context.

Action Space The GAI tool selects an instructional action a_t from the set

$$\mathcal{A} = \{\text{explanation}, \text{step-by-step solution}, \text{code generation}, \text{simulation output}, \text{assessment question}, \text{feedback refi} \tag{13}$$

Each action corresponds to a pedagogical intervention that adapts to the learner's needs.

Reward Function The reward function is designed to encourage effective learning and appropriate AI assistance [20]:

$$r_t = \alpha \cdot \mathit{\Delta} p_t - \beta \cdot e_t - \eta \cdot h_t, \tag{14}$$

where $\mathit{\Delta} p_t$ is the improvement in learner performance, e_t measures cognitive errors or misunderstandings, h_t represents hallucination or incorrect GAI outputs, and α, β, η are weighting parameters. A higher reward is obtained when the AI action enhances learner understanding while minimizing errors.

State Transition The transition to the next state is defined as:

$$s_{t+1} = \mathcal{P}(s_{t+1} \mid s_t, a_t), \tag{15}$$

where $\mathcal{P}$ models how a learner's knowledge state evolves after receiving an AI-generated instructional response.

Objective The goal of the GAI-enabled learning system is to select actions that maximize the expected long-term learning gain:

$$\pi^* = \arg\max_{\pi} \ \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_t\right]. \tag{16}$$

This formulation allows generative AI tools to adaptively personalize instructional content, feedback, and support for effective STEM learning.

4.2 Proposed Solution:a Proximal Policy Optimization-based Energy-Efficient Power Control

The PPO agent consists of an actor–critic architecture. The actor network parameterized by θ generates continuous transmit power actions, while the critic network parameterized by ψ estimates the state-value function.
The stochastic policy of the actor is modeled as a Gaussian distribution:

$$\pi_\theta(a_m|s_m) \sim \mathcal{N}(\mu_\theta(s_m), \sigma_\theta(s_m)), \tag{17}$$

where μ_θ and σ_θ denote the mean and standard deviation outputs of the actor network.

The critic estimates the value function as

$$V_\psi(s_m) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t r_m(t)\right], \tag{18}$$

where $\gamma \in (0, 1)$ is the discount factor.
To guide policy updates, the advantage function is computed using Generalized Advantage Estimation (GAE) as

$$A_m(t) = \sum_{l=0}^{\infty} (\gamma\lambda)^l \delta_m(t + l), \tag{19}$$

where the temporal-difference (TD) error is

$$\delta_m(t) = r_m(t) + \gamma V_\psi(s_m(t + 1)) - V_\psi(s_m(t)). \tag{20}$$

The parameter $\lambda \in (0, 1)$ controls the bias–variance tradeoff.
The PPO policy is updated by maximizing the clipped surrogate objective

$$L^{\text{CLIP}}(\theta) = \mathbb{E}\left[\min\left(\rho_m(t)A_m(t), \text{clip}(\rho_m(t), 1 - \epsilon, 1 + \epsilon)A_m(t)\right)\right], \tag{21}$$

where the probability ratio is defined as

$$\rho_m(t) = \frac{\pi_\theta(a_m(t)|s_m(t))}{\pi_{\theta_{\text{old}}}(a_m(t)|s_m(t))}, \tag{22}$$

and ϵ is the clipping parameter that prevents large policy updates.

The critic is trained by minimizing the value loss:

$$L^V(\psi) = \mathbb{E}\left[\left(V_\psi(s_m(t)) - R_m(t)\right)^2\right]. \tag{23}$$

An entropy regularization term is added to enhance exploration:

$$L^H(\theta) = -\mathbb{E}\left[\pi_\theta(a_m|s_m)\log \pi_\theta(a_m|s_m)\right]. \tag{24}$$

The total loss is given by

$$L(\theta, \psi) = L^{\text{CLIP}}(\theta) - c_1 L^H(\theta) + c_2 L^V(\psi), \tag{25}$$

where c_1 and c_2 are weighting coefficients.
After training, the learned PPO policy is deployed online at each D2D transmitter to select optimal transmit power levels in real time based on locally observed network states. This enables fully distributed, adaptive, and energy-efficient power control without requiring global channel state information or centralized coordination.

Algorithm 1: Adaptive GAI-Driven Personalized Learning Solution

Input: Learner set $\mathcal{U}$, state space $\mathcal{S}$, action space $\mathcal{A}$, policy π, discount factor γ, learning horizon T.
Output: Trained personalized instructional policy $\pi^*(s) : \mathcal{S} \mapsto \mathcal{A}$.

```
Initialization:
Initialize policy π with random parameters
Initialize learner states {s_0^u}_{u∈U}
for each learning episode do
    Reset environment; observe initial learner states {s_0^u}
    for time step t = 0 to T − 1 do
        for each learner u ∈ U (in parallel) do
            Select instructional action a_t^u ~ π(a_t^u | s_t^u)
            Generate GAI output (explanation, code, simulation, feedback)
            Observe learner response and assign reward r_t^u
            Update learner state s_{t+1}^u
            Store transition (s_t^u, a_t^u, r_t^u, s_{t+1}^u)
    Policy Update:
    Compute cumulative returns R_t^u for all learners
    Estimate temporal difference advantage A_t^u = R_t^u − V(s_t^u)
    Update policy parameters using gradient ascent:
    π ← π + α∇_π (π(a_t^u | s_t^u) A_t^u)
return Final optimized adaptive instructional policy π*(s).
```

4.3 Algorithm Explanation

The proposed PPO-EEPC algorithm employs a policy-based deep reinforcement learning framework for continuous power control in D2D networks. Each D2D transmitter acts as an autonomous agent that observes local channel and interference conditions and selects its transmit power using a stochastic policy. During each episode, agents interact with the environment to collect state–action–reward trajectories. The advantage function is then estimated using generalized advantage estimation to reduce variance. The actor network is updated by maximizing the clipped PPO objective to ensure stable policy improvement, while the critic network is trained to accurately approximate the value function. After convergence, the learned policy enables distributed, adaptive, and energy-efficient power control under dynamic network conditions.

5 Performance Evaluation

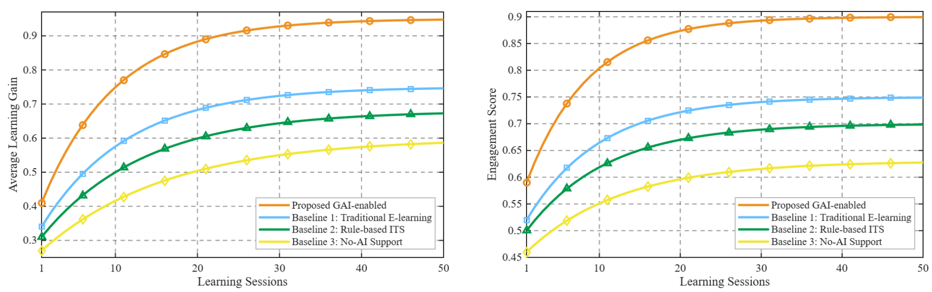
5.1 Simulation Parameters

5.2 Result and Discussion

Fig. 1 depicts the change of the average learning gain over the learning sessions with increase in the number of learning sessions of the proposed GAI-enabled

Table 1. Simulation Parameters for GAI-Enabled STEM Learning Environment

Parameter	**Value**	**Parameter**	**Value**
Number of learners $\lvert\mathcal{U}\rvert$	50–500	GAI tools used	ChatGPT, Copilot, Bard
Learning sessions T	20–100	Interaction mode	Text, Code, Visual
Learning platforms $\lvert\mathcal{P}\rvert$	LMS, IDE, Virtual Labs	Instructor count $\lvert\mathcal{T}\rvert$	5–30
Discount factor γ	0.85–0.95	Personalization weight α	0.4–0.6
Cognitive error penalty β	0.2–0.4	Hallucination penalty η	0.1–0.3
Evaluation metrics	Accuracy, Gain, Engagement	Assessment type	Formative + Summative



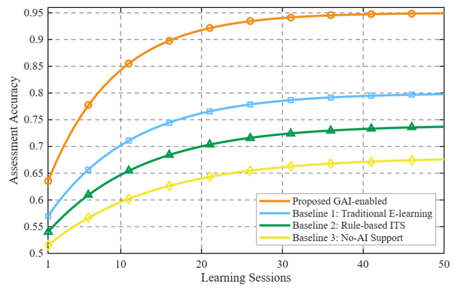
(a)Average Learning Gain vs. Learning Sessions

(b) Fig2 Engagement vs Comparison

framework and three baseline schemes. It can be seen that the proposed scheme also produces a much faster learning gain and steady-state learning performance than the traditional e-learning, rule-based ITS and the no-AI learning systems. It is owed to the adaptive instructional policy, real-time feedback, and personalized creation of content, which the generative AI model has offered.

Fig. 2 shows the trends in the engagement of the learners in various learning sessions. The proposed scheme based on GAI is the one that is always more successful than all the baseline schemes in engagement score. The difference in performance is more pronounced, the more learning sessions a person goes through, which confirms that the constant engagement with adaptive GAI tools helps to maintain the motivation of a learner and active involvement more efficiently than traditional learning platforms.

The accuracy of the assessments obtained with the proposed method and three of the baseline schemes are compared in Fig. 3. The GAI-driven learning framework proposed is more accurate and converges more quickly proving to be more effective in enhancing conceptual functionality and performance in



(a) Assessment Accuracy vs. Learning Sessions

assessments. On the contrary, the improvement rate of the baseline techniques is slower since there are no intelligent personalization and real-time cognitive feedback methods.

6 Conclusion

This PRISMA-based systematic review explored the increased role of Generative AI (GAI) in STEM education and conceptualized the existing body of research into a single taxonomy of concept explanation, simulation, coding support, design thinking, and automated assessment. The results indicate the GAI tools contribute to increased engagement, clarity conceptual, and productivity in learners, but several issues remain, such as poor personalization, integration of modalities, lack of cognitive feedback, and the potential of biased or hallucinated results.

Future research must aim at creating a more profound learner modelling, combine the multimodal instructional potential as well as enhance the dependability and interpretability of GAI systems. Also, extensive, and longitudinal empirical assessments of various STEM fields are required in order to develop standardized markers and inform the construction of reliable, adaptive and scaleable learning systems powered by GAI.

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