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Unlocking Potential: Key Factors Shaping Undergraduate Self-Directed Learning in AI-Enhanced Educational Environments

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Abstract: This study investigates the factors influencing undergraduate students' self-directed learning (SDL) abilities in generative Artificial Intelligence (AI)-driven interactive learning environments. The advent of generative AI has revolutionized interactive learning environments, offering unprecedented opportunities for personalized and adaptive education. Generative AI supports teachers in delivering smart education, enhancing students' acceptance of technology, and providing personalized, adaptive learning experiences. Nevertheless, the application of generative AI in higher education is underexplored. This study explores how these AI-driven platforms impact undergraduate students' self-directed learning (SDL) abilities, focusing on the key factors of teacher support, learning strategies, and technology acceptance. Through a quantitative approach involving surveys of 306 undergraduates, we identified the key factors of motivation, technological familiarity, and the quality of AI interaction. The findings reveal the mediating roles of self-efficacy and learning motivation. Also, the findings confirmed that improvements in teacher support and learning strategies within generative AI-enhanced learning environments contribute to increasing students' self-efficacy, technology acceptance, and learning motivation. This study contributes to uncovering the influencing factors that can inform the design of more effective educational technologies and strategies to enhance student autonomy and learning outcomes. Our theoretical model and research findings deepen the understanding of applying generative AI in higher education while offering important research contributions and managerial implications.

Keywords: generative AI; self-directed learning; teacher support; learning strategies; technology acceptance; self-efficacy

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1. Introduction

Artificial Intelligence (AI) has been around for a considerable time, offering significant potential for personalized education to cater to learners' differences and needs [1]. Generative AI, a field based on machine learning, particularly deep learning, has recently gained substantial attention. The advent of generative AI has revolutionized interactive learning environments, offering unprecedented opportunities for personalized and adaptive education. Generative AI refers to machine learning models that can create new content, including text, images, and even personalized learning pathways [2]. Generative AI possesses powerful capabilities to autonomously create novel and meaningful content, employing various methods to produce high-quality text, images, audio, and other media formats [3]. These technologies have shown the potential to adapt to individual learner needs, providing immediate feedback and facilitating interactive learning experiences. They have profoundly impacted educational research and practice, driving educational innovations and transforming traditional teaching methods and learning strategies.

Generative AI and AI–human collaboration have facilitated the development of conversational AI based on natural language processing, achieving breakthroughs in information retrieval, knowledge representation, content creation, and knowledge reasoning [4].

Recent studies have shown that students benefit significantly from the prompts provided by generative AI tools like ChatGPT and Bing Chat, demonstrating a degree of critical thinking when utilizing this technology [5,6]. Diwan et al. found that AI-based learning content generation and learning pathway augmentation contribute to improving learner engagement. The research by Li et al. highlighted the tremendous potential of ChatGPT in promoting self-directed language learning (SDLL), offering new insights into learning technology innovation and AI-assisted self-directed learning (SDL) research [7,8]. Additionally, experimental studies have indicated that students exhibit higher intrinsic motivation, improved learning performance, and positive attitudes in GenAI-supported scenarios [9]. Lu et al. found that pre-service teachers who used generative AI scored higher in teacher self-efficacy and higher-order thinking in both the experimental and control groups [10]. These findings imply that generative AI, such as ChatGPT, offers numerous advantages in educational settings. It provides students with personalized learning experiences, enhances learning efficiency, and supports teachers' professional development [10]. Despite generative AI's novel capabilities in improving education quality, the human element remains irreplaceable. Nevertheless, existing studies ignore the mechanism of self-directed learning (SDL) when students apply generative AI. SDL is a process in which individuals take the initiative to diagnose their learning needs, formulate goals, identify resources, and evaluate outcomes [11]. Previous SDL research has highlighted the importance of motivation, resource availability, and institutional support in fostering SDL [12], but it remained unclear in classrooms augmented by AI. While this theoretical puzzle is of great interest for academic research, it is also of great educational value and managerial relevance, because quality education is recognized as important United Nation sustainable development goals [13].

To address this knowledge gap, this study embraces the Generative Learning Theory as the theoretical lens to explore the mechanisms and interactions underlying self-directed learning in generative AI-supported interactive environments [14]. It seeks to measure changes in students' self-directed learning abilities and investigate future pathways for smart education practice. This research could facilitate the effective integration of generative AI in teaching, helping educators provide personalized instruction to students. Based on the above, we propose two research questions below:

- RQ1: How does generative Artificial Intelligence (GenAI) support self-directed learning?
- RQ2: What factors influence students' self-directed learning abilities in generative AI-driven interactive environments?

We meticulously developed a questionnaire grounded in established self-regulated learning scales pertinent to AI–human interaction, incorporating critical dimensions such as goal setting and time management [15,16]. To ensure its suitability for a generative AI learning environment, we carefully refined the dimension descriptions and introduced additional items. Following a rigorous expert evaluation and a comprehensive pilot study, the questionnaire demonstrated robust reliability. A subsequent survey of 306 undergraduate students revealed that technological familiarity and learning motivation significantly impact self-directed learning capabilities, with self-efficacy, learning strategies, and teacher support functioning as mediating variables.

Venturing into the research insights of future education generative AI, this study made three contributions. As a theoretical contribution, this study presents a conceptual model that encompasses critical factors explaining generative AI and self-directed learning. We uncovered the human elements of self-efficacy, autonomous learning ability, and learning motivation in this mechanism. The theoretical insights from this study contribute to extending the Generative Learning Theory to thrive in a world of constant technological changes. Secondly, our study provided key implications to educators for tomorrow, where technological advancements and new pedagogical theories continually reshape the landscape. We argue that teacher support and technology acceptance are critical for adapting to the shifting demands of their profession and the diverse needs of their students. Thirdly, our research findings provide important managerial implications for policymakers in education. The future of education is not about choosing to use AI or abandon AI, but it is about fostering a catalyst for a lifelong passion for self-direct learning facilitated by AI.

2. Literature Review

2.1. Mechanisms of Generative AI Facilitating Generative Learning

The Generative Learning Theory posits that learning is an active process [14]. The generative model theorizes research insights in educational psychology, viewing learning as a constructive cognitive process and considering human cognitive learning, abilities, and attitudes [14]. The Generative Learning Theory posits that learners actively engage in generating, organizing, and integrating information to construct knowledge. Learners must not solely rely on the passive reception of external information. They should generate representations such as diagrams, images, tables, or charts based on their existing cognitive structures and sensory information from the environment. They autonomously create learning activities to deepen their understanding, actively interpreting and making meaning of the information.

Following this theoretical lens, Fiorella and Mayer further argued that generative learning activities involve learners' active engagement to deepen their understanding of the course material. The key principles of this theory include encouraging active participation through creation, hypothesis, and experimentation; integrating new content with existing cognitive structures; and promoting diverse learning strategies such as summarizing, organizing, connecting, and drawing as generative learning strategies.

Moser and Lewalter highlighted the alignment between the Generative Learning Theory and Constructivist Theory, asserting that learning involves comparison, adjustment, and reorganization to construct new concepts and knowledge [17]. For instance, learners need to adopt heuristic and exploratory approaches when solving problems and acquiring knowledge, positively impacting their ability to tackle mathematical challenges [18]. This involves observing and analyzing problem patterns, seeking regularities, and applying these patterns to new contexts [19]. Continuous reflection and metacognition are necessary for optimizing learning processes and strategies to improve performance [20]. In addition, ongoing sharing and interaction facilitate knowledge construction and sharing [21].

Generative Artificial Intelligence (AI), with its generalization, transfer, and creative capabilities, can drive the reconstruction of existing concepts and the construction of new cognition. Additionally, it enhances heuristic and exploratory learning while promoting reflective learning. Through sustained interaction with learners, AI also transforms metacognitive approaches (Figure 1).

2.2. Promoting Cognitive Construction and Conceptual Reconstruction

The generative learning process aligns with the Cognitive Constructivist Theory, emphasizing learners' active generation and reconstruction of knowledge to understand and solve problems. In this process, students actively explore, process, and integrate information, thereby fostering the construction and reconstruction of personal knowledge structures, leading to deeper learning and comprehension [22]. Generative Artificial Intelligence (AI) leverages generative models to accumulate parameters for sequential tasks and supports iterative learning and optimization. This enables the AI to adapt to new data through continuous learning, rapidly updating knowledge and integrating cross-domain information. By continually generating, comparing, and reconstructing, generative AI enhances its transferability and generalization capabilities, akin to knowledge integration and cognitive enhancement processes [23]. Generative AI, using models such as Generative Adversarial Networks (GANs), can generate text and images while revealing hidden structures in complex data distributions, offering new approaches to solving problems in cognitive science and potentially aiding cognitive science research [24].

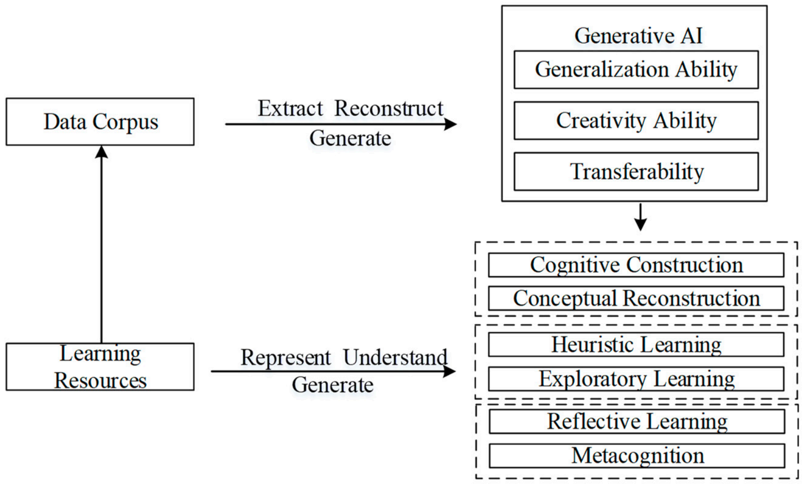

Figure 1. Mechanisms of generative AI facilitating generative learning.

2.3. Enhancing Heuristic and Exploratory Learning

Combining generative AI with heuristic and exploratory learning can provide students with rich and dynamic learning environments, thereby enhancing their initiative, creativity, and critical thinking skills. Utilizing knowledge graphs, vector databases, and Retrieval-Augmented Generation (RAG), generative AI can design more flexible and effective knowledge representation and generation mechanisms. For example, it can design and generate various questions, case studies, and challenges, encouraging learners to reflect and apply their knowledge, thereby promoting the development of critical thinking and problem-solving skills [25]. Generative AI possesses generalization capabilities that allow knowledge and skills learned in one task to be transferred to others. Additionally, it can generate creative and imaginative content, including innovative designs and scientific hypotheses [26].

2.4. Facilitating Reflective Learning and Metacognition

Generative AI can design learning activities and tasks, regulate learning plans, and monitor and evaluate the learning process, aiding students in self-reflection and self-regulation. This supports the Generative Learning Theory's view that learners should be aware of and regulate their learning strategies. For instance, it can pose questions during the learning process, such as "How do I understand this concept?" and "What is the reason for my difficulty?" These questions help students deepen their understanding of their cognitive processes, thus fostering reflective learning and metacognitive abilities [27]. Generative AI can also simulate human cognitive processes. Through strategies like Reflexion and Self-Refine prompts, it can evaluate the quality of generated content and adjust it according to preset standards. It can explore multiple problem-solving perspectives based on user input, compare and analyze differences among these perspectives, and synthesize and reassess them to eliminate discrepancies, thereby enhancing self-reflection and reasoning abilities [28].

3. Hypothesis Development

Generative Artificial Intelligence (AI) provides tools and environments that elevate the paradigm of generative learning by empowering students to actively engage in their learning processes. Generative AI encourages students to deepen their understanding of knowledge through linking, organizing, integrating, and reflecting. With the support of generative AI, students can take control of their learning, set personal learning goals, direct their learning paths, evaluate their progress, and reflect on their learning processes.

Research shows that generative AI significantly enhances learning efficacy, motivation, and knowledge construction by providing personalized learning content and interactive experiences [29]. Additionally, it fosters changes in teaching models and strategies, effectively stimulating learning interest, increasing student engagement, and improving learning outcomes [30]. Teacher support is crucial, as it provides the emotional, cognitive, and behavioral support needed to stimulate students' interest and motivation [31]. Therefore, generative learning within generative AI-driven interactive learning environments can be seen as a new learning system influenced by the key factors of teacher support, students' technological acceptance, and self-directed learning strategies.

3.1. Enhancing Teacher Support Capabilities with Generative AI

Teachers are pivotal in steering students to employ AI as an impetus for their learning capacities. Teacher support is a crucial factor influencing learning abilities, directly and significantly positively affecting students' academic adaptation, engagement, and satisfaction. The integration of teacher support and Artificial Intelligence (AI) can be categorized into two approaches: AI-supported Teacher and Teacher-supported AI. The former focuses on how AI technologies can enhance teaching effectiveness, improve instructional efficiency, and offer better-differentiated instruction for teachers [32]. The latter concentrates on how students can utilize AI's data retrieval capabilities under teacher guidance to obtain personalized learning experiences, precise learning resources, and effective instructional guidance [33]. In the context of smart classroom teaching, generative AI can assist teachers in optimizing instructional strategies and curriculum design [34]. In intelligent content generation, it helps tailor teaching materials to meet specific educational goals and student needs [35]. Furthermore, in intelligent educational data analysis, generative AI enables teachers to better understand student behavior patterns and provide tailored teaching methods [36].

The integration of generative AI in enhancing teacher support capabilities is broad-reaching. For example, within the dialogic learning model, AI-enabled intelligent inquiry fosters the development of higher-order thinking and questioning skills, thereby deepening knowledge mastery and enhancing cognitive abilities [37]. Additionally, generative AI assists teachers in discerning variations in students' knowledge acquisition, interaction patterns, and depth in programming learning support, subsequently influencing learning outcomes. Teacher support encompasses not only the transmission of knowledge but also provides psychological, emotional, and behavioral support [38].

Generative AI enables the real-time analysis of student learning, metacognition, and behavior, supporting teachers in guiding students. Leveraging large language models and multimodal technologies, AI can generate diverse learning resources such as text, images, audio, and video. It can also understand the mental health of individual students and groups, thereby providing comprehensive cognitive, emotional, and behavioral assessments and diagnostic support. Investing in teacher support not only refines their teaching practices but also embodies AI with effective learning strategies for their students. In summary, this study proposes the following hypotheses:

H1. *In generative AI-driven interactive learning environments, teacher support can directly influence students' learning strategies.*

H2. *In generative AI-driven interactive learning environments, teacher support can directly influence students' learning motivation.*

3.2. Ensuring Adequate Technology Acceptance for Generative AI

Generative AI requires users to possess specific competencies, as it provides information to support problem-solving and retrieves and generates multimodal data resources.

However, overreliance on technology without critical thinking can detrimentally affect students' learning. Due to the inherent limitations of training on incomplete or biased data, generative AI can sometimes produce erroneous or nonsensical information, known as the hallucination effect, which necessitates discernment and judgment from users. For instance, while generative AI can propose adaptive instructional content and strategies, the effectiveness may fall short of standards [39]. It can offer suggestions for classroom management and learning assessment, but the content is often based on preset prompts and may not meet the specific needs of teachers [40]. Furthermore, while generative AI can analyze student assignments and provide dialogic feedback, these interactions may lack explanatory depth and occasionally exhibit flawed logical reasoning [41].

The hallucination effect of generative AI can lead to misinterpretations among both teachers and students, prompting some schools and teachers to approach its integration into teaching environments cautiously. Studies using the Technology Acceptance Model (TAM) have examined the behavioral intentions of teachers and students regarding the adoption of AI technologies. The TAM consists of perceived usefulness (PU) and perceived ease of use (PEOU) [42]. PU refers to the recognition of AI technology's benefits in learning, while PEOU focuses on the convenience of operating and interacting with the technology. Through the TAM, deeper insights into the levels of acceptance of AI technology in education can be gained, enabling the proposal of suitable training and support measures to enhance understanding and ensure correct application.

Despite these challenges, the perceived ease of using generative AI remains a key factor driving its widespread adoption. Its natural language processing capabilities enhance user-friendliness and multifunctionality, making it a widely used educational tool, which few AI technologies have achieved before. However, accessibility and ease of use do not necessarily translate into effective and meaningful use, especially in learning and teaching contexts. The perceived usefulness of generative AI, like other digital tools, relies on proficient use, particularly the flexible application of Prompt Engineering. In the realm of large language models, prompts are articulated as natural language sentences or fragments, including descriptions, commands, inquiries, and requests, that trigger the generative AI's responses based on patterns learned during training. The perceived usefulness of generative AI largely depends on the quality of the prompts it receives; when integrated with subject knowledge and critical thinking, it can potentially enhance learning engagement.

Therefore, this study proposes the following hypothesis:

H3. *The level of acceptance of generative AI technology can directly influence students' self-directed learning abilities.*

3.3. Adapting Self-Directed Learning Strategies through Generative AI

Generative AI supports students in transitioning their cognitive processes to select learning information from AI-generated content and integrate it with existing knowledge. This aligns with generative learning strategies that emphasize selecting, organizing, and integrating learning content [43]. For instance, generative AI can facilitate self-paced learning, personalized learning paths, and immersive experiences, boosting learning motivation and engagement [44]. It can also increase willingness to communicate in specific languages through chat interactions, maintaining dialogue and generating personalized language learning materials [45]. Additionally, AI offers feedback and personalized learning support and assessment roles, either as a peer or mentor [46]. It can effectively enhance students' problem-solving abilities and learning satisfaction through online cooperative learning models [47].

Generative AI supports learners by enabling goal-setting, retrieving and creating multimodal learning resources, generating adaptive learning plans, and providing continuous feedback and evaluation, driving adjustments to their existing learning strategies. Unlike traditional self-directed learning (SDL), which often lacks real-time support and interaction from teachers and peers, AI facilitates ongoing collaboration with teachers and peers. This transformation enables learners to engage in higher levels of human–AI collaboration, transforming their self-management, problem-solving, and continuous learning methods by actively interacting with AI to generate personalized learning plans, resources, feedback, and assessments.

As a new form of AI application, generative AI possesses uncertainties and developmental stages. The Technology Acceptance Model (TAM), based on the Theory of Reasoned Action, analyzes users' attitudes and behavioral intentions toward technology, serving as a direct factor for teachers and students to determine the use of AI-assisted teaching and learning. Perceived usefulness gauges the likelihood of enhancing performance through generative AI in teaching and autonomous learning. Simultaneously, when perceived ease of use indicates simplicity and learnability, it fosters positive attitudes towards using AI as a teaching and learning tool, bolstering autonomous learning intentions among students. This underscores the direct positive impact of perceived ease of use on students' willingness for autonomous learning. In line with this, we propose:

H4. *Learning strategies supported by generative AI can indirectly influence self-directed learning ability through the mediating effect of technology acceptance.*

3.4. Boosting Learning Motivation and Self-Efficacy with Generative AI

In generative learning, self-efficacy pertains to individuals' self-assessment of their learning capabilities and behaviors. It represents students' self-perception and assessment of their capability to accomplish learning tasks [48]. Research underscores that learning motivation and self-efficacy remain critical factors within AI educational environments and interact with factors such as technology acceptance and learning strategies [49]. For instance, in AI programming learning, self-efficacy, AI literacy, and course satisfaction directly influence learning interest and willingness [50]. Generative AI teaching platforms enhance students' perceived interaction with AI during writing skill training, demonstrating a strong connection between interaction strategies, self-efficacy, and learning experience [51]. AI-assisted foreign language teaching significantly boosts student engagement, promoting learning motivation and self-directed learning through personalized learning experiences [52].

Generative AI offers timely feedback and adjusts problem difficulty, offering swift responses to help students gauge their learning status, recognize their strengths and weaknesses, and feel more confident in mastering knowledge. Simultaneously, the problems generated by generative AI maintain an appropriate level of difficulty, motivating students to sustain their interest in learning and progressively enhance their skills. The flexibility to arrange learning schedules according to an individual's pace fosters the habit and ability of self-directed learning while reducing anxiety, allowing learners to study in a more relaxed state. Overall, generative AI aids in enhancing students' learning motivation and self-efficacy by offering personalized learning experiences, timely feedback, challenging yet manageable tasks, and adaptive learning paths. Considering the above, we propose:

H5. *In generative AI-driven interactive learning environments, students' learning motivation can directly influence their self-directed learning ability.*

H6. *In generative AI-driven interactive learning environments, learning strategies can indirectly influence learning motivation through the mediation of self-efficacy.*

H7. *In generative AI-driven interactive learning environments, self-efficacy can indirectly influence self-directed learning ability through the mediating impact of learning motivation.*

3.5. Research Model

A research model is demonstrated in Figure 2 to guide our investigations on the proposed hypotheses.

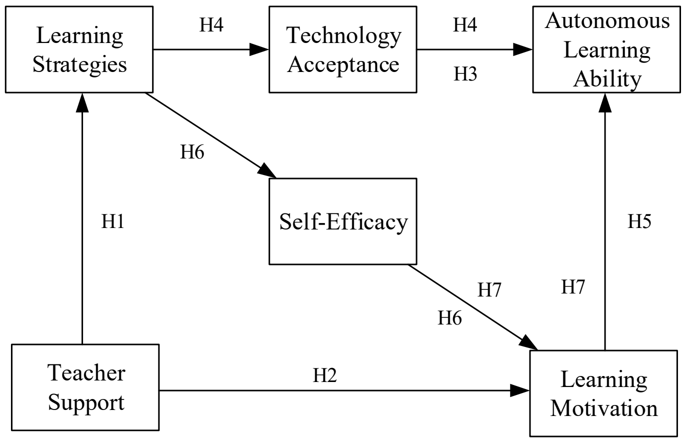

Figure 2. The conceptual model of the study.

Based on the analysis of learning processes and their associated factors, generative AI-driven interactive learning environments represent a comprehensive array of learning resources that support learners in engaging with generative learning. These environments encompass not only the material conditions that underpin the learning process but also non-material elements such as learning strategies, the learning atmosphere, and interpersonal relationships.

Teacher support and learning strategies are crucial components of the learning environment. They assist learners in better processing information, enhancing understanding and memory and increasing learning efficiency and motivation. Teacher support can be subdivided into emotional support, academic support, behavioral support, and organizational support. Learning strategies include cognitive strategies, metacognitive strategies, resource management strategies, social strategies, and technical strategies.

The role of teacher support and learning strategies in promoting students' self-directed learning abilities is further amplified by the capabilities of generative AI, which can offer creative content generation functions. This allows learners to express their ideas and knowledge in more creative and expressive ways, thereby enhancing their self-efficacy. Moreover, the technology provides real-time feedback and personalized learning experiences, helping users better understand their learning progress and needs and boosting their confidence and motivation in their learning capabilities.

4. Methods

4.1. Participants

The sample group for this study consists of undergraduate students from diverse academic disciplines who used generative AI tools in their coursework. Throughout the instructional process, instructors proficiently employed generative AI to aid in instructional design, adapt and generate assessment content according to disciplinary differences, and intelligently evaluate learning outcomes. Students actively engaged with the generative learning content. The data for this study were collected through an online survey, ensuring scientific rigor in the data collection process. Before the commencement of the study, the purpose was clearly explained to the participants, emphasizing their right to withdraw at any time during the study. We assured participants that all collected data would remain confidential and used exclusively for research purposes. The two waves of surveys were conducted in December 2023. We distributed the questionnaire links via the WeChat and QQ platforms to ensure convenient and efficient data collection. A total of 315 questionnaires were distributed, and after excluding 9 invalid responses, we obtained 306 valid samples, resulting in an effective sample rate of approximately 97%. This study employed a stratified random sampling method to select undergraduate students aged 18 to 23, encompassing all academic years from freshman to senior. Participants were sourced from a wide array of academic disciplines and utilized generative AI tools in their coursework, ensuring the sample's balance and representativeness.

Among the 306 valid samples, the distribution was as follows: 25% freshmen (77 students), 24% sophomores (73 students), 26% juniors (80 students), and 25% seniors (76 students). Participants spanned various academic fields, including humanities (e.g., linguistics and history), sciences (e.g., physics and chemistry), and arts (e.g., visual arts and music). The gender distribution was balanced, with 48% male (147 students) and 52% female (159 students). In terms of technological background, 39% (120 students) were from technology-related majors such as computer science, educational technology, and information technology, while 61% (186 students) were from non-technology majors, including literature, arts, and education. This diverse sample composition ensured comprehensive applicability and representativeness of the research findings, aligning with the characteristics of the contemporary undergraduate demographic. Of the 306 participants, 39% were enrolled in technology-related majors, and the gender distribution was nearly equal, accurately reflecting the characteristics of the contemporary undergraduate demographic.

4.2. Instrument

This study utilized a 37-item survey questionnaire, focusing on assessing factors such as students' technology acceptance, self-efficacy, learning strategies, learning motivation, and teacher support concerning students' self-regulated learning abilities, particularly within generative AI-driven interactive learning environments. The survey was divided into two parts. The first part collected demographic information about the participants, such as gender, age, and academic background. The second part comprised the main questionnaire, which included six key constructs: self-efficacy, learning strategies, learning motivation, technology acceptance, teacher support, and self-regulated learning ability. The questionnaire's dimensions and items were adapted from existing self-regulated learning scales relevant to AI–human interaction [15,16]. These scales were appropriately modified to fit the characteristics of generative AI-driven interactive learning environments.

4.3. Data Analysis

In this study, we employed Structural Equation Modeling (SEM) as a comprehensive analytical approach to thoroughly evaluate and validate the theoretical model. SEM integrates the principles of factor analysis and regression analysis, excelling in uncovering complex causal relationships and interactions among multiple variables. Adhering strictly to the classical two-step procedure proposed by Bagozzi and Yi [53], we utilized AMOS 26 for data processing and analysis.

At the outset of the research, we conducted rigorous reliability and validity tests using SPSS 26.0 to ensure the robustness and accuracy of our findings. To perform a reliability analysis, we calculated Cronbach's α coefficients for each variable. As shown in Table 1, all six latent variables exhibited Cronbach's α values exceeding the commonly accepted threshold of 0.7 [54], with values ranging from 0.714 to 0.891, indicating high measurement reliability. The calculation of Composite Reliability (CR) also supported the internal consistency of the model, with each latent variable showing CR values above the 0.7 standard, demonstrating excellent convergent validity [55]. Additionally, the Average Variance Extracted (AVE) values were all above the 0.5 threshold, indicating good scale validity [55]. As illustrated in Table 1, each construct's CR exceeded 0.7, and each construct's AVE was greater than 0.5. The results of this study reveal the outstanding convergent validity of the scale, further corroborating the strong and substantial intrinsic correlations among the latent variables.

Subsequently, we conducted a thorough assessment of the measurement model to ensure data reliability, convergent validity, and discriminant validity, laying a solid foundation for the subsequent in-depth analysis. Descriptive statistics and correlation analyses were performed using SPSS 26.0 software(Version: 28.0.0.0 (190)) to examine the relationships among the variables. The results indicated that the mean scores of all constructs on a

1 to 5 rating scale were above 1.9. Additionally, significant positive correlations were found between self-regulated learning ability and learning motivation, self-efficacy, learning strategies, teacher support, and technology acceptance. These findings laid the foundation for the further exploration of mediating effects.

Table 1. Reliability test and validity test.

Potential Variables	Number of Items	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Autonomous Learning Ability	7	0.804	0.800	0.667
Technology Acceptance	6	0.723	0.719	0.562
Learning Motivation	5	0.714	0.718	0.561
Learning Strategies	6	0.891	0.888	0.799
Self-efficacy	6	0.832	0.835	0.717
Teacher Support	4	0.783	0.778	0.637

Thereafter, we conducted linear regression analysis to test specific hypotheses and determine the direct impact of independent variables on the dependent variable. This analysis helped identify the factors influencing students' self-regulated learning ability. To ensure the robustness of the model, we calculated multicollinearity statistics, including Tolerance and Variance Inflation Factor (VIF), to detect potential multicollinearity issues among the predictor variables. Following this, we rigorously tested the structural model to confirm the accuracy of model fit and structural validity.

Finally, using AMOS 26 software (Version: 28.0.0.0 (190)) and the maximum likelihood estimation method, we systematically tested the seven core hypotheses of the study. We utilized Structural Equation Modeling (SEM) to analyze the complex relationships among the variables. SEM allows for the simultaneous estimation of direct and indirect effects. AMOS 26 was chosen for its exceptional reliability and robust analytical capabilities, making it the ideal tool for this complex analysis task. Through these rigorous procedures and scientific analyses, we provided strong empirical support for the evaluation and validation of the theoretical model.

5. Results

5.1. Descriptive Statistics and Correlation Analysis

The means, standard deviations, and correlation coefficients between the variables are presented in Table 2. The results, calculated using SPSS, indicate that, within the 1 to 5 rating scale, the mean values for all the constructs are above 1.9, ranging from 1.922 (self-efficacy; SD = 0.9712) to 2.277 (learning strategies; SD = 1.1389). There are significant positive correlations between self-directed learning ability and learning motivation, self-efficacy, learning strategies, teacher support, and technology acceptance. These relationships provide a necessary foundation for the further exploration of mediating effects.

Table 2. Descriptive statistics and correlation analysis table.

Variables	Mean	Standard Deviation	Autonomous Learning Ability	Technology Acceptance	Learning Motivation	Learning Strategies	Self-Efficacy	Teacher Support
Autonomous Learning Ability	2.043	0.9576	1					
Technology Acceptance	2.116	1.0415	0.556 **	1				
Learning Motivation	2.232	1.1112	0.502 **	0.393 **	1			
Learning Strategies	2.277	1.1389	0.472 **	0.486 **	0.445 **	1		
Self-efficacy	1.922	0.9712	0.480 **	0.489 **	0.559 **	0.571 **	1	
Teacher Support	2.232	1.1934	0.338 **	0.444 **	0.492 **	0.408 **	0.424 **	1

Note: ** $p < 0.01$.

5.2. Linear Regression Analysis

A regression analysis was conducted to examine the factors influencing students' self-regulated learning ability, as shown in Table 3. Controlling for related variables, significant positive relationships were found between self-regulated learning ability and learning motivation (b = 0.233, $p < 0.001$), learning strategies (b = 0.123, $p < 0.01$), and technology acceptance (b = 0.328, $p < 0.001$). Additionally, technology acceptance was significantly positively related to self-efficacy (b = 0.178, $p < 0.01$), learning strategies (b = 0.147, $p < 0.01$), and teacher support (b = 0.188, $p < 0.001$). Learning motivation also had significant positive relationships with self-efficacy (b = 0.355, $p < 0.001$) and teacher support (b = 0.253, $p < 0.001$). Similarly, both self-efficacy and teacher support were significantly positively related to learning strategies and learning motivation.

Table 3. Linear regression analysis of the influencing factors on autonomous learning ability.

Outcome Variable	Predictor Variable	Unstandardized Coefficient	Standardized Coefficient	t-Value	Multicollinearity Statistics	
					Tolerance	VIF
Autonomous Learning Ability	Technology Acceptance	0.328	0.357	7.100 ***	0.652	1.534
	Learning Motivation	0.233	0.271	5.158 ***	0.598	1.672
	Learning Strategies	0.123	0.146	2.784 **	0.597	1.675
Technology Acceptance	Learning Strategies	0.147	0.160	3.059 **	0.600	1.668
	Teacher Support	0.188	0.216	4.460 ***	0.703	1.422
	Self-efficacy	0.178	0.166	2.994 **	0.536	1.865
Learning Motivation	Teacher Support	0.253	0.272	5.796 ***	0.730	1.370
	Self-efficacy	0.355	0.311	5.878 ***	0.575	1.739
Learning Strategies	Self-efficacy	0.396	0.338	6.278 ***	0.582	1.717
	Teacher Support	0.105	0.110	2.206 *	0.674	1.483

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

The tolerance values for the regression model of the factors influencing self-regulated learning ability ranged from 0.536 to 0.730, and all VIF values were below the criterion of 5, indicating that there was no multicollinearity issue among the predictor variables in the regression equation. Next, the PROCESS macro will be utilized to further examine the multiple mediation effects and explore the relationships between the variables. Linear regression analysis showed that learning motivation had a significant positive effect on self-regulated learning ability (b = 0.233, $p < 0.001$), supporting hypothesis H5. Technology acceptance had a significant positive effect on self-regulated learning ability (b = 0.328, $p < 0.001$), supporting hypothesis H3.

5.3. Assessment of Direct, Indirect, and Total Effects

Table 4 details the seven interaction pathways among factors such as technology acceptance, learning strategies, and self-regulated learning ability within generative AI-driven interactive learning environments. By analyzing the path coefficients and critical ratios, it is shown that, for instance, the path coefficient for teacher support to learning strategies is 0.594 and, for teacher support to learning motivation, is 0.36, with C.R. > 1.96 and $p \leq 0.001$. This indicates that teacher support can significantly and positively influence both learning strategies and learning motivation directly, confirming hypotheses H1 and H2. Similarly, the same pattern applies to paths such as "technology acceptance → self-regulated learning ability" and "learning motivation → self-regulated learning ability", confirming hypotheses H3 and H5. These results reveal the deep-seated intrinsic relationships between factors within generative AI-driven interactive learning environments, providing essential theoretical support for understanding and optimizing the application of generative AI.

Table 4. Results of hypotheses testing for direct relationships via SEM.

Relationships	Estimate	S.E.	C.R.	*p*
Teacher Support → Learning Strategies	0.594	0.074	8.035	***
Teacher Support → Learning Motivation	0.360	0.065	5.501	***
Learning Strategies → Self-efficacy	0.585	0.045	13.006	***
Learning Strategies → Technology Acceptance	0.460	0.047	9.824	***
Self-efficacy → Learning Strategies	0.525	0.068	7.757	***
Technology Acceptance → Autonomous Learning Ability	0.583	0.083	7.022	***
Learning Strategies → Autonomous Learning Ability	0.329	0.062	5.293	***

Note: *** $p < 0.001$.

To evaluate the model fit, a series of standardized criteria was employed. The Adjusted Goodness of Fit Index (AGFI) was 0.917, exceeding the threshold of 0.90, indicating a well-adjusted model. The Goodness of Fit Index (GFI) was 0.959, suggesting a good model fit. Both the Tucker–Lewis Index (TLI) at 0.964 and the Normed Fit Index (NFI) at 0.961 surpassed their respective acceptance thresholds, further indicating a good model fit. The Root Mean Square Error of Approximation (RMSEA) was 0.058, below the standard threshold of 0.08, showing that the model's approximate error was within an acceptable range. The Critical N (CN) was 260, exceeding the required minimum of 200, demonstrating sufficient sample stability. The Chi-Square to Degrees of Freedom ratio (X^2/df) was 2.166, falling within the ideal range of 1 to 3, further supporting the model's acceptable fit. Based on these comprehensive evaluations, the model demonstrates an overall fit that ranges from acceptable to good.

Using a chained mediation model helps to understand how self-regulated learning ability is influenced by multiple factors. This model quantifies the indirect effects of independent variables on the dependent variable and their 95% confidence intervals, providing a more comprehensive explanation. By understanding the role of mediating variables, we can more accurately predict changes in the dependent variable, aiding in the development of effective generative teaching practices, as illustrated in Figure 3. Table 5 presents a continuous multiple mediation model where self-efficacy, learning strategies, technology acceptance, learning motivation, and teacher support influence self-regulated learning ability.

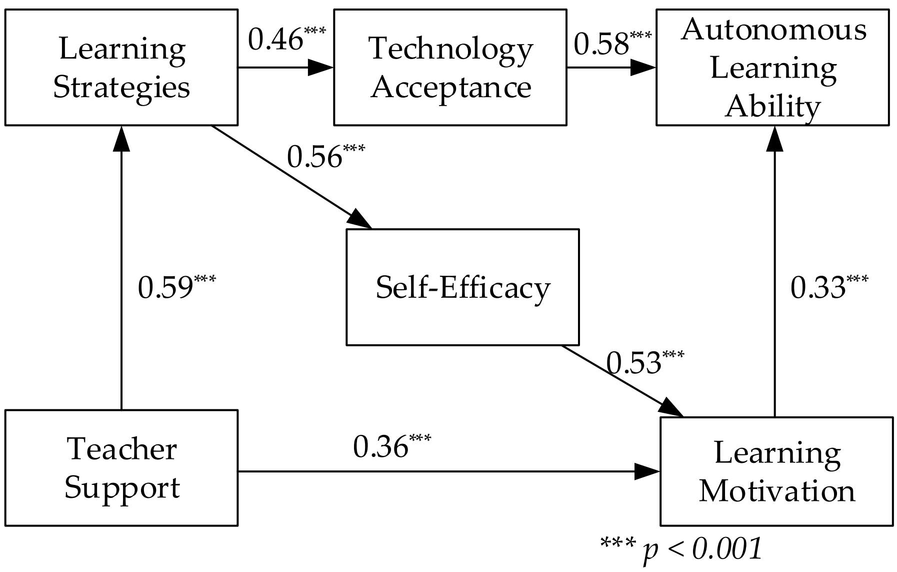

Figure 3. Path diagram of factors influencing self-regulated learning ability in generative AI-driven interactive learning environments.

Table 5. The results of multiple mediation effect testing.

Indirect Path	Indirect Effect (b)	95% Confidence Interval (CI) for Indirect Effect	Corresponding Hypothesis	Result
Path 1: Learning Strategies → Technology Acceptance → Autonomous Learning Ability	0.175 ***	[0.120, 0.234]	H3	Supported
Path 2: Learning Strategies → Self-efficacy → Learning Motivation	0.025 ***	[0.005, 0.048]	H5	Supported
Path 3: Self-efficacy → Learning Motivation → Autonomous Learning Ability	0.188 ***	[0.123, 0.262]	H6	Supported

Note: *** $p < 0.001$.

Path 1 demonstrates that learning strategies in generative AI-driven interactive learning environments are within the 95% CI (the 95% confidence interval) for the indirect effect, indicating the range within which the true indirect effect is expected to fall 95% of the time.

Learning environments can significantly positively influence self-regulated learning ability through the mediating effect of technology acceptance, supporting hypothesis H4. Path 2 shows that learning strategies in generative AI-driven interactive learning environments can significantly positively influence self-regulated learning ability through the mediating effect of self-efficacy, supporting hypothesis H6. Path 3 indicates that self-efficacy in generative AI-driven interactive learning environments can significantly positively influence self-regulated learning ability through the mediating effect of learning motivation, supporting hypothesis H7.

Based on the integration of numerous pathways and data analyses, we have found that teacher support not only directly facilitates the improvement of learning strategies and learning motivation but also indirectly enhances students' self-efficacy and self-regulated learning ability. Learning strategies directly influence technology acceptance and self-efficacy and indirectly affect self-regulated learning ability and learning motivation. The extent of students' acceptance of technology and the strength of their learning motivation can directly influence their self-regulated learning ability. The interaction among factors such as learning motivation, self-regulated learning ability, and learning strategies collectively constructs a complex network that influences students' self-regulated learning ability. In the application of educational technology and classroom teaching practices, a profound understanding of these interrelationships is crucial for establishing effective educational interventions and optimizing learning environments.

6. Discussion

The findings highlight the critical role of motivation, technological familiarity, and the quality of AI interactions in fostering SDL among undergraduate students. These insights suggest that educational institutions should focus on enhancing these factors to optimize the effectiveness of AI-driven learning environments. Building upon our research model (Figure 3), this study extends the exploration of factors influencing students' self-directed learning ability within generative AI-driven interactive learning environments. The findings validate the expanded model's efficacy in explaining the determinants of university students' self-directed learning capabilities in such environments. Among the various factors examined, hypothesis H3 (technology acceptance) demonstrated the most significant direct effect on self-directed learning ability ($\beta = 0.58$, $p < 0.001$). The literature consistently identified technology acceptance as a pivotal factor in enhancing self-regulated and self-directed learning capacities [56]. Schiavo et al. and Chiu et al. further illustrated that AI literacy and acceptance significantly bolster learning outcomes and self-efficacy [57,58]. In contrast, hypothesis H5 (learning motivation) also showed a positive influence, albeit with a smaller path coefficient ($\beta = 0.33$, $p < 0.001$). The enhancement of motivation not only cultivates a positive disposition towards technology among students, prompting them to engage more proactively with AI tools for learning, but also strengthens their self-directed learning capabilities through active participation and interaction [59]. The personalized and dynamically adaptive learning experiences facilitated by generative AI allow highly motivated students to more effectively harness these resources for autonomous learning. Moreover, motivation functions as a mediating factor between technology acceptance and learning outcomes, thereby indirectly augmenting students' self-directed learning abilities [60]. These results indicate that technology acceptance has a greater impact on self-directed learning ability than learning motivation. This suggests that, in generative AI-driven interactive learning environments, the degree of technology acceptance is the primary factor affecting students' self-directed learning ability.

Additionally, H4 indicates that learning strategies indirectly influence self-directed learning ability through the mediating role of technology acceptance. This implies that effective learning strategies can enhance students' acceptance of technology, making them perceive the use of technology in generative AI-driven interactive learning environments as beneficial for improving their learning efficiency and outcomes [61]. When students recognize that learning strategies facilitate technology acceptance, they are more likely to proactively explore and apply various technological resources to support their learning, ultimately fostering their self-directed learning ability and lifelong learning mindset. Enhancing technology acceptance through learning strategies is relatively complex and requires collaborative efforts from both educators and students. Setting clear learning goals, cultivating learning interest, adopting effective learning methods, actively promoting and demonstrating technology applications, and providing personalized technical support and guidance can help students better understand and utilize technological tools. This, in turn, improves their technology acceptance and enhances their self-directed learning ability.

H7 posits that self-efficacy indirectly influences self-directed learning ability through the mediating role of learning motivation. Individuals with high self-efficacy are more likely to believe in their capability to complete learning tasks, thereby exhibiting stronger learning motivation [62]. Learning motivation serves as the intrinsic drive that propels students to engage in learning activities. Highly motivated students are more inclined to explore learning methods and strategies actively, manage their learning process, and evaluate and adjust their learning outcomes, as suggested by Lo et al. [63]. These behaviors are critical components of self-directed learning ability.

In the Structural Equation Model of this study, H1 reveals that teacher support has the most significant and substantial impact on learning strategies among all the constructs ($\beta = 0.59$, $p < 0.001$). This finding indicates that, with teacher support, students are more likely to develop and effectively apply learning strategies. Generally, with encouragement and guidance from teachers, students feel more confident in facing learning challenges, which leads them to experiment with new learning methods and strategies. This aligns with the perspective of Hoferichter et al. [64]. H2 shows that teacher support significantly affects learning motivation ($\beta = 0.36$, $p < 0.001$), suggesting that students feel valued and recognized under teacher support, providing the drive for continuous improvement and greatly enhancing learning motivation. This finding is consistent with previous conclusions by scholars [65]. These hypotheses indicate that, when students receive teacher support, their learning environment and psychological state significantly improve, promoting the use of learning strategies and enhancing learning motivation. Furthermore, H6 posits that learning strategies indirectly influence learning motivation through the mediating role of self-efficacy. The research substantiates this hypothesis by demonstrating that the proficient deployment of self-regulated learning strategies is pivotal for attaining educational objectives. Furthermore, self-efficacy is identified as a fundamental prerequisite for the successful implementation of these strategies [66]. Improved learning strategies enhance students' learning efficiency and performance, subsequently boosting their self-efficacy. Through cognitive and affective effects, this indirectly increases students' learning motivation.

7. Conclusions, Limitations, and Future Research

This study underscores the potential of generative AI to support SDL in higher education. We endeavor to make three contributions to the literature. As a theoretical contribution, we apply the Generative Learning Theory to AI, and education involves leveraging AI technologies to enhance active learning processes and foster deeper understanding among students. This study sheds new light on generative AI in education studies by presenting a conceptual model. This study, through the Structural Equation Modeling method, elucidates the interplay among different factors within generative AI-driven interactive learning environments and how generative AI directly or indirectly influences self-regulated learning ability through self-efficacy, learning motivation, and technology acceptance models. Our findings argue to use AI technologies to empower students as active participants in their self-learning processes, promoting deeper understanding, personalization, reflection, and collaboration in educational settings. Firstly, teacher support, as a significant external factor, can transform students' learning strategies and enhance their learning motivation. Therefore, there is a need to promptly revise the existing teaching concepts and methods to keep pace with the era of AI education. Secondly, the capacity for technology acceptance is a critical factor in enhancing self-regulated learning ability within generative AI-driven interactive learning environments, posing new requirements and challenges for students' technological awareness and digital literacy. Additionally, the enhancement of learning strategy levels by generative AI warrants in-depth analysis, especially as AI has altered the existing methods of information processing, selective focus, learning assistance, and self-testing. Finally, this Structural Equation Model reaffirms the validity of self-efficacy theory, self-determination theory, and achievement motivation theory, underscoring the ongoing need to strengthen students' intrinsic motivation to enhance self-regulated learning ability, regardless of technological advancements. By addressing the key influencing factors, educators and technologists can design more effective learning environments that empower students to take charge of their learning journeys.

As a practical contribution, this paper proposes the following practical pathways for relevant generative learning models:

(1) Cultivating Artificial Intelligence digital literacy: strengthening intrinsic motivation

The current wave of digitization and automation is driving educational transformation, where understanding and applying AI have become integral components of digital literacy, reflected across various levels, including digital awareness, digital skills, digital thinking, and digital ethics. Both teachers and students should grasp the basic concepts, history, major technologies, and application areas of Artificial Intelligence. This involves understanding the processes of data collection, cleansing, analysis, and interpretation related to generative AI, as well as mastering the fundamental concepts of AI algorithms and their problem-solving capabilities. Effective interactions with generative AI systems, including usage methods, command formats, and scripting tools, should be learned to enhance human–machine communication skills. Simultaneously, understanding the technical limitations of generative AI, including potential fairness, transparency, interpretability, bias, and reasoning errors of large language models, is essential. Continuous learning and knowledge updates are necessary to adapt to the changes brought about by the AI era.

Enhancing digital literacy and understanding the capabilities and limitations of AI systems is crucial for knowing where they can assist and when human intervention is required. When individuals have sufficient understanding and mastery of generative AI and digital resources, they may develop a greater interest in generative learning, driving them to explore and delve deeper. By integrating digital literacy with intrinsic motivation, a more engaging learning environment can be created, stimulating individuals' enthusiasm for learning and fostering innovation.

(2) Exploring human integration with generative Artificial Intelligence: transforming teacher perspectives

In generative AI-driven interactive learning environments, the fusion of humans and machines necessitates a shift for teachers from traditional knowledge transmitters to learning facilitators. In traditional teaching models, teachers primarily engage in knowledge impartation tasks, whereas the application of generative AI enables students to autonomously acquire knowledge and information. Therefore, teachers need to redefine their roles, emphasizing igniting students' learning interests and nurturing their innovation abilities and problem-solving skills. Simultaneously, teachers must also address potential issues and challenges brought about by generative AI. When utilizing generative teaching resources, critical thinking is essential. Teachers should meticulously select and utilize instructional materials to ensure their correctness in terms of values and objectives.

The shift in teachers' perspectives also requires a profound consideration of educational objectives. Future education should prioritize the cultivation of students' comprehensive qualities and innovation capabilities rather than solely pursue knowledge mastery. Consequently, teachers need to re-examine their educational philosophies, adapt to complex intelligent teaching environments, and make students' holistic development the core objective of teaching. This entails transitioning from an emphasis on theoretical knowledge to prioritizing the cultivation of students' practical skills, critical thinking, and creativity.

(3) Constructing generative learning strategies: facilitating deep understanding

The generative learning process requires learners to construct perceptions of problems, scenarios, and experiences, facilitating a deeper comprehension of knowledge rather than passively receiving information. Integrating generative learning into generative AI-driven interactive learning environments and learning strategies entails encouraging students to focus on reasoning and reflection, mastering the analysis, decomposition, and evaluation of each step of complex problems. Generative AI can enhance reasoning and reflection abilities through techniques like prompting through thought chains and guiding large language models to generate explicit intermediate reasoning steps before producing final answers. This technique has been proven to significantly enhance the performance of generative AI across various reasoning tasks. Generative AI can be pre-trained or fine-tuned using datasets containing explicit reasoning to strengthen its ability to handle complex reasoning problems, including deductive, inductive, and abductive reasoning forms.

The reasoning process of generative AI for problem-solving can promote students' reflection on the learning process rather than simply generating answers. Referring to the analytical process of generative AI based on deep learning algorithms as "inference" rather than mere "computation" is because this process emulates human reasoning or decision-making processes. The primary function of deep learning algorithms is to learn from complex, high-dimensional data and extract patterns, resembling the process of concluding observations—a form of reasoning. It is also effective in applications such as prediction, decision-making, handling uncertainty, and dealing with fuzzy problems. Additionally, it can adapt to new data patterns through fine-tuning, similar to human cognitive learning processes.

(4) Enhancing generative learning experiences: boosting self-efficacy

Based on multimodal large-scale models, generative AI can generate various data types such as text, images, audio, and 3D models, providing personalized learning experiences for students. Moreover, multimodal large-scale models can utilize techniques like Multimodal Instruction Fine-Tuning (M-IT), Multimodal Implicit Context Learning (M-ICL), Multimodal Chains of Thought (M-CoT), and Large-scale Assisted Visual Reasoning (LAVR) to mimic human perception of the world. This enables interactive instruction–response pairs, including multimodal dialogues, factual knowledge reasoning dialogues, image and 3D scene descriptions, visual feature generalization, and even the conversion of visual and linguistic inputs into concrete reasoning, facilitating context-aware human–machine interaction.

With support from multimodal generative AI, multimedia educational content no longer requires manual editing. Teachers can better utilize text, audio, video, animations, and interactive elements to enhance learning experiences. By combining various forms such as instructional videos, virtual laboratories, and interactive courseware, teachers can generate customized learning content, enhancing student interaction with the instructional materials, meeting their learning needs and preferences, and fostering interest and participation.

This study, through profound consideration of the transformation of generative learning models, constructs and validates a conceptual model that examines the relationships among self-efficacy, learning motivation, strategies, technological acceptance, and teacher support, illustrating how generative AI fosters emergent learning models. Empirically, it explores how to promote educational intelligence and digital transformation. However, this study has limitations, primarily concerning the subjective perceptions of the survey respondents, leading to uncertainties. Future research should corroborate these findings with additional data and account for external objective factors. Collecting more qualitative data through various channels such as interviews, observations, and classroom recordings can provide richer information. Longitudinal studies can observe changes in students' self-directed learning abilities over time in generative AI-driven interactive learning environments. Additionally, considering other factors that may affect self-directed learning, such as learning styles, personality traits, and emotional factors, and incorporating them into the analysis is crucial. Amidst this, the teacher's role in imparting ethical guidance for AI usage becomes critical. Future research is called upon to explore how teachers ensure students' ethical application of AI, including, but not limited to, data privacy and social impacts.

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