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AN ADAPTIVE E-LEARNING ENVIRONMENT BASED ON GENERATIVE ARTIFICIAL INTELLIGENCE AND GENERATIVE FEEDBACK, AND ITS IMPACT ON COGNITIVE ACHIEVEMENT AND MOTIVATION TO LEARN AMONG STUDENTS OF EDUCATIONAL TECHNOLOGY AND COMPUTERS

Ashraf Mohamed Mohamed Elbradei[1], Abeer Bedair Basuny[2], Nagwa Elshamy Elshamy Mohamed[3], Amira Ahmed Fouad Hassan El-Okkiah[4]

[1,2]Associate Professor, Department of Educational Technology and Computers, Faculty of Specific Education, Kafr Elsheikh University, Egypt.
[3]Lecturer at the Department of Educational Technology and Computers - Faculty of Specific Education - Kafr Elsheikh University
[4]Associate Professor, Department of Educational Technology and Computers, Faculty of Specific Education, Kafr Elsheikh University, Egypt.

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Corresponding author: Ashraf Mohamed Mohamed Elbradei
(elbradei@spe.kfs.edu.eg)

ABSTRACT

The current research aims to determine the effect of the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (concise - explanatory) in an adaptive e-learning environment on the cognitive achievement and motivation to learn among students of educational technology and computer science. To achieve this goal, an adaptive electronic learning environment was applied to the research sample consisting of (80) students from the second level of the Department of Educational Technology and Computer Science at the Faculty of Specific Education, Kafr El-Sheikh University, and they were distributed into four main groups, each group consisting of (20) students, A group using the adaptive e-learning (traditional) and generative feedback style (Concise), a group using the adaptive e-learning style (generative artificial intelligence) and generative feedback style (Concise). A group using the adaptive e-learning pattern (traditional) and the generative feedback (Explanatory) pattern, and a group using the adaptive e-learning (generative artificial intelligence) pattern and the generative feedback pattern (Explanatory) with an adaptive e-learning environment, according to the variables of the current research. The cognitive achievement test and the learning motivation scale were administered to the research sample beforehand, to determine the level of achievement and motivation of the students before conducting the research experiment, and these scales were administered to the students afterward, The results indicated that the use of the adaptive e-learning style (generative artificial intelligence) and the generative feedback style (Explanatory) leads to an increase in cognitive achievement and raises the motivation to learn among students, with statistically significant differences. The interaction between them leads to the highest results between the groups, with no statistically significant differences in the interaction.

KEYWORDS: Adaptive e-learning environment, Adaptive e-learning style, Generative feedback style, Generative artificial intelligence, Cognitive achievement, Motivation to learn.

1. INTRODUCTION

As a result of the rapid and unprecedented advancements in artificial intelligence, significant transformations have occurred in the educational sector, in alignment with Egypt's Vision 2030. Education in the 21st century is undergoing an unprecedented transformation, with traditional teaching methods no longer able to compete with adaptive learning (Melzer, 2019). Modern learning approaches focus on meeting the individual needs of students, thereby enhancing their understanding, comprehension, and motivation to learn. (Zhang et al., 2020).

Teaching performance must evolve in parallel with technological advancement, as education continually adapts to new tools and technologies (Timotheou et al., 2023). Digital transformation has brought significant changes to teaching and learning methods worldwide (Mhlanga, 2022). Recently, technology-based learning has seen a notable increase in popularity, with growing use of software, applications, and digital learning platforms.

Despite the numerous benefits that technology offers in education, significant challenges remain in its effective integration. One of the foremost challenges is providing learning experiences specifically designed to meet the diverse needs and learning styles of students (Greenhow et al., 2022). This requires innovation in the development and delivery of high-quality, relevant educational content. Moreover, the role of teachers remains crucial in creating a supportive and motivating learning environment, as their responsibilities extend beyond traditional instruction to include facilitation, assessment, and inspiring students.

Adaptive learning systems represent a transformative shift in educational technology, as they dynamically personalize the learning process in accordance with learners' needs, preferences, and continuously evolving performance levels (Capuano N, Caballé S.2020) , (Wang S, et al.2023). This dynamic personalization directly supports personalized learning across diverse educational contexts. These systems rely on artificial intelligence techniques, particularly machine learning and deep learning, enabling the real-time processing of large volumes of learner data(Gheibi O, Weyns D, Quin F,2021), (Harati H,etal., 2021). Such computational capabilities facilitate the delivery of personalized learning experiences that address cognitive development and enhance emotional engagement, thereby positively influencing both the academic and affective dimensions of the learning process(Kaouni M,et al , 2023)

According to Wang et al. (2023), adaptive learning is a new way of teaching and learning that changes to fit each student's current performance. Using complicated algorithms and data analysis, this method constantly checks a student's interactions, answers and progress, changing the content, level of difficulty and resources as needed. With this, the learner's current knowledge and skills are kept in mind throughout the learning process, which promotes efficiency and focused growth.

Generative artificial intelligence stands out as a promising solution to address these challenges, as it has the ability to automatically generate new content based on patterns extracted from training data, enabling the production of more diverse, personalized, and relevant educational resources for the needs of both students and teachers (Baidoo-Anu, D., & Ansah, L. K. ,2023)

Generative artificial intelligence is likely to be perceived as a valuable tool if it provides effective and appropriate solutions that help teachers overcome challenges and meet their instructional needs. Its ability to support differentiated learning, adapt curricula to align with established standards, and offer personalized support to students can enhance teachers' perceptions of its usefulness and significance in the educational process (Baido-Ano & Ansah, 2023).

Generative artificial intelligence can produce content specifically designed to meet students' needs, thereby enhancing their engagement and understanding. Furthermore, given the ongoing demands on teachers to keep up with changes in curricula and learning standards, generative AI can generate content aligned with current curricula and standards, helping teachers prepare diverse and relevant instructional materials (Yu & Guo, 2023).

Several studies on the use of generative artificial intelligence in education have concluded that these tools hold significant potential to enhance classroom learning. Their innovative approaches contribute to student engagement, the adaptation of instructional materials, and individualized learning, thereby improving the efficiency and coherence of educational activities. By adopting these technological innovations, education can adapt to the challenges of the digital age while maintaining its relevance and impact (Bahroon et al., 2023; Baido-Ano & Anisa, 2023; Ratten & Jones, 2023; Ruiz Rojas et al., 2023).

Despite the rapid adoption of artificial intelligence in adaptive learning, fundamental challenges remain that hinder its effective, ethical, and equitable implementation. These challenges highlight the tension between the immense potential of technology and the need to maintain sustainable and balanced educational practices. (Yan, L. S., et al , 2023)

Furthermore, concerns have been raised regarding the potential of generative artificial intelligence to replace human roles in education, as it may reduce the need for faculty members and diminish human interaction within the learning process. Questions have also been raised about the quality of AI-generated instructional content, which may lack the depth and accuracy provided by human teachers, potentially affecting the overall quality of education (Brixaitis & Rose, 2023).

Effectively addressing these issues is essential for defining the role of generative artificial intelligence in higher education curricula. Educational institutions and instructors should establish comprehensive guidelines that promote the responsible use of AI, guide students in utilizing AI tools effectively and ethically, and support innovation in teaching and learning models. (Fergus, S.,et al., 2023) , (Chen, L.,et al ., 2020)

Achieving these objectives requires teachers to adopt carefully designed instructional strategies grounded in a deep understanding of how students interact with artificial intelligence technologies. This includes examining how students use the tools, their responses to AI-generated content, and the extent to which these technologies influence their cognitive and behavioral skills. It also necessitates designing teaching practices that account for individual learner differences and balance the benefits of AI capabilities with the promotion of learning and student motivation. (Davy Tsz, et al., 2025).

As generative artificial intelligence continues to expand in educational settings, generative feedback mechanisms have emerged as a vital and increasingly significant area of research. The value of immediate feedback was recognized as early as 1981, when psychologist B.F. Skinner proposed the theory of reinforcement learning, emphasizing that learning effectiveness improves substantially when timely and precise feedback is provided. (Lipnevich, A. A., & Panadero, E. ,2021). Skinner advocated for structured instructional designs that deliver feedback at every stage of the learning process. However, providing immediate feedback to large groups of students remains a practical challenge for educators, which has driven the development of AI-supported automated feedback systems, demonstrating promising potential in addressing these challenges. (Skinner, B. F.,1981)

Although previous studies have explored the role of generative artificial intelligence in education, a clear gap remains in systematically analyzing its impact on students' learning initiative and self-regulatory capacities, particularly within learning environments that emphasize practical applications. (Lyu, Y., & Ding, R. ,2025). Moreover, the adoption of this technology should not be viewed merely as the implementation of an educational tool; rather, it also reflects the interplay between learning motivation, educational culture, and social frameworks. This necessitates a comprehensive analysis to determine how these factors collectively influence the effective use of generative artificial intelligence in education. (Sarker, S.,et al., 2019)

Modern educational literature indicates that the effectiveness of digital learning heavily depends on the ability of learning environments to adapt to the individual needs of learners, with AI-driven adaptive learning considered one of the most promising approaches in this field (Kardan et al., 2015; Peng et al., 2019). Adaptive learning provides students with personalized learning pathways based on continuous analysis of their behaviors and achievement levels, thereby enhancing their understanding and mastery of the subject matter (Kem, 2022). Moreover, adaptive feedback is recognized as a critical component for improving cognitive achievement and motivating learners, as it delivers immediate and precise responses tailored to each student's level and information-processing capacity (Cho et al., 2020; Wang et al., 2019). However, there is a lack of studies that examine the integration of generative AI-based adaptive learning and generative feedback, particularly in the context of students in educational technology and computer science. This group can particularly benefit from self-assessment tools and targeted feedback to enhance their academic performance and learning motivation. Understanding the interaction between these two variables—generative AI-based adaptive learning and generative feedback—and their combined impact on cognitive achievement and motivation is therefore a crucial step toward designing more effective intelligent learning environments that respond to individual learner needs. This underscores the significance of the present study.

2. THEORETICAL FRAMEWORK

In this section, we provide a comprehensive overview of generative artificial intelligence

(GenAI), from its fundamental principles to its latest and most advanced forms. We also explore how it works, gradually moving from simple methods to generative applications, while discussing the educational theories that frame the use of generative AI in education. In addition, we highlight the role of generative feedback, in its brief and explanatory forms, and its impact on cognitive achievement and learning motivation among students of educational technology and computer science. Therefore, the theoretical framework of this research comes in four main themes as follows:

2.1. *The first theme: Generative Artificial Intelligence (GenAI)*

Generative artificial intelligence (Generative AI or GenAI) is a subfield of artificial intelligence that uses generative models to generate text, images, videos, audio, software code or other forms of data. These models learn the underlying patterns and structures of their training data and use them to produce new data(*Pasick, Adam, 2023)* in response to input, which often comes in the form of natural language prompts

Generative artificial intelligence, a branch of artificial intelligence, is a promising technology with immense potential to transform teaching and learning methods (Gimier et al., 2024). Understanding how to integrate this technology effectively is crucial for maximizing its positive impact on education.

Since the beginning of the 21st century, artificial intelligence has witnessed rapid development that has brought about significant changes in multiple fields, particularly cultural and educational ones (Obderbeck, 2019). Recent developments, especially the development of generative models capable of producing unique textual and visual content, are among the most prominent features of this progress (Bandi et al., 2023).

2.1.1. *Hierarchical Evolution from Artificial Intelligence to Generative AI*

The terms artificial intelligence, machine learning, and deep learning are widely used, though they refer to different aspects of this evolving field (Zeadally et al., 2020). Understanding the fundamental connections between them is essential when exploring algorithms and neural networks, particularly for advanced applications such as generative AI, while considering the broader context in which these concepts emerged. The following is a presentation of the most important of these concepts, which can be explained as follows:

Artificial Intelligence: Similar to a computer systems analyst, this branch of computer science focuses on designing and developing systems capable of performing tasks typically carried out by humans, as explained by Simon (1995). These tasks include problem-solving, understanding natural language, pattern recognition, and decision-making (Khanzode & Sarode, 2020).

Machine learning (ML): Machine learning is an important field in artificial intelligence, where algorithms and statistical models enable systems to perform specific tasks without the need for explicit programming instructions, relying instead on pattern detection and drawing inferences from data (Chou, 2021).

Deep learning: is a branch of machine learning that relies on multi-layered neural networks, hence its name. These models draw their structure and functions from the human brain, particularly from the interconnection of neurons (Lu et al., 2015).

Generative AI: In the context of deep learning, generative AI refers to models and algorithms designed to create new content or data that mimic the original data they were trained on. These models discover and reproduce patterns, structures, and distributions inherent in the data (Kao et al., 2023). The learning process is based on analyzing the content used in training to develop a statistical model. When the generative AI is provided with a specific input, this model is used to predict the expected response, which leads to the generation of new content (Bringolfsen et al., 2023).

2.1.2. *Concepts related to generative artificial intelligence*

Generative artificial intelligence (AI) is considered one of the most prominent modern technologies that enables automated systems to produce data and content autonomously (Rane, 2024). such as foundation models (Moor et al., 2023), pre-training (Radford et al., 2018), fine-tuning (Han et al., 2024), prompts (Han et al., 2024), parameters (Peeperkorn et al., 2024) and overfitting (Variš & Bojar, 2021) to work well in this complicated area.

Therefore, we will explain the basic concepts of generative artificial intelligence, which will help researchers understand how generative models work, make better decisions, and develop new ideas in creating AI-powered content:

Foundation Models: A foundation model is the core structure used by generative AI to autonomously generate data (Moor et al., 2023). Examples include GPT and variational autoencoders (VAEs), often forming adversarial networks (GANs), with each model suited for generating specific types of content such as text or images (Dogan et al., 2023).

Pre-training: Pre-training allows the model to learn fundamental features and patterns from large, diverse datasets before fine-tuning, using self-supervised or guided learning (Moor et al., 2023).

Fine-tuning: Fine-tuning adapts a pre-trained model to a specific task or dataset, updating parameters at a lower learning rate to improve task-specific performance and efficiency (Han et al., 2024; Howard & Ruder, 2018).

Prompts: A prompt guides generative AI to produce desired outputs (Heston & Khun, 2023). They can be simple or complex and include zero-shot, one-shot, or few-shot types, which differ in the amount of example information provided to the model (Fahes et al., 2023; Schick & Schütze, 2022).

Parameters: Parameters control LLM behavior and are tuned during training to improve NLP tasks. Key elements include embeddings, attention mechanisms, feedforward networks, and layer normalization, all affecting accuracy, speed, and efficiency (Shoeybi et al., 2019; Hoffmann et al., 2022; Wang et al., 2019).

Overfitting: Overfitting occurs when models memorize training data too closely, limiting generalization. Causes include high complexity, small datasets, poor hyperparameter settings, or long training (Zhu & Rao, 2023; Yang et al., 2023).

2.1.3. The potential of generative artificial intelligence in reshaping adaptive learning in education

Intelligent adaptive environments constitute core components of intelligent adaptive learning systems, as they monitor user interactions, measure learners' levels of engagement, and assess knowledge acquisition. These environments form the foundation of real-time learning personalization through the continuous observation of learner behavior and the adaptation of content presentation methods to meet individual needs. They also function as decision-support frameworks by modifying instructional content through adjusting task difficulty levels, providing additional learning materials, and recommending personalized feedback strategies (Bimba AT et al., 2017). Based on behavioral and performance data, these systems contribute to guiding the most appropriate learning pathways for each learner individually. (Bagunaid W et al.,2024).

Teachers face numerous challenges in improving their instructional performance, including adapting to diverse learning styles, providing appropriate instructional materials, offering effective feedback, and creating a supportive learning environment. Generative AI is expected to help address these challenges and assist teachers in enhancing the quality of instruction (Frey & Osborne, 2023).

Generative AI–driven adaptive learning environments represent a contemporary digital embodiment of the mastery learning approach developed by Bloom. Mastery learning divides knowledge into smaller units for gradual learning, followed by periodic assessments. Students receive corrective feedback and remedial support as needed until they achieve mastery of the material, after which they progress to the next unit (Murray & Pérez, 2015). Generative AI programs implement this approach by adapting tasks and learning cycles, leveraging feedback, assessment, and guided sequencing to meet the individual needs of each learner. (Akpan, B. ,2020).

The ease of learning generative AI is closely linked to effective teaching practices, as it affects teachers' ability to master the technology. Availability of supportive resources—such as tutorials, user guides, and instructional videos—along with an intuitive interface, facilitates this process. These findings align with previous research showing that simple and clear interfaces help teachers quickly learn and use generative AI effectively (Prasad Agrawal, 2023).

The Potential of Generative Artificial Intelligence in Reshaping Adaptive Learning in Education: Generative artificial intelligence encompasses tools and techniques capable of transforming adaptive learning by providing personalized educational content that meets the needs of each learner, enhancing engagement and motivation, and improving knowledge acquisition. These capabilities play a pivotal role in developing flexible and individualized learning models aligned with students' abilities and learning styles

A fundamental feature of these systems is their classification frameworks, which categorize learners based on their academic performance, motivation, engagement, and learning styles. (Bernard J, Popescu E, Graf S,2022) These frameworks directly support the delivery of adaptive content by enabling differentiated and personalized learning pathways for each learner. For instance, students who demonstrate high curiosity and active engagement can be directed toward exploratory tasks, whereas learners who require additional support receive enhanced resources and formative feedback tailored to their needs.(Shafique R,et al ,2023) , (Hu J, Jin G, 2024)

Adaptive learning systems integrate cognitive and emotional modeling to monitor learners' emotional states, such as frustration or boredom, using behavioral and physiological indicators. (Yadegaridehkordi E,2019). These insights enable timely emotional support, enhancing learner motivation, supporting academic performance, and fostering sustained engagement (Subha,S., et al,2023) , (Essa SG, Çelik T, 2023)

Generative artificial intelligence (GAI) is fundamentally transforming the production, evaluation, and feedback of educational materials through automation, personalization, and real-time adaptation to learner needs. Based on a comprehensive analysis of a wide range of studies, we offer a holistic view of how GAI can be applied in these areas. Based on the latest research and theoretical frameworks in this field, this section also reviews the ability of generative AI to predict optimal strategies for improving learning pathways.

Generative artificial intelligence has attracted growing attention due to its advanced innovative capabilities. By leveraging deep learning techniques, generative AI enables the creation of diverse content, including text, images, audio, and video, excelling in creative and interactive tasks. In the field of education, it offers substantial potential for supporting adaptive learning, providing immediate feedback, and assisting with academic tasks such as data analysis, literature review, and report writing, thereby improving learning outcomes. Moreover, its ability to support complex problem-solving and advance research through accurate outputs and clear guidance positions it as a transformative tool in modern educational environments (White, J., et al., 2023) , (Khlaif, Z. N. et al. , 2023)

2.1.4. Generative AI in Content Creation

Generative AI has revolutionized content creation, providing tools that enable the automatic generation of massive amounts of personalized educational content for each learner. These developments can be categorized into two main groups: .(Guettala,M et al., 2024)

A. Automated generation of questions, assignments and learning materials

Generative AI can automatically create questions (multiple-choice or short-answer), full assignments aligned with the curriculum, and engaging learning materials such as simulations, diagrams, and visual aids, saving teachers time and enhancing student learning (Kurdi et al., 2020; Gimpel et al., 2023)

B. Personalized Content for Different Learning Styles and Paces

Generative AI can tailor educational content to students' learning styles and speeds, providing audio, visual, or interactive materials, and adjusting complexity or pace to match individual needs (Leiker et al., 2023).

- Generative AI in Assessment and Feedback:

Generative AI enhances assessment by enabling automated grading of both objective and subjective tasks, reducing bias and improving fairness (Doo et al., 2023). It also provides personalized feedback tailored to each student's needs, delivered in text, audio, or visual formats (Nysom, 2023).

2.1.5. Challenges related to generative artificial intelligence

Although generative artificial intelligence possesses a strong capability to learn from vast amounts of data, its training datasets may contain inherent biases, inaccurate information, or outdated content, which can be reproduced in the generated outputs. Consequently, some outputs of generative AI may lack the required accuracy, particularly in highly specialized and sensitive domains, potentially leading to misconceptions among learners. Therefore, it is essential to cultivate students' critical judgment and systematic evaluation skills when using AI tools, in order to mitigate uncritical acceptance of AI-generated content and ensure its responsible use.(Ausín, T.,2021), (Wach, K. et al., 2023).

These challenges encompass technical, ethical, social, and cultural aspects, such as data privacy issues, algorithmic bias, model interpretability, infrastructure limitations, and the ability to adapt to different cultural contexts, along with trade-offs related to learner engagement levels. (Holmes, W., et al., 2019)

Furthermore, concerns have been raised regarding the potential of generative artificial intelligence to replace human roles in education, as it may reduce the need for faculty members and diminish human interaction within the learning process. Questions have also been raised about the quality of AI-generated instructional content, which may lack the depth and accuracy provided by human teachers, potentially affecting the overall quality of education (Brixaitis & Rose, 2023).

Furthermore, generative artificial intelligence may exacerbate the digital divide, as this technology is accessible to only a limited number of institutions or students, creating disparities in learning opportunities and access to quality education (Manuro et al., 2023). Implementation and institutional readiness also pose significant challenges, as many educational institutions may lack the infrastructure, resources, and expertise needed to adopt these technologies effectively, potentially limiting their optimal use or leading to failure (Conkie et al., 2023).

The use of generative artificial intelligence in education may lead to the exploitation of student data in undesirable or unethical ways. Additionally, AI-generated content may contain inaccurate information or reinforce existing biases, posing further challenges to ensuring the quality and integrity of education (Chan,C & Ho,W, 2023).

Data privacy is one of the most prominent concerns regarding artificial intelligence in education. These systems rely heavily on collecting large amounts of learner data, including behavioral records, assessment results, and even biometric indicators.(El Mestari SZ, et al., 2024)

The risk of algorithmic bias is closely linked to privacy issues. When AI systems are trained on limited-diversity datasets, the outputs may unintentionally reinforce educational inequalities. Continuous auditing and improvement strategies demonstrate the importance of addressing this bias to ensure fair educational recommendations and effective learning. (Aquino,Y, 2023) , (Mavrogiorgos K, et al., 2024) .To ensure fairness, developers should construct comprehensive training datasets and conduct regular audits to detect and mitigate bias. (Kaouni M, et al., 2023)

Another major challenge is the limited interpretability of complex AI models, especially those based on deep learning. These obscure models often lack transparency, making it difficult for teachers and students to understand or validate the decisions made by AI. (Gulum M, 2021)

Although the study by Fan, L. et al. (2025) offers valuable scholarly contributions, it is not without methodological limitations. Most notably, its reliance on self-reported data may introduce biases in students' assessments of their use of artificial intelligence or their actual learning outcomes. This discrepancy between perceived and actual learning may negatively affect motivation and engagement. To address these limitations, future research is recommended to employ multiple data sources, including objective performance indicators, teacher evaluations, and learning platform log data.

Moreover, excessive reliance by students on artificial intelligence tools may undermine their capacity for independent thinking, which runs counter to the primary goal of education: fostering critical thinking. Therefore, developing effective strategies for integrating generative AI into educational practice, while mitigating its potential negative effects, represents a critical issue that warrants in-depth discussion. (Bak-Coleman, J. et al, 2023)

2.2. The second theme: generative feedback

Student motivation and engagement are considered central to enhancing learning effectiveness, particularly in the context of the dynamic and often volatile educational environments that teachers have increasingly faced in recent years. Providing students with feedback during their learning activities is an effective strategy for boosting motivation and improving their learning experience (Fidan & Gencsel, 2022). Accordingly, student motivation and engagement can be further enhanced through the implementation of feedback mechanisms that deliver genuine educational value and support active, interactive learning (Kuklic et al., 2023).

Students' feedback literacy is of particular importance, as effective engagement with feedback requires a high level of skill and cognitive effort on the part of learners (Van der Kleij, 2020). Feedback literacy refers to the set of knowledge, skills, and dispositions that enable students to interpret feedback information and use it effectively to improve their academic work or adapt their learning strategies (Carless & Boud, 2018). Students with a high level of feedback literacy are better able to overcome barriers related to receiving, understanding, interpreting, and applying feedback in their learning practices (Van der Kleij, 2020).

2.2.1. The potential of generative artificial intelligence in providing generative feedback

In recent years, higher education has witnessed the initial adoption of generative artificial intelligence (Generative AI) in assessment and feedback practices (Rudolph et al., 2023). This form of artificial intelligence is based on large language models, which are large-scale artificial neural networks pre-trained on vast amounts of textual data, enabling them to generate linguistic outputs that closely resemble human writing. Several researchers have highlighted a number of potential educational advantages of generative AI, including interactivity, anxiety reduction, enhanced communicative authenticity, learner-centeredness, opportunities for repeated practice, and scalability (Jeon et al., 2023; Rawas, 2024). These characteristics enable generative AI tools to provide feedback on students' work through more engaging, flexible, and dialogic interactions that closely approximate human feedback (Ali et al., 2023).

Generative artificial intelligence offers promising opportunities to enhance digital learning environments (Morgan Stanley, 2023), such as its use in automated assessment, providing feedback to learners, and improving the overall learning experience (Kuklic et al., 2023 : Whalen et al., 2023). However, despite these significant potentials, research in this field faces notable challenges due to the novelty of generative AI technologies, including the lack of advanced solutions, limited specialized expertise, and the absence of widely adopted practices for integrating generative AI into digital education and feedback mechanisms (Hopper et al., 2024).

Moreover, artificial intelligence can provide rich information about students' needs as revealed during subsequent reviews. The iterative and ongoing feedback and reflection mechanisms offered by AI enable students to collect feedback from multiple experiences, create their own feedback loops, and monitor their progress toward self-defined improvement goals. Additionally, generative AI can provide personalized suggestions to students in a non-judgmental manner through an easy-to-use interface (Huang et al., 2023; Wongvorachan et al., 2022), and can even review students' work or correct their errors directly upon request (Casaló, L. V.et al., 2024).

Generative feedback represents one of the prominent applications of generative artificial intelligence in digital education, aiming to provide immediate and personalized responses to learners in a way that adapts to their individual needs and knowledge levels. This type of feedback differs from traditional feedback methods in its ability to generate dynamic and non-predefined responses, whether simple, such as indicating the correctness or incorrectness of an answer, or detailed, including explanations, hints, or suggestions to improve performance, thereby enhancing deep understanding and promoting critical thinking (Wang et al., 2019; Cho et al., 2020). By continuously analyzing student behavior and performance data, generative AI tools can design iterative feedback loops that help students review concepts, correct errors, and organize their knowledge in an individualized and continuous manner (Huang et al., 2023; Casenici et al., 2023).

Moreover, these mechanisms provide a safe and low-anxiety learning environment, particularly for learners who fear social evaluation or making mistakes in front of teachers and peers, thereby enhancing motivation and encouraging ongoing practice (Tai & Chen, 2024).

However, generative feedback faces challenges related to the accuracy and reliability of the information and the potential to produce biased or contextually inappropriate responses, necessitating careful design and application to ensure its effectiveness in promoting cognitive achievement and learning motivation (Thorp, 2023; Rawas, 2024).

Generative artificial intelligence offers novel capabilities for providing feedback to learners, enabling the delivery of precise and personalized responses to each individual student—responses that may be difficult or impossible to achieve through traditional methods that do not involve human instructors. Consequently, it is essential for research studies to examine how AI-supported feedback influences students' motivation, academic performance, and overall learning experience. (Zhang, A., et al., 2025)

Generative AI (GenAI) tools are increasingly being employed to provide feedback to students within classroom settings, whether through direct interactive dialogues or by reviewing work and offering improvement suggestions. However, despite the rapid adoption of these tools, there remains a lack of critical research evaluating the quality and accuracy of the feedback they generate, including its relevance to students' academic levels and its effectiveness in promoting deep learning and cognitive achievement. (Herb, A., & Lloyd, C. ,2024).

However, the integration of next-generation artificial intelligence into assessment practices raises significant challenges and multiple ethical concerns, including the risks of generating biased or misleading information, issues of academic misconduct and plagiarism, and the potential for overreliance on technology (Dawson, 2021; Su et al., 2023; Thorpe, 2023). Accordingly, it is essential to develop a systematic understanding of how generative artificial intelligence can be employed effectively and responsibly, in ways that mitigate its potential risks while simultaneously enhancing student engagement in assessment and feedback processes.

More importantly, it should be recognized that AI-supported feedback environments do not operate independently of learners' characteristics; rather, they inevitably interact with students' personal factors, such as their cognitive abilities, motivations and expectations, prior knowledge and experiences, and level of academic maturity. This interaction leads to combined and interactive effects on how students receive and engage with feedback (Han, 2019; Nieminen et al., 2022; Shen & Chung, 2023).

Artificial intelligence can provide students with an effective means of overcoming contextual constraints associated with receiving feedback, as it enables continuous access at any time without being limited by scheduling conflicts, which are common challenges in interactions with human instructors (Huang et al., 2023). It also allows learners to request feedback whenever needed without delay (Lee et al., 2022) and without being subject to social monitoring or evaluation by others. Moreover, artificial intelligence can create a less anxiety-inducing learning environment for students who may hesitate to seek feedback due to social anxiety or fear of human criticism. In this regard, Tai and Chen (2024) found that students experienced lower levels of anxiety when making linguistic errors while interacting with chatbots and reported greater comfort in performing learning tasks, as they were aware that the chatbots were artificial systems rather than real individuals.

Moreover, artificial intelligence can provide rich information about students' needs as revealed during subsequent reviews. The iterative and ongoing feedback and reflection mechanisms offered by AI enable students to collect feedback from multiple experiences, create their own feedback loops, and monitor their progress toward self-defined improvement goals. Additionally, generative AI can provide personalized suggestions to students in a non-judgmental manner through an easy-to-use interface (Huang et al., 2023; Wongvorachan et al., 2022), and can even review students' work or correct their errors directly upon request (Casaló, L. V.et al., 2024).

However, generative artificial intelligence faces several limitations that may hinder students' effective engagement with feedback processing. Thorpe (2023) notes that AI systems may occasionally produce inaccurate, unclear, or even fabricated responses when addressing students' questions. In addition, Tariq, N et al. (2025) highlight concerns related to the reliability and validity of outputs generated by AI tools. Moreover, generative AI relies heavily on its training data; when these data contain embedded biases, the resulting feedback may be inaccurate or unfair in evaluating students' work (Rawas, 2024). If students accept such feedback uncritically, this may lead to superficial engagement with learning processes or a reduction in their learning motivation (Berman & Ajjawi, 2023).

2.2.2. *Types of generative feedback*

In digital learning environments supported by generative AI, generative feedback takes various forms to address learners' diverse cognitive needs and can be broadly categorized into two types : concise feedback and explanatory feedback.

Concise feedback is one of the most common forms of feedback in digital learning environments due to its effectiveness in providing quick and practical assessments of learner performance. This type of feedback is characterized by brevity and clarity, indicating whether an answer is correct or incorrect, or assigning a specific score without offering extensive explanations, allowing students to immediately verify the accuracy of their responses (Shute, 2008). Concise feedback is particularly effective in supporting repetitive learning, such as repeated practice in solving mathematical problems or language exercises, helping students quickly identify and correct basic errors before moving on to more complex concepts or tasks (Narciss, 2008).

Concise feedback provides direct and immediate responses, such as indicating whether an answer is correct or incorrect, or giving a percentage score, enabling students to quickly check their performance without requiring detailed explanations. This type of feedback is particularly useful for reinforcing repetitive learning or managing large numbers of students, as it delivers rapid assessment that guides learners toward correcting fundamental errors (Shute, 2008).

Concise feedback is also useful for managing large classes or online learning environments, as it provides teachers with a quick method to deliver an overall assessment to students without the need to review each individual work in detail (Gikandi et al., 2011). Studies indicate that this type of feedback enhances learners' time efficiency and increases the frequency of interaction with educational content, which in turn promotes self-directed and independent learning (Van der Kleij et al., 2015).

Despite its simplicity, concise feedback can be motivating for students when applied thoughtfully, as it allows learners to continuously gauge their progress and guides them toward targeted review or intensive practice of skills that have not yet been mastered (Shute, 2008; Narciss, 2008). However, research indicates that its effectiveness is highest when combined with other types of feedback, such as explanatory feedback, enabling a balance between speed and clarity on one hand, and depth and understanding on the other (Bittner et al., 2019; Bisra et al., 2018).

Explanatory feedback, on the other hand, goes beyond merely indicating whether an answer is correct or incorrect. It provides detailed explanations, hints, or suggestions aimed at fostering deeper understanding and enhancing learners' analytical and applied skills. This type of feedback enables students to interpret the reasons behind their success or failure on a given task, guiding them to refine learning strategies or reorganize acquired knowledge for application to new problems (Wang et al., 2019; Cho et al., 2020). Studies have shown that explanatory feedback positively impacts cognitive achievement, stimulates intrinsic motivation for learning, and enhances autonomy in learning strategies, especially when provided repeatedly and progressively in alignment with the student's level and capacity to process information (Boud & Molloy, 2013; Narciss, 2008).

Studies show that explanatory feedback enhances cognitive achievement because it helps students process errors deeply and understand fundamental concepts, rather than relying on superficial memorization (Narciss, 2008; Bittner et al., 2019). It also boosts learning motivation by providing personalized content that reflects the individual student's level and encourages them to adjust their learning strategies, rather than relying solely on general comments (Bisra et al., 2018).

An important feature of explanatory feedback is that it supports self-directed learning and continuous assessment, allowing students to internalize feedback, review their errors, and retry tasks within a supportive and safe learning environment. This enhances learner autonomy and reduces error-related anxiety (Shute, 2008; Wang et al., 2019). Furthermore, in the context of AI-supported digital learning, explanatory feedback can be generative and dynamic, adapting to the student's level and learning style while providing real-time, personalized guidance, thereby increasing its effectiveness in improving cognitive achievement and enhancing engagement with the learning content (Cho et al., 2020; Bittner et al., 2019).

Detailed feedback provides explanations, hints, or suggestions aimed at deepening the learner's understanding and enhancing their ability to apply knowledge to new problems, making it a central focus in studies on effective learning (Wang et al., 2019). Recent research has highlighted its potential to improve the learning experience and motivate students, with Cho et al. (2020) confirming its ability to enhance academic achievement within the context of formative assessment. In analyzing the effectiveness of different types of feedback, Daniels & Bulut (2020) examined the impact of various levels and forms of feedback on learning, emphasizing the pivotal role of detailed feedback in strengthening students' understanding and developing their cognitive skills.

Research indicates that combining both concise and explanatory feedback can enhance student engagement with educational content, increase motivation, and improve cognitive achievement, while maintaining a balance between speed and efficiency on one hand, and depth and comprehension on the other (Bittner et al., 2019; Bisra et al., 2018).

2.3. The Third theme Educational theories supporting the variables of the current research

Educational theories have given considerable attention to understanding the role that artificial intelligence can play in enhancing learning and improving its effectiveness. For instance, constructivist theory views learning as an active process in which learners gradually build knowledge through interaction with the educational environment, exploration, critical reflection, and engagement in real-world problem-solving. (Kim, M., & Adlof, L. ,2023) This theory emphasizes the crucial role of the learner in forming concepts and understanding the relationships between ideas, highlighting that learning is more effective when it is learner-centered and provides opportunities for self-experimentation and continuous review of acquired concepts. In this context, generative artificial intelligence can support constructivist principles by offering personalized educational content, interactive tools, and activities that foster critical thinking, as well as providing immediate feedback that helps students assess their progress and continuously refine their understanding of concepts. (Piaget, J., 2001) , (Suvarna, N. R., & Kumar, N. ,2023)

Understanding the pedagogical foundations of generative AI–driven adaptive learning environments is essential for comprehending their design and functionality. These foundations form the core framework of such environments, providing insight into how educational content and learning pathways can be tailored to meet the needs of each learner. (Qian, Y. ,2025) They also pave the way for in-depth research on the effectiveness of these environments, strategies for their enhancement, and the expansion of their applications across diverse educational contexts.(Zhao, Y., & Chen, X. ,2025).

Several researchers have highlighted the limited attention given to pedagogical foundations in empirical studies on the use of generative artificial intelligence in adaptive learning environments, emphasizing the need for research that balances technological advancement with the validation of educational theories (Bremgartner et al., 2015; Zwacki-Richter et al., 2019; Bartolomé et al., 2018). In this context, the present study reviews key pedagogical frameworks, philosophies, and theories that form the basis for designing generative AI–enhanced adaptive learning environments, ensuring the integration of educational practices with technological capabilities.

The effectiveness of generative artificial intelligence (GenAI) and generative feedback in education is grounded in a set of educational theories that explain how they support the learning process and facilitate student development, as follows:

Constructivism Theory : emphasizes that knowledge is built through the learner's interaction with the environment and educational content, with a focus on the individual's prior experiences (Piaget, 1972; Vygotsky, 1978). Within this framework, generative artificial intelligence provides a flexible learning environment that can adapt content and feedback according to the learner's level, thereby enhancing individual knowledge construction and supporting self-directed and experiential learning.

The Information Processing Theory : posits that learning occurs through the processing of information and its transfer into long-term memory via attention, encoding, and retrieval (Atkinson & Shiffrin, 1968). Generative feedback, whether concise or explanatory, provides learners with opportunities to process information repeatedly and systematically, reducing cognitive load through repeated guided cues and real-time error correction, thereby facilitating the transfer of knowledge to new tasks.

Bandura's Social Learning Theory (1977) : emphasizes the interactive nature of learning, suggesting that learning occurs through observing models and acquiring skills via imitation and practice. Generative AI enables students to interact with intelligent systems that simulate human-like behaviors in providing feedback, thereby offering a model for systematic thinking and problem-solving, while enhancing motivation by building learners' self-confidence during the learning process.

Adaptive Learning Theory : emphasizes the importance of providing personalized content and instructions tailored to the learner's individual abilities and needs (Brusilovsky, 2001). The integration of generative AI with generative feedback enables the adaptation of difficulty levels, the timing of feedback delivery, and its type (concise or explanatory) according to each learner's capacity to process information, thereby enhancing both cognitive achievement and motivation.

Self-Determination Theory :emphasizes the fulfilment of three basic psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 2000). Generative feedback in AI-enhanced learning environments provides learners with opportunities to receive personalized, non-judgmental feedback, strengthen their sense of competence, and motivate them to take control of their own learning paths, thereby supporting sustained and autonomous learning motivation.

2.4. The Fourth theme: Contributions of current research variables to learning outcomes

Although previous studies have explored the role of generative artificial intelligence in education, a clear gap remains in systematically analyzing its impact on students' learning initiative and self-regulatory capacities, particularly within learning environments that emphasize practical applications. (Lyu, Y., & Ding, R. ,2025). Moreover, the adoption of this technology should not be viewed merely as the implementation of an educational tool; rather, it also reflects the interplay between learning motivation, educational culture, and social frameworks. This necessitates a comprehensive analysis to determine how these factors collectively influence the effective use of generative artificial intelligence in education. (Sarker, S.,et al., 2019)

Within the education sector, generative artificial intelligence presents distinct advantages by enabling personalized and adaptive learning experiences. It facilitates a diverse array of educational opportunities, including real-time feedback, automated generation of instructional resources, adaptive content delivery, and the creation of interactive learning environments. Collectively, these capabilities enhance the effectiveness, engagement, and individualization of the learning process, thereby supporting more meaningful and learner-centered educational outcomes. (Kikalishvili, S.,2024) , (Bak-Coleman, J.

et al. 2023)

In this context, it is essential to understand how students in educational technology utilize generative artificial intelligence and how it is integrated into their daily learning processes, particularly within the framework of Egyptian social culture and the current practice-oriented education system. Accordingly, the significance of this study lies in addressing the existing empirical research gap regarding the impact of generative artificial intelligence on learning behaviors, academic achievement, and students' motivation to learn. While this study does not aim to propose new theoretical frameworks, its data and observations may contribute to a deeper understanding of established educational theories and potentially inform the development of new theoretical perspectives in this domain.

Generative artificial intelligence facilitates problem-based and collaborative learning by providing practical activities that encourage students to apply theoretical knowledge effectively in real-world contexts. It also supports the development of critical thinking, reflective communication, and problem-solving skills, thereby enhancing students' preparedness to tackle complex future challenges. (Kikalishvili, S. , 2024) , ((Ahn, S. J., et al., 2022) .Moreover, generative AI deepens students' understanding of abstract concepts and stimulates their motivation to engage in experimental and design-based projects by promoting active and reflective learning practices. (Cheng, S. C. et al., 2019), (Gallent-Torres, C et al., 2023).

For instance, Escalante et al ,2023 employed generative artificial intelligence to provide multidimensional suggestions within automated writing assessment systems, while Hao et al.,2022 developed AI-based evaluation tools. However, these systems often fall short in delivering deep cognitive insights, particularly in helping students identify and address core issues in argumentative writing. (Banihashem, S. K.,2024) , (Er, E.,et al ., 2024). One potential way forward is to integrate human expertise with generative AI feedback to enhance the quality and depth of student support. (Ruiz de Zarobe, Y., & Cañas, J. ,2025).

The study by Ying, L., et al. (2025) provides a systematic analysis of adaptive learning environments in the educational domain, outlining their pedagogical foundations, AI-supported applications, and the key challenges and opportunities associated with their practical implementation. It also explains how learner data are utilized to analyze behavioral patterns and dynamically adapt content and learning pathways, thereby contributing to improved learning outcomes. In addition, the study reviews the design frameworks of adaptive learning environments, their core algorithms, and performance evaluation criteria across diverse educational contexts, while highlighting major challenges such as data privacy concerns and faculty support, and exploring future directions for the development of adaptive technologies.

An Adaptive Learning Platform (ALP) is an e-learning environment that employs adaptive technologies to dynamically personalize educational content to meet the individual learning needs of students. Through this personalized learning approach, each learner receives content tailored to their characteristics, abilities, and learning styles, which contributes to improved learning outcomes and enhanced effectiveness (Peng et al., 2019).

These platforms, which are often supported by artificial intelligence technologies (Kardan et al., 2015), rely on the continuous analysis of learner data—such as prior knowledge and learning preferences (Jando et al., 2017)—to construct detailed learner profiles. Based on these profiles, the platforms adapt instructional resources and recommend personalized learning pathways, enabling each student to progress along an individualized path toward mastery (Kem, 2022).

In contrast, traditional teaching methods in e-learning environments often follow a "one-size-fits-all" approach where the same educational resources and content are provided to all students without adaptation to their individual needs or knowledge levels. (El-Sabagh, H. A. ,2021). Although this approach has limited capacity to address learners' individual differences, it remains necessary in many classrooms, especially those characterized by large class sizes and limited instructional time, making the provision of uniform content more practical and efficient (Sharma et al., 2017).

Some traditional academic institutions may continue to rely on non-adaptive e-learning systems due to low adoption rates or the high initial costs associated with developing the infrastructure required for adaptive learning and content personalization. However, this uniform approach to instruction can hinder the progress of advanced learners while increasing the burden on students who struggle to grasp the course material (Hwang et al., 2020)

Generative artificial intelligence, combined with adaptive learning approaches, offers new opportunities, such as producing instant learning materials customized for each student. It is also conceivable that a system would be designed in which tasks and tests are automatically selected to challenge the student in accordance with his prior knowledge, thus contributing to making the learning process more efficient and concise (Allasade & Bayes, 2023).

Numerous studies have highlighted the critical role of feedback in enhancing learners' motivation and active engagement in the learning process (Bittner et al., 2019; Oeste-Reiß et al., 2016; Wambsganss et al., 2022), as well as its role in supporting self-explanation and developing learners' self-regulatory skills (Bisra et al., 2018; Hefter & Berthold, 2020). This impact is particularly evident in educational settings that rely on formative assessment, where adaptive feedback demonstrates its capacity to tailor content and guidance according to each student's level and individual needs, thereby improving learning effectiveness and educational outcomes (Llorens et al., 2014; Llorens et al., 2016).

Although various forms of feedback are provided to learners, studies have shown that generative feedback is a particularly effective tool in the learning process, as it helps reduce cognitive load, increase learner motivation, and improve academic performance. Generative feedback can range from simple verification of responses (e.g., correct/incorrect or a percentage score) to detailed feedback that explains why an answer is right or wrong, with the option of providing the correct answer or offering guidance without revealing it. (Mekheimer, M. ,2025).

Students hold varied perceptions of feedback (Daniels & Bulut, 2020; Sai et al., 2023). Previous studies have demonstrated the effectiveness of different forms of generative feedback, particularly detailed feedback, in enhancing digital learning. However, these studies have also highlighted the need for further refinement of these mechanisms to align with the evolving demands of the continuously advancing digital learning era (Cho et al., 2020; Botello et al., 2023).

Studies have shown that integrating generative AI into learning environments can enhance learners' intrinsic motivation and active engagement in learning. Generative AI enables learners to receive immediate and accurate feedback that adapts to each student's level and information-processing ability, thereby enhancing their sense of competence and control over the learning process (Cho et al., 2020; Wang et al., 2019).

Generative AI–based adaptive learning environments provide a less threatening learning setting compared to direct human interaction, allowing students to request feedback without fear of criticism or social accountability, thereby increasing their willingness to engage and participate (Tai & Chen, 2024).

In addition, by customizing content and feedback style according to the student's preferences, generative AI enhances the learner's sense of autonomy and control over their learning path, thereby supporting ongoing self-directed learning motivation (Deci & Ryan, 2000). Moreover, generative AI creates an interactive learning environment capable of simulating human-like dialogues, which increases student engagement and motivates more active participation in the learning process (Ali et al., 2023).

Studies addressing this gap and integrating generative artificial intelligence for feedback provision remain notably scarce, with only a few exceptions targeting highly specific cases, such as supporting legal or argumentative writing for law students (Weber et al., 2023; Wambsganss et al., 2022). Nevertheless, employing generative AI to provide feedback to students could potentially enhance learner motivation and engagement, improve academic performance, and enrich the overall learning experience. To address this gap, the present research proposes a novel approach for integrating generative AI into education through the concept of generative feedback. Therefore, this study seeks to evaluate how the use of artificial intelligence affects students' learning behaviors, their level of academic achievement, and their motivation to learn, in addition to identifying the most effective strategies for integrating an adaptive learning style based on artificial intelligence and generative feedback.

2.5. Search problem

Despite technological advancements in employing e-learning management systems in education, they are limited to standardized educational models that do not take into account the individual differences between students. The full potential of adaptive learning is not utilized to tailor content and activities to each student's needs. Furthermore, feedback patterns within these environments are traditional and do not adequately contribute to fostering deep understanding or enhancing motivation to learn.

With the rapid development of generative artificial intelligence (AI) technologies, the potential has emerged for developing adaptive e-learning environments that rely on analyzing learner data and generating immediate, personalized feedback, thus contributing to improved learning outcomes. However, research addressing the application of generative AI within adaptive learning environments remains scarce. In particular, with regard to studying the effect of the interaction between adaptive learning style (traditional vs. generative AI-based) and generative feedback style (concise vs. explanatory) on cognitive achievement and motivation to learn.

Therefore, the research problem is defined as the need to investigate the effectiveness of employing generative artificial intelligence in building an adaptive e-learning environment. The study reveals the impact of the interaction between adaptive learning patterns and generative feedback patterns on the development of cognitive achievement and motivation to learn among students of educational technology and computer science, which contributes to providing a scientific and applied model that can be used in developing e-learning practices.

2.6. Research objectives

1. Reaching the design standards that must be considered when using an adaptive e-learning environment.
2. Measuring the impact of the adaptive e-learning style (traditional - generative artificial intelligence) in the adaptive e-learning environment.
3. Measurement and pattern of generative feedback (concise - explanatory) in an adaptive e-learning environment.
4. Measuring the impact of the interaction between (adaptive e-learning style / generative feedback style) in the adaptive e-learning environment on students' cognitive achievement and motivation to learn

2.7. The importance of research

The importance of this research lies in employing generative artificial intelligence within an adaptive e-learning environment, and studying the impact of the interaction between adaptive learning and generative feedback on developing cognitive achievement and motivation to learn. This contributes to the development of e-learning practices and supports the move towards personalized smart education, which in turn contributes to:

1. This research contributes to a deeper scientific understanding of the use of traditional adaptive learning and the generative AI-based approach currently under development.
2. The application of generative AI is not merely as a support tool, but as an active element in building feedback and improving learning outcomes.
3. Developing the design of online courses in Moodle by providing a practical model for building an adaptive learning environment that relies on automatically and intelligently guiding learning paths.
4. Improving students' cognitive achievement by employing the feedback style best suited to the learner's nature.
5. To foster a motivation to learn among educational technology students by providing a suitable, adaptive learning environment.
6. To present a practical model that can be used in developing online courses on the Moodle platform.

2.8. Research limits

1. Second-level students in the Department of Educational Technology and Computer Science at the Faculty of Specific Education, Kafr El-Sheikh University
2. Two types of adaptive e-learning (traditional - generative artificial intelligence).
3. Two types of generative feedback (concise - explanatory).
4. Measuring cognitive achievement and motivation to learn in an adaptive e-learning environment for students.

3. RESEARCH DESIGN AND PARTICIPANTS

3.1. Research Methodology

The research uses the descriptive approach to identify the specifications and standards of the adaptive e-learning environment, and the quasi-experimental approach to measure the effect of the interaction between the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (concise - explanatory) on the cognitive achievement and motivation to learn among students.

3.2. Experimental Design

The current research employs an experimental design to demonstrate the impact of independent research variables (adaptive e-learning style and generative feedback style) on the cognitive achievement and motivation to learn among educational technology and computer science students. Based on these independent variables, (2x2) experimental design was used, as illustrated in the following table.

Table

Experimental Design of the Research		
generative feedback pattern	**Adaptive e-learning style**	
	Traditional	generative artificial intelligence
Concise	Experimental Group (1) traditional + Concise	Experimental Group (2) generative artificial intelligence + Concise
Explanatory	Experimental Group (3) traditional + Explanatory	Experimental Group (4) generative artificial intelligence + Explanatory

3.3. Participants in the research experiment

The research sample consisted of 80 male and female students in the second year of the Department of Educational Technology and Computer Science at the Faculty of Specific Education, Kafr El-Sheikh University, and they were distributed into 4 homogeneous groups of 20 students in each group as follows:

a. **Group 1:** Uses adaptive e-learning (traditional) and generative feedback (Concise).
b. **Group 2:** Uses adaptive e-learning (generative artificial intelligence) and generative feedback (Concise).
c. **Group 3:** Uses adaptive e-learning (traditional) and generative feedback (Explanatory).
d. **Group 4**: Uses adaptive e-learning (generative artificial intelligence) and generative feedback (Explanatory).

3.4. Search tools

1. Achievement test assigned (production of educational images).
2. Learning Motivation Scale.
3. An adaptive e-learning environment, which is an electronic platform on which adaptive learning design is available according to the research variables, and the Moodle learning management system was used.

3.5. Research hypotheses

1- There are statistically significant differences at the significance level ($\alpha \geq 0.05$) between the mean scores of the experimental groups using the adaptive e-learning style (traditional - generative artificial intelligence) on cognitive achievement.

2- There are statistically significant differences at the significance level ($\alpha \geq 0.05$) between the mean scores of the experimental groups that use the generative feedback pattern (Concise - Explanatory) on cognitive achievement.

3- There are statistically significant differences at the significance level of ($\alpha \geq 0.05$) between the mean scores of the four experimental groups due to the effect of the interaction between the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (concise - explanatory) on cognitive achievement.

4- There are statistically significant differences at the significance level of ($\alpha \geq 0.05$) between the mean scores of the experimental groups using the adaptive e-learning style (traditional - generative artificial intelligence) on motivation to learn.

5- There are statistically significant differences at the significance level ($\alpha \geq 0.05$) between the mean scores of the experimental groups that use the generative feedback pattern (concise - explanatory) on motivation to learn.

6- There are statistically significant differences at the significance level ($\alpha \geq 0.05$) between the mean scores of the four experimental groups, due to the interaction effect between the adaptive e-learning style (traditional – generative artificial intelligence) and the generative feedback style (concise – explanatory) on motivation to learn.

4. SEARCH PROCEDURES

4.1. First: The preparation and equipment stage

4.1.1. Defining the Educational Content

The course for producing educational images for the second level of the Department of Educational Technology and Computer Science at the Faculty of Specific Education, Kafr El-Sheikh University, was determined, the scientific content was identified, a list of educational objectives was prepared, and all files related to the course were collected with the aim of using them to generate content with generative artificial intelligence.

4.1.2. Provide Instructions

This step aims to clarify how the student can adapt to the proposed e-learning environment. Therefore, instructions were presented to the students participating in the research experiment, clarifying what is required of them, such as how to use the Moodle learning management system platform and access it, dealing with the scientific content published on the platform and available to each group according to the search variables, and how to move between parts of the course according to the student's progress level.

4.1.3. Defining and selecting experimental groups

The cognitive achievement test and the e-learning motivation scale were applied before conducting the research experiment on a large number of second-level students in the Department of Educational Technology and Computer Science at the Faculty of Specific Education, Kafr El-Sheikh University, and only 80 students were selected from among the students who had low scores in cognitive achievement and a low level of motivation to learn , The students were divided into four main groups of 20 students each, so that there would be homogeneity and equivalence among the groups, since any change in the cognitive level and motivation to learn afterwards is due to the effect of the research variables.

4.2. Second: Design and Production Phase

4.2.1. Building an adaptive e-learning environment

An adaptive learning environment refers to one that automatically changes the learning content, path, or provides support according to the learner's performance, interaction, and needs. In this research, adaptation was applied to performance, which may be traditional, following fixed rules, or based on generative artificial intelligence.

The Moodle learning content management system is considered the best as it allows educational content to be presented in more than one format: PDF files, videos, lessons. It is divided into three levels (basic, intermediate, and advanced). To implement these procedures, completion tracking and quiz reports were activated to clarify indicators (grade, completion time, number of attempts, browsing pattern) and to judge the student's performance in order to provide the appropriate method for him.

4.2.2. Distributing students across an adaptive learning environment

The data of the participating students (name, username, and password) was entered into the Learning Management System (LMS). There were 80 students. The students were then categorized into four groups on the LMS based on the research variables, as follows:

a. **Group 1: 20** students using an adaptive learning environment with adaptive e-learning style (traditional) and a generative feedback style (concise).
b. **Group 2: 20** students using an adaptive learning environment with adaptive e-learning style (generative artificial intelligence) and a generative feedback style (concise).
c. **Group 3: 20** students using an adaptive learning environment with an adaptive e-learning style (traditional) and a generative feedback style (Explanatory).
d. **Group 4: 20** students using an adaptive learning environment with an adaptive e-learning style (generative artificial intelligence) and a generative feedback style (Explanatory).

4.2.3. Building Adaptive Learning Patterns on the Moodle Learning Management System

The learning content was divided into three levels, and the student was guided according to the following adaptive pathways:

1. **High:** Provided with advanced content
2. **Medium:** Provided with standard content
3. **Low:** Provided with supportive content

4.2.4. Traditional Adaptive Learning Pattern

Relies on displaying content according to the restriction of access to resources, or the completion of the activity, the logical conditions for navigation, and the tools are set up in the learning management system. If the score is less than 60%, it displays supporting content.

4.2.5. The adaptive learning model based on generative artificial intelligence

Relies on analyzing student performance and suggesting scientific content produced with artificial intelligence tools. Google's notebooklm tool was used to analyze the scientific content and produce AI lessons as an alternative to the original content on the platform, and display it to the student according to the student's grade.

4.2.6. Building Generative Feedback Patterns

Generative feedback consists of messages and content that show the student the result of their performance and explain why their performance has declined, thus helping them choose the right path while navigating through different parts of the content.

4.2.7. Generative feedback Concise

Direct feedback that focuses on the correctness of the answer (only the correct answer is given). It presents concise scientific content quickly without detailed explanation and was implemented in Moodle using Quiz + Feedback.

4.2.8. Generative Feedback Explanatory

Feedback that displays (the reason for the error - the method of answering - educational guidance), presents detailed scientific content with an explanation suitable for understanding, and is implemented in Moodle by creating general feedback and combined feedback and linking them to the level of the error, then displaying an explanation, guidance, or educational support.

4.2.9. Building measurement and evaluation tools

The measurement and evaluation tools in the current research were determined in light of the dependent variables to be measured and their impact on the independent variables. Therefore, an assessment tool for cognitive achievement was designed using an objective achievement test, and a motivation scale for learning was used using an adaptive e-learning environment.

1-Objective cognitive achievement test

The objective achievement test aims to measure the cognitive aspect of the educational image production course for the research sample, in light of the educational objectives of the course. The achievement test is applied beforehand to the research sample in order to determine the homogeneity of the groups, and the achievement test is applied after hand in order to identify the effect of the independent variables of the research on cognitive achievement.

The objective test consisted of 20 multiple-choice questions and 20 true/false questions, all covering aspects of the educational content. The achievement test questions were graded by recording (1) for each correct answer and (0) for each incorrect answer, resulting in a total score of (40) for all test questions. The test duration was set at 45 minutes.

2-Learning Motivation Scale

This scale aims to measure the motivation to learn among students studying computer science and e-learning courses at the undergraduate level. The statements of the learning scale by Nasra Jaljal (2007) were used as is without modification, this scale includes 22 statements that measure the different aspects of motivation to learn, and it has been tested on a sample of educational technology students at the Faculty of Specific Education, computer teachers. Therefore, this scale is considered suitable for application to the current research sample.

The Likert scale is used to measure the rating through 5 responses: (Disagree "1" - Somewhat Agree "2" - Sometimes Agree "3" - Often Agree "4" - Always Agree "5"). The total score on the scale represents the student's degree of motivation to learn. Then, the total score obtained by the student is divided by the number of items on the scale (22). The rating of students' motivation to learn is as follows:

1. A student's score greater than (3) indicates high motivation to learn.
2. A student's score less than (3) indicates low motivation to learn.
3. A student's score equal to (3) indicates medium motivation to learn.

4.3. Third: The research experiment implementation stage

4.3.1. Pre-evaluation of research tools

1- Cognitive Achievement Test

The pre-test of cognitive achievement was administered to the research sample before they were exposed to the main research variables in order to ensure that all experimental groups were homogeneous and the level of cognitive achievement was equal. To verify that there were no differences between the scores of the pre-test of achievement, the One-Way ANOVA test was applied, as shown in the results of Table 1.

Table 1

ANOVA					
Differences between students' scores on the pre-test of cognitive achievement					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.950	3	2.983	.212	.887
Within Groups	1067.000	76	14.039		
Total	1075.950	79			

The results in Table 1 show a significance level higher than 0.05, which indicates that there are no differences between the experimental research groups, as well as the homogeneity of the participating students in terms of the level of cognitive achievement, and that the differences that appear afterward for cognitive achievement are due to the effect of the independent variables of the research.

2- Learning Motivation Scale

The pre-learning motivation scale was applied to the research sample before they were exposed to the main research variables in order to ensure that all experimental groups were homogeneous and that the level of motivation to learn was similar for all groups and low. To verify that there were no differences between the scores of the pre-learning motivation scale, the One-Way ANOVA test was applied, as shown in the results of Table 2.

Table 2

ANOVA					
Differences between students' scores on the pre-learning motivation scale					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.018	3	.006	.211	.889
Within Groups	2.213	76	.029		
Total	2.231	79			

The results in Table 2 show a significance level higher than 0.05, indicating that there are no differences between the experimental research groups, and that there is homogeneity among the participants in terms of motivation to learn, and that the differences that appear afterward in motivation to learn are due to the effect of the independent variables of the research

4.3.2. Applying dimensional measurement tools

The cognitive achievement test and the post-learning motivation scale were administered, and the averages for all four experimental groups were calculated based on the scores obtained, in order to arrive at the research results and confirm the hypotheses.

5. RESEARCH RESULTS AND DISCUSSION

5.1. Presenting the results related to cognitive achievement

The averages of the post-test cognitive achievement scores were calculated for each experimental group, and the independent variables were identified as the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (Concise - explanatory) The results are shown in Table 3.

Table 3

Average scores in the post-test cognitive achievement test for each experimental group					
generative feedback pattern	**Adaptive e-learning style**	**group**	**N**	**Mean**	**Std. Error**
Concise	Traditional	1	20	30.95	3.235
	generative artificial intelligence	2	20	34.50	3.268
Explanatory	Traditional	3	20	32.90	1.618
	generative artificial intelligence	4	20	35.70	3.246

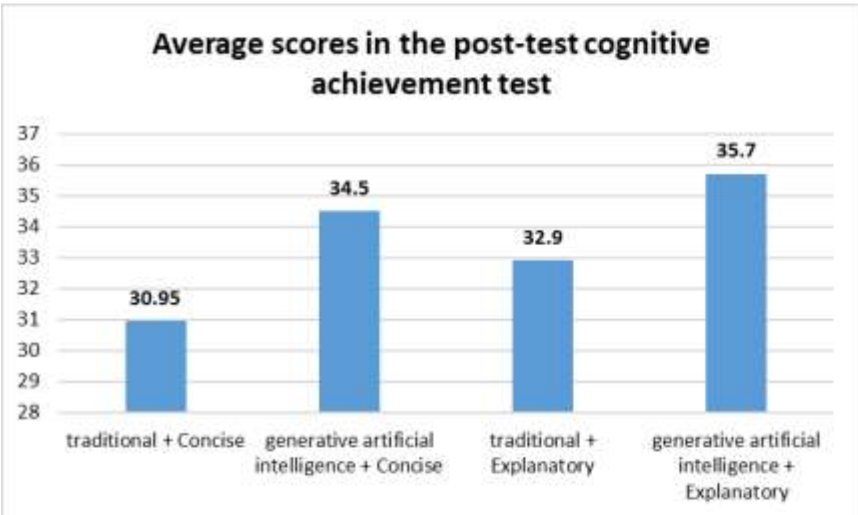

Figure:

The results of the previous table show a difference between the average scores of the cognitive achievement test among the four experimental groups according to the independent research variables, which requires conducting various statistical analyses and confirming the existence of statistically significant differences and proving the validity of the research hypotheses related to cognitive achievement.

A two-way analysis of variance (ANOVA) was performed on the students' scores in the post-test cognitive achievement test to clarify the statistical differences between the research variables, the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (Concise - explanatory), and to confirm the existence of interaction between the variables, as shown in the results of Table 4.

Table 4

Two-way analysis of variance between students' scores on the post-test cognitive achievement test					
Source	**Type III Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
Corrected Model	254.038[a]	3	84.679	9.871	.000
Intercept	89847.013	1	89847.013	10473.768	.000
Adaptive e-learning style	201.612	1	201.612	23.503	.000
generative feedback pattern	49.613	1	49.613	5.783	.019
Adaptive e-learning * generative feedback	2.813	1	2.813	.328	.569
Error	651.950	76	8.578		
Total	90753.000	80			
Corrected Total	905.988	79			

Hypothesis No. (1): "There are statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the experimental groups using the adaptive e-learning style (traditional - generative artificial intelligence) on cognitive achievement."

In the previous table No. 4, it is clear that the significance level is significant at the level of 0.01 in the first variable, the adaptive e-learning pattern, with a degree of freedom (1). This indicates that there are significant differences between the mean scores of the post-test cognitive achievement test for the experimental groups that use the adaptive e-learning style (traditional - generative artificial intelligence). To determine the direction of the hypothesis, the averages of the groups using the adaptive e-learning (traditional) pattern with 40 students and the adaptive e-learning (generative artificial intelligence) pattern with 40 students were calculated, regardless of the other variable, as shown in Table 5.

Table 5

Average scores of the post-test cognitive achievement in the adaptive e-learning style			
Adaptive e-learning style	**N**	**Mean**	**Std. Error**
Traditional	40	31.92	2.711
generative artificial intelligence	40	35.10	3.272

From the previous table, the adaptive e-learning style (generative artificial intelligence) has the highest average score of (35.10), which indicates that (generative artificial intelligence) works to greatly raise the cognitive achievement of students.

Based on the previous result, hypothesis number (1) was accepted and the direction of the difference was determined, which is: "There are statistically significant differences at the significance level of (α ≥ 0.05) between the mean scores of the experimental groups using the adaptive e-learning style (traditional - generative artificial intelligence) on cognitive achievement in favor of the experimental groups using the adaptive e-learning style (generative artificial intelligence)."

Hypothesis No. (2): "There are statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the experimental groups that use the generative feedback pattern (Concise - Explanatory) on cognitive achievement."

From the results of Table 4, it is clear that the significance level is significant at the 0.01 level in the second variable, the generative feedback pattern, with a degree of freedom (1), which indicates that there are significant differences between the mean scores of the post-test cognitive achievement test for the experimental groups that use the generative feedback pattern (Concise - explanatory). To determine the direction of the hypothesis, the means of the groups using the generative (Concise) feedback pattern (40 students) and the generative (explanatory) feedback pattern (40 students) were calculated, regardless of the other variable, as shown in Table 6.

Table 6

Average scores on the cognitive achievement test in the generative feedback pattern			
generative feedback pattern	N	Mean	Std. Error
Concise	40	32.72	3.679
Explanatory	40	34.30	2.901

From the previous table, it is clear that the generative feedback pattern (Explanatory) had the highest average score of (34.30), which indicates that the generative feedback pattern (Explanatory) leads to a significant increase in the level of cognitive achievement among students.

Based on the previous result, hypothesis No. (2) was accepted and the direction of the difference was determined, which is: “There are statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the experimental groups that use the generative feedback pattern (Concise - Explanatory) on cognitive achievement, in favor of experimental groups using the generative feedback pattern (Explanatory)”.

Hypothesis No. (3): “There are statistically significant differences at the significance level of (α ≥ 0.05) between the mean scores of the four experimental groups due to the effect of the interaction between the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (concise - explanatory) on cognitive achievement”.

From the results of Table No. 4, it is clear that the significance level is (0.569), which is not statistically significant in the interaction between the first variable (adaptive e-learning pattern) and the second variable (generative feedback pattern) with a degree of freedom.(1) , This indicates that there are no significant differences between the mean scores of the post-test cognitive achievement test for the four experimental groups that use the interaction between the two variables, and the calculation of the mean scores of the cognitive achievement test for each experimental group is shown in Table 7.

Table 7

Average scores of the post-test cognitive achievement test for each experimental group					
generative feedback pattern	Adaptive e-learning style	group	N	Mean	Std. Deviation
Concise	Traditional	1	20	30.95	3.235
	generative artificial intelligence	2	20	34.50	3.268
Explanatory	Traditional	3	20	32.90	1.618
	generative artificial intelligence	4	20	35.70	3.246

From the previous table, the fourth group, which uses the adaptive e-learning style (generative artificial intelligence) and the generative feedback style (Explanatory), has the highest average score of (35.70) and leads to a significant increase in cognitive achievement among students.

Based on the previous result, hypothesis number (3) was rejected, meaning that: “There are no statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the four experimental groups due to the interaction effect between the adaptive e-learning style (traditional – generative artificial intelligence) and the generative feedback style (Concise – explanatory) on cognitive achievement.”

5.2. Presenting the results of the motivation to learn scale

The averages of the post-learning motivation scale scores were calculated for each experimental group, with the two independent variables being the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (concise - explanatory). The results are shown in Table 8.

Table 7

Average scores on the post-test motivation to learn scale for each experimental group					
generative feedback pattern	**Adaptive e-learning style**	**group**	**N**	**Mean**	**Std. Error**
Concise	Traditional	1	20	3.22	.145
	generative artificial intelligence	2	20	3.38	.149
Explanatory	Traditional	3	20	3.30	.072
	generative artificial intelligence	4	20	3.43	.148

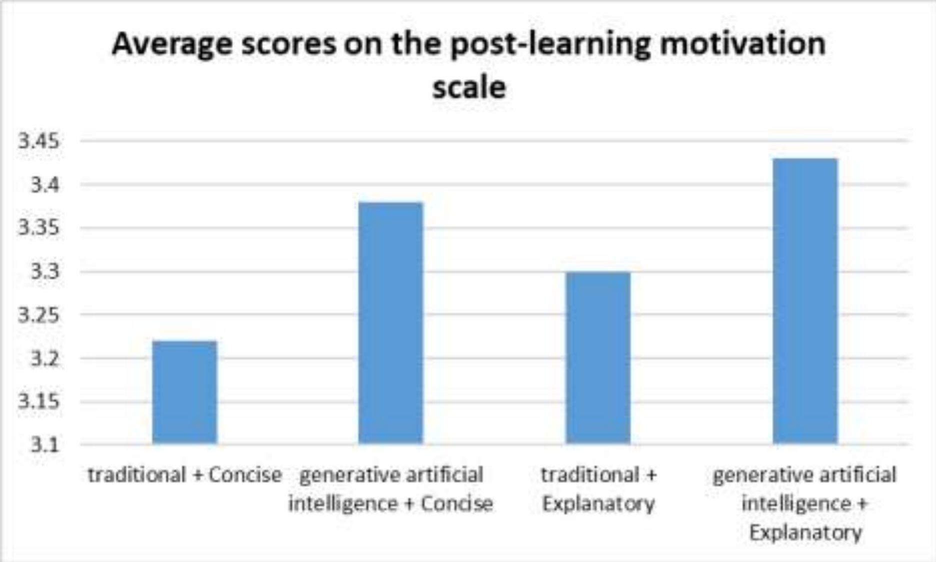

Figure:

The results of the previous table show that there is a difference between the average scores within the four experimental groups according to the independent research variables, which requires conducting various statistical analyses and confirming the existence of statistically significant differences and proving the validity of the research hypotheses regarding motivation to learn.

A two-way analysis of variance (ANOVA) test was applied to the students' scores on the post-test motivation to learning scale to show the statistical differences in the research variables, the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (Concise - explanatory), as well as to show the interaction between the two variables, as shown in Table 8.

Table 8

Two-way analysis of variance between students' scores on the post-test motivation to learn scale					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected Model	.518[a]	3	.173	9.726	.000
Intercept	890.512	1	890.512	50171.355	.000
Adaptive e-learning style	.410	1	.410	23.123	.000
generative feedback pattern	.102	1	.102	5.720	.019
Adaptive e-learning style * generative feedback pattern	.006	1	.006	.335	.564
Error	1.349	76	.018		
Total	892.379	80			
Corrected Total	1.867	79			

Hypotheses No. (4): There are statistically significant differences at the significance level of (α ≥ 0.05) between the mean scores of the experimental groups using the adaptive e-learning style (traditional - generative artificial intelligence) on motivation to learn.

From the previous table No. 8, it is clear that the significance level is significant at the 0.01 level in the first variable, the adaptive e-learning pattern, with a degree of freedom (1) , This indicates that there are significant differences between the mean scores of the post-test motivation to learn scale for the experimental groups using the adaptive e-learning style (traditional - generative artificial intelligence), To determine the direction of the hypothesis, the averages of the groups using the adaptive e-learning (traditional) pattern with 40 students and the adaptive e-learning (generative artificial intelligence) pattern with 40 students were calculated, regardless of the other variable, as shown in Table 9.

Table 9

Average scores on the post-learning motivation scale in the adaptive e-learning model			
generative artificial intelligence	N	Mean	Std. Error
Traditional	40	3.26	.122
generative artificial intelligence	40	3.40	.149

From the previous table, it is clear that the average score for the motivation to learn scale is above 3, which indicates that the level of motivation to learn is (high), and the adaptive e-learning style (generative artificial intelligence) has the highest average score of (3.40) and leads to a significant increase in the level of motivation to learn among students.

Based on the previous result, hypothesis number (4) was accepted and the direction of the difference was determined, which is: There are statistically significant differences at the (α ≤ 0.05) level between the mean scores of the experimental groups using the adaptive e-learning model (traditional – generative artificial intelligence) on motivation to learn, in favor of the experimental groups using the adaptive e-learning model (generative artificial intelligence).

Hypothesis No. (5): "There are statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the experimental groups that use the generative feedback pattern (concise - explanatory) on motivation to learn."

Table No. 8 shows that the significance level is significant at the 0.01 level in the second variable, the generative feedback pattern with a degree of freedom (1). This indicates that there are significant differences between the mean scores of the post-test motivation to learn scale for the experimental groups that use the generative feedback pattern (concise - explanatory). To determine the direction of the hypothesis, the averages of the groups using the generative feedback pattern (concise) with 40 students and the generative feedback pattern (explanatory) with 40 students were calculated, regardless of the other variable, as shown in Table 10.

Table 10:

Average scores of the post-test motivational learning scale in the generative feedback pattern			
generative feedback pattern	N	Mean	Std. Error
Concise	40	3.30	.166
Explanatory	40	3.37	.132

From the previous table, it is clear that the average score for the level of motivation to learn is higher than 3, which indicates that the level of motivation is (high). The generative feedback pattern (interpretive) has the highest average score of (3.37) and leads to a significant increase in the level of motivation to learn among students.

Based on the previous result, hypothesis number (5) was accepted and the direction of the difference was determined, which is: " There are statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the experimental groups using the generative feedback pattern (Concise– explanatory) on motivation to learn, in favor of the experimental groups using the generative feedback pattern (explanatory)".

Hypothesis No. (6): "There are statistically significant differences at the significance level (α ≥ 0.05) between the mean scores of the four experimental groups, due to the interaction effect between the adaptive e-learning style (traditional – generative artificial intelligence) and the generative feedback style (concise – explanatory) on motivation to learn".

From the results of Table No. 8, it is clear that the significance level is (0.564), which is not statistically significant in the interaction between the first variable (adaptive e-learning pattern) and the second variable (generative feedback pattern) with a degree of freedom (1). This indicates that there are no statistically significant differences between the mean scores of the post-test motivation to learn scale for the four experimental groups using the interaction between the two variables. The mean scores of the post-test motivation to learn for each experimental group are calculated as shown in Table 11.

Table 11:

Average scores on the learning motivation scale for each experimental group					
generative feedback pattern	**Adaptive e-learning style**	**group**	**N**	**Mean**	**Std. Deviation**
Concise	Traditional	1	20	3.22	.145
	generative artificial intelligence	2	20	3.38	.149
Explanatory	Traditional	3	20	3.30	.072
	generative artificial intelligence	4	20	3.43	.148

The table above shows that the fourth group, which uses the adaptive e-learning style (generative artificial intelligence) and the generative feedback style (interpretive), has the highest average score of (3.43) and leads to a significant increase in the students' motivation to learn (high).

Based on the previous result, hypothesis No. (6) was rejected, which is: “There are no statistically significant differences at the significance level of ($\alpha \geq 0.05$) between the mean scores of the four experimental groups due to the effect of the interaction between the adaptive e-learning style (traditional - generative artificial intelligence) and the generative feedback style (Concise - explanatory) on the motivation to learn.”

6. DISCUSSION

The previous analysis provided a comprehensive exploration of the impact of AI use on students’ learning behaviors, academic achievement, and motivation to learn, as well as identifying the most effective strategies for integrating AI-based adaptive learning and generative feedback.

The results of the current study indicate a clear superiority of the adaptive learning environment supported by generative artificial intelligence over the traditional adaptive environment in terms of both cognitive achievement and learning motivation among students of educational technology and computer science. These findings can be interpreted in light of the interactive and generative characteristics of generative artificial intelligence, compared with the relatively limited adaptive mechanisms found in traditional learning environments.

At the level of cognitive achievement, the results show that the generative adaptive environment enabled students to develop a deeper understanding of scientific concepts. This can be attributed to the ability of generative artificial intelligence to provide dynamic explanatory feedback that goes beyond merely identifying errors to explaining their underlying causes and offering guided alternatives and solutions. These findings are consistent with previous studies indicating that AI-supported explanatory feedback contributes to reducing surface learning and enhancing deep cognitive processing of content (Shute, 2008; Wang et al., 2019; Cho et al., 2020). In contrast, traditional adaptive environments often rely on fixed or pre-defined feedback patterns, which limits their ability to respond accurately to the diversity of students’ error patterns and their individual cognitive needs.

The results revealed the superiority of the generative AI–supported environment in enhancing students’ learning motivation, which can be explained through several interrelated factors. The generative environment provided continuous dialogic interaction that closely resembled human communication, thereby strengthening students’ sense of immediate support and guidance and reducing anxiety associated with making mistakes. These findings are consistent with previous studies by Tai and Chen (2024) and Ali et al. (2023), which demonstrated that interaction with non-judgmental intelligent systems enhances learner engagement and increases readiness for learning.

These results can also be interpreted in light of Self-Determination Theory (Deci & Ryan, 2000), as generative artificial intelligence contributed to satisfying learners’ basic psychological needs. It enhanced learners’ sense of autonomy by allowing them to control their learning pathways and request feedback at any time, supported their sense of competence through personalized feedback that accurately reflected their actual progress, and fostered a sense of relatedness through continuous dialogic interaction, even when this interaction occurred with an intelligent system rather than a human instructor.

The results indicate that the adaptive environment supported by generative artificial intelligence was more capable of accommodating individual differences among learners compared to the traditional adaptive environment. While the latter often relies on predefined adaptation rules (such as progression across fixed difficulty levels), generative artificial intelligence demonstrates a greater capacity to analyze students’ real-time responses, patterns of thinking, and interaction histories, and to generate content and feedback that dynamically adapt accordingly. This interpretation aligns with the principles of Adaptive Learning Theory (Brusilovsky, 2001) and Information Processing Theory (Atkinson & Shiffrin, 1968).

The results showed that students in the generative learning environment demonstrated higher levels of engagement and learning persistence. This can be attributed to the nature of generative feedback, which encourages continuous review, repeated attempts, and the construction of self-regulated learning loops, rather than merely receiving final, summative comments as is often the case in some traditional adaptive learning environments. These findings support recent trends emphasizing that the integration of artificial intelligence with adaptive feedback enhances learners' motivation to learn This result is consistent with the research findings with (Bittner et al., 2019; Bisra et al., 2018).

Generative AI can be an effective tool if teachers believe in its ability to enhance the effectiveness of learning. This includes its capability to produce educational materials specifically designed to meet students' needs and preferences, in addition to providing appropriate feedback to support the improvement of students' understanding and academic performance. These findings align with previous studies that have indicated that the ability of generative AI to generate additional educational materials or automatically provide relevant resources can reduce teachers' workload, allowing them to focus more on direct interactions with students (George, 2023).

Overall, the findings of the present study confirm that the added value of generative artificial intelligence lies not only in its ability to adapt to students' levels, but also in its capacity for intelligent generative interaction that integrates personalization, explanation, and both psychological and cognitive support. Nevertheless, this advantage does not diminish the importance of the teacher's pedagogical role, nor does it negate the need for ethical guidelines and quality standards to ensure the responsible use of artificial intelligence in education.

7. CONCLUSION

In conclusion, this research illuminates the findings of this study, it can be concluded that implementing adaptive learning based on generative AI, coupled with adaptive feedback, represents a promising approach to enhancing learning outcomes in higher education, particularly for students in Educational Technology and Computer Science. The results demonstrated the superiority of the generative AI–supported adaptive environment over the traditional adaptive environment in fostering both cognitive achievement and learning motivation. This reflects the added value of intelligent generative interaction, which is capable of providing personalized, immediate, and explanatory feedback tailored to the individual needs of learners.

The study also demonstrated that integrating adaptive learning with generative feedback contributes to accommodating individual differences among students and enhances their active engagement and persistence in learning. This is achieved by supporting deep understanding, encouraging self-review, and fostering continuous learning loops. These factors, in turn, positively impact cognitive achievement and learning motivation. These findings align with contemporary theoretical perspectives in constructivist learning, adaptive learning, and self-determination theory, which emphasize the importance of personalization, interaction, and cognitive and psychological support in promoting effective learning.

This research ultimately concludes that making optimal use of generative artificial intelligence technologies in education requires an awareness of their limitations and challenges, and the necessity of employing them within clear educational and ethical frameworks, while maintaining the pivotal role of the teacher in educational guidance and support.

8. RECOMMENDATIONS AND FURTHER RESEARCH

8.1. Recommendations

The research recommends intensifying future studies that address the design of adaptive learning models based on generative artificial intelligence in various educational disciplines, and studying their long-term impact on learning outcomes, in addition to developing quality standards that ensure the responsible and effective use of these technologies in digital educational environments.

Expanding the integration of generative artificial intelligence in university education: Universities and higher education institutions are advised to adopt adaptive learning systems supported by generative artificial intelligence, particularly in practical and technical disciplines such as educational technology and computer science, given their ability to improve cognitive achievement and enhance motivation to learn.

Training teachers on the use of generative artificial intelligence: Training programs should be provided to teachers to familiarize them with how to effectively employ generative artificial intelligence, including designing personalized educational content, providing immediate and interpretive feedback, and managing interactive and safe learning environments.

Developing ethical policies and frameworks: It is essential to establish ethical controls and standards that ensure the responsible use of artificial intelligence in education, including protecting student data, avoiding bias in feedback, and ensuring the quality of generative content.

Encouraging independent self-learning: It is recommended to use generative artificial intelligence to promote self-learning and continuous learning among students, by providing interactive and dynamic feedback that supports independence, competence and control over the learning path.

8.2. Further Research

Studying individual differences and their impact on responding to generative feedback: It is important to explore how the impact of generative artificial intelligence varies on students according to their abilities, learning styles, and level of prior experience.

Analyzing the effect of combining different types of generative feedback: Future research could study the effectiveness of combining brief and interpretive feedback in improving deep learning and academic achievement.

Psychological and behavioral impact assessment: It is suggested to study the impact of generative artificial intelligence on students' long-term motivation, learning anxiety, and self-confidence.

Exploring applications of generative artificial intelligence in multiple educational fields: Future studies include comparisons between different disciplines (e.g., humanities versus technical sciences) to understand the possibilities of adaptation and generation in multiple contexts.

Improve the design of generative feedback systems: Directing research to develop more accurate and reliable generative AI algorithms, capable of providing personalized and immediate feedback while minimizing potential errors or biases.

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