Analyzing the Impact of AI Text Generators on Learning Styles, Technological Dependency, and Critical Thinking among Accounting Students

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***Abstract*—The integration of Artificial Intelligence Text Generators (AITGs), such as ChatGPT, Copilot, Gemini, and QuillBot, in education has raised critical questions about their impact on student learning. This study examines the influence of AITGs on learning styles, technology dependency, and critical thinking among accounting students, with synchronous and asynchronous learning methods as moderating variables. Using The Unified Theory of Acceptance and Use of Technology (UTAUT) as a framework, data were collected from 106 undergraduate accounting students and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that AITGs enhance critical thinking and contribute to technology dependency but do not significantly affect students' learning styles. Additionally, synchronous learning strengthens the relationship between AITGs use and critical thinking, while asynchronous learning does not show a significant moderating effect. These findings highlight the dual role of AITGs in promoting cognitive skills and fostering technology reliance. The study provides practical insights for educators and policymakers into the strategic integration of AITGs to balance their benefits with the risks of dependency.**

***Keywords*—Artificial Intelligence (AI) text generators, learning styles, critical thinking, technology dependency, synchronous learning, asynchronous learning, The Unified Theory of Acceptance and Use of Technology (UTAUT) framework**

I. Introduction

The development of Artificial Intelligence (AI) in the mid-20th century has led to its integration into the modern life, with revolutionary implications across various sectors, including healthcare, finance, manufacturing, and education [1, 2]. In the field of education, AI-driven technologies, including AI Text Generators (AITGs), are receiving considerable attention for their potential to transform traditional teaching methods and enhance learning outcomes [3, 4]. AITGs, such as ChatGPT and Gemini, provide students with tools that assist in generating written content, making them increasingly popular in academic settings.

However, their impact on learning styles, critical thinking, and technology dependency, particularly among accounting students, raises significant questions concerning the influence of these tools on educational outcomes, especially in synchronous and asynchronous learning environments. Although some studies indicate that AITGs may enhance students' performance and problem-solving abilities [4, 5], concerns about dependency and ethical implications persist [6, 7], emphasizing the necessity for further research.

This study contributes to the existing literature by addressing critical gaps in the understanding of AITGs' educational impacts. While prior research has predominantly explored the technical capabilities and general benefits of AITGs, this study examines their specific effects on learning style, critical thinking, and technology dependency within the domain of accounting education. Furthermore, it evaluates the moderating roles of synchronous and asynchronous learning environments, which have received limited attention in existing studies. By providing empirical evidence on these nuanced interactions, the research offers novel insights into the strategic use of AITGs for enhancing educational outcomes while mitigating potential risks.

Despite the growing application of AITGs in academic contexts, there is a lack of empirical research examining their direct impact on learning styles, critical thinking, and technology dependency, particularly among accounting students. The extant literature has primarily focused on the functionality and popularity of these tools, yet has not fully examined the deeper implications of their use across different learning environments [8–10]. Despite the capacity of AITGs, such as ChatGPT, to provide correct or partially correct responses, there has been inadequate focus on how these tools impact the advancement of critical thinking abilities or result in potential over-reliance on technology [5, 11].

As several researchers have observed, an excessive reliance on AI may result in reduced critical thinking and decision-making abilities among students. Given that the field of accounting education has traditionally relied on conventional methods, it is important to gain an in-depth understanding of how AITGs impact students in both synchronous and asynchronous learning environments. This study addresses these gaps by investigating the mediating role of AITGs and the moderating effect of synchronous and asynchronous learning methods on students' learning outcomes.

Considering the aforementioned knowledge gaps, this study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as the primary theoretical framework for investigating the acceptance and usage of AITGs among accounting students. The UTAUT model, based on four core constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) [12], provides a robust basis for understanding factors driving the adoption of AITGs in education.

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II. Literature Review

A. Artificial Intelligence Text Generators (AITGs)

AITGs are a subset of Natural Language Processing (NLP) within the broader field of AI, designed to generate text with human language characteristics [13]. AITGs, including models such as ChatGPT, Copilot, and QuillBot, have a wide range of applications in education. They can be utilized to assist students in various tasks, including summarization, paraphrasing, and essay writing [14, 15]. Recent AITG developments, especially ChatGPT and GPT-4, have shown impressive abilities in generating high-quality, human-like text [16, 17]. These technologies have transformed the way students interact with complex materials. AI text generators can help students understand complex language and basic accounting principles, which are essential for academic and professional success.

In addition to improving students' academic writing and cognitive skills, AITGs have shown their potential in supporting learners with unique needs, for instance, the effectiveness of generative conversational AI in fostering English communication skills among students with mild intellectual disabilities. This finding underscores the adaptability of AITGs in addressing diverse educational needs and promoting inclusivity in learning environments [18].

In accounting education, AITGs are gaining prominence for enhancing writing quality, particularly in assignments that require critical analysis of financial reports or ethical considerations in accounting practices [6]. Additionally, AITGs facilitate memory retention by automating tools such as quizzes, thereby assisting students in obtaining a more comprehensive understanding of accounting standards and regulations [19]. These tools promote deeper cognitive engagement and foster analytical skills essential for interpreting financial data [20].

However, significant limitations persist. While AITGs such as ChatGPT are excel in explaining basic accounting principles, they struggle with complex tasks such as multi-step cost allocation and detailed financial statement preparation [21]. Similarly, excessive reliance on AITGs could hinder students' ability to meet the profession's evolving demands [22]. Further, AITGs may disrupt traditional assessments and generate biased outputs in fields such as accounting, where professional judgment is important [23]. Furthermore, an overreliance on AI in decision-making may result in ethical concerns, particularly with regard to accuracy and standards. AITGs frequently provide accurate responses without offering an explanation, which may impede students' capacity to develop critical thinking skills [9].

While studies highlight AITGs' potential to enhance educational outcomes, limited research explores how these tools mediate the relationships between learning styles, technology dependency, and critical thinking. Furthermore, the moderating effects of synchronous and asynchronous learning environments remain underexplored, warranting further investigation into their long-term educational impact.

B. The Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT has been widely used for evaluating technology acceptance and implementation across diverse contexts [24, 25]. Its predictive power makes it especially relevant for understanding the adoption of educational tools in higher education [26]. By integrating construct such as trust and risk perception, UTAUT offers a robust framework for examining factors influencing technology use [27]. UTAUT identifies four key factors driving technology acceptance [28]:

1) Performance Expectancy (PE)

Performance Expectancy (PE) refers to the degree to which an individual anticipates that utilizing a specific technology will enhance their performance. The constructs of perceived usefulness, job-fit, and outcome expectations contribute to the formation of PE. PE has a significant impact on students continued use of online learning platforms [29]. Previous research observed a positive relationship between PE and university students' use of AITGs [10]. This study examined the role of PE in accounting students' adoption of AITGs.

2) Effort Expectancy (EE)

Effort Expectancy (EE) refers to the perceived ease of use of a technology, encompassing factors such as perceived ease of use and ease of learning. As a previous study found, EE exerts a positive influence on students' intention to adopt AITGs [20]. Additionally, the positive correlation between EE and the adoption of AITGs among students [30].

3) Social Influence (SI)

Social Influence (SI) refers to the extent to which individuals' adoption of technology is influenced by the opinions and behaviors of peers, educators, or influential figures. SI significantly influences technology adoption among students in India [31].

4) Facilitating Conditions (FC)

Facilitating Conditions (FC) refer to the availability of the technical infrastructure and support necessary for technology use. Studies indicated that FC have a positive effect on students' use of AITGs [10, 30].

C. Learning Styles (LS)

The concept of Learning Styles (LS) refers to the methods that individuals tend to favor when acquiring, processing, and retaining new information [32]. These styles differ across learners, influenced by biological characteristic, including brain structure and genetic factors, personality traits, cognitive abilities and psychological differences [33–36]. One of the most widely recognized frameworks for classifying learning styles is Fleming's VARK model (1992), which categorizes learners according to four distinct preferences:

- Visual learners, who process information best through images, diagrams, or videos.
- Auditory learners, who benefit from listening, group discussions, and verbal repetition.
- Reading/Writing learners, who excel with text-based materials, notes, and written exercises.
- Kinesthetic learners, who learn through hands-on experiences, practical applications, and physical engagement.

AITGs provide personalized assistance tailored to diverse learning preferences, enhancing comprehension through customized outputs. AITGs can generate tailored responses, thereby facilitating students' comprehension of unfamiliar concepts. AITGs have the potential to enhance learning by automating tasks such as literature reviews and data analysis, thereby allowing educators to dedicate their attention to more creative and analytical pursuits [37]. Recent studies indicate that a considerable number of students are employing AITGs to facilitate their learning processes. AITGs serve not only to identify solutions but also to foster creativity, improve class engagement, and enrich learning outcomes [38]. However, impact variations suggest the need to explore how AITGs align with different learning styles.

D. Technology Dependency (TDP)

The pervasive integration of technology has transformed education and raised concerns about overreliance [39]. This dependency is associated with the accessibility and convenience that technology affords in a range of sectors, including education, communication, and healthcare [40]. In the field of education, the advent of technology has brought about a revolutionary transformation in teaching, making the learning process more engaging and efficient [41].

However, while AITGs offer efficiency and creativity, they may foster dependency. The simplicity of AITGs may foster over-reliance and impede independent thought [42]. This issue is particularly pertinent in the field of accounting, where automation may result in a reduction in hands-on experience, potentially leading to the decline of essential skills [43]. Furthermore, concerns pertaining to data privacy and the potential for decision-making risks emerge with increased technology dependency [44].

E. Critical Thinking (CTG)

Critical Thinking (CTG), comprising skills such as analysis, evaluation, and inference, is essential for academic and professional success [45]. In the field of accounting, the development of critical thinking is of paramount importance in preparing for the professional responsibilities, such as providing financial recommendations and conducting comprehensive analyses [46]. Students who possess robust critical thinking abilities are better positioned to address accounting challenges, generate novel concepts, and communicate in a logical manner [47]. These skills are essential for developing novel approaches to financial reporting, audit practices, and compliance strategies, which are increasingly important in an era of rapid technological and regulatory change. Such abilities enhance students' decision-making capabilities. However, their use may also discourage independent cognitive effort, underscoring the need for balanced application [44].

F. Synchronous Learning Method (SLM)

Synchronous learning is an educational approach characterized by real-time interactions between students and instructors. These interactions typically occur through virtual platforms or in physical classrooms, fostering immediate feedback and active participation. This method is structured around fixed schedules, requiring learners and educators to engage simultaneously in sessions such as live lectures, discussions, or collaborative activities.

Synchronous learning method involves real-time interactions that foster active participation and immediate feedback [48]. This method enhances student engagement, particularly in complex forensic accounting [49]. The integration of AITGs into synchronous learning environments has shown potential in augmenting these advantages. AITGs can complement synchronous learning by simplifying concepts and offering instant assistance [50]. These tools enable students to focus on higher-order cognitive processes, such as analysis and evaluation, rather than solely on information retrieval. However, overreliance on AI may limit critical thinking and hands-on learning opportunities [42].

G. Asynchronous Learning Method (ALM)

The asynchronous learning method is characterized by its emphasis on flexibility and self-paced study, allowing students to access and engage with educational materials at their convenience without being bound by a fixed schedule [50]. This pedagogical approach is predominantly supported by digital resources, including pre-recorded lectures, instructional videos, reading materials, and online assignment, which can be accessed at any time from any location. It accommodates diverse schedules and fosters independent problem-solving.

The incorporation of AITGs into asynchronous learning environments has further augmented its capabilities by providing tools for summarization, paraphrasing, and generating insights. These technologies empower students to efficiently process large volumes of information and focus on more analytical aspects of their studies. However excessive reliance on these tools can potentially stifle creativity and original thinking, as students may become dependent on AI-generated content rather than developing their own intellectual abilities [51]. Exploring the moderating role of asynchronous learning in AITGs usage is critical for addressing these concerns.

H. Research Aims and Questions

This study aims to examine the impact of pivotal theoretical constructs on students' adoption and utilization of AITGs. A primary focus of this study is to elucidate the manner in which these tools influence critical educational outcomes, including learning styles, technology dependency, and critical thinking. Additionally, the research explores the moderating role of synchronous and asynchronous learning methods in shaping these relationships, providing a nuanced perspective on the interplay between AI technologies and different learning environments. By addressing these complex dynamics, this study contributes to the expanding body of scholarship on the integration of AI in education, offering both theoretical advancements and practical guidance for educators and institutions. The findings of this study will inform the development of optimized pedagogical strategies that leverage the benefits of AITGs while addressing potential challenges, ensuring that educational practices remain aligned with the innovative and skill-driven requirements of Industry 4.0. Thus, the research questions for this study are:

- Does performance expectancy affect the use of AITGs among accounting students?
- Does effort expectancy affect the use of AITGs among accounting students?
- Does social influence affect the use of AITGs among accounting students?

- Does facilitating conditions affect the use of AITGs among accounting students?
- Does the use of AITGs affect the learning styles of accounting students?
- Does the use of AITGs affect the technology dependency of accounting students?
- Does the use of AITGs affect the critical thinking skills of accounting students?
- Does the synchronous learning method significantly moderate the relationship between AITGs use and accounting students' learning style?
- Does the synchronous learning method significantly moderate the relationship between AITGs use and accounting students' technology dependency?
- Does the synchronous learning method significantly moderate the relationship between AITGs use and accounting students' critical thinking skills?
- Does the asynchronous learning method significantly moderate the relationship between AITGs use and accounting students' learning style?
- Does the asynchronous learning method significantly moderate the relationship between AITGs use and accounting students' technology dependency?
- Does the asynchronous learning method significantly moderate the relationship between AITGs use and accounting students' critical thinking skills?

I. Hypotheses

These hypotheses are informed by the UTAUT and research on AITGs in accounting education. The study also examines how synchronous and asynchronous learning methods moderate the relationship between AITGs and key learning outcomes. The following hypotheses aim to test these relationships empirically.

- H1: Performance expectancy affects the use of AITGs among accounting students.
- H2: Effort expectancy affects the use of AITGs among accounting students.
- H3: Social influence affects the use of AITGs among accounting students.
- H4: Facilitating conditions affects the use of AITGs among accounting students.
- H5: The use of AITGs affects the learning styles of accounting students.
- H6: The use of AITGs affects the level of technology dependency among accounting students.
- H7: The use of AITGs affects the critical thinking skills of accounting students.
- H8: Synchronous learning moderates the impact of AITGs on accounting students' learning styles.
- H9: Synchronous learning moderates the impact of AITGs on technology dependency among accounting students.
- H10: Synchronous learning moderates the impact of AITGs on critical thinking among accounting students.
- H11: Asynchronous learning moderates the effect of AITGs on accounting students' learning styles.
- H12: Asynchronous learning moderates the effect of AITGs on technology dependency among accounting students.
- H13: Asynchronous learning moderates the effect of AITGs on critical thinking among accounting students.

III. Materials and Methods

This study employed a quantitative approach to enhance the validity and reliability of its findings. Data were collected from 106 undergraduate accounting students who had utilized AITGs in their coursework. The sample size was determined by using G*Power analysis, ensuring that the study exceeded the minimum requirement of 85 respondents, thus providing sufficient statistical power. Data were collected through an online survey utilizing validated scales adapted from the UTAUT framework. The questionnaire measured four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, as well as three learning outcomes: learning styles, technology dependency, and critical thinking. Responses were recorded using a 6-point Likert scale (1 = Strongly Disagree to 6 = Strongly Agree) to encourage decisive answers. The collected data were analyzed using SmartPLS 4.0 software, applying Partial Least Squares Structural Equation Modeling (PLS-SEM). The collected data were analyzed using SmartPLS 4.0 software, applying PLS-SEM. The hypotheses were tested using Bootstrapping (5.000 resamples), and significance was determined based on t-values and *p*-values. The reliability and validity of the constructs were assessed through Composite Reliability (CR), Average Variance Extracted (AVE), Variance Inflation Factor (VIF), and Discriminant validity.

IV. Result and Discussion

A. Results

This section presents the findings from the PLS-SEM analysis. The demographic profile of the respondents is presented in Table 1 in the Method section, providing an overview of gender distribution and batch representation.

Table 1. Demographic respondents

Categories		Frequency	Percentage (%)
Gender	Male	36	34
	Female	70	66
Batch	2022	6	5.6
	2023	10	9.4
	2024	52	49.05
	2025	11	10.3
	2026	10	9.4
	2027	10	9.4
	2028	7	6.6

This table presents the demographic profile of respondents based on their expected year of graduation, serving as an indicator of their generational classification. The data confirm that the participants predominantly belong to Generation Z, a cohort characterized by high levels of digital literacy and familiarity with emerging technologies. This makes them particularly relevant for studies investigating the educational implications of AITGs.

1) Measurement model assessment

Table 2 presents the assessment of the measurement model, including CR, AVE, average factor loadings, and the VIF range for each construct. These metrics evaluate the reliability and convergent validity of the model. The summarized results are provided in Table 2, while full details are available in Table A1.

Table 2. Summary of measurement model assessment

Variables	Composite Reliability (CR)	Average Variance Extracted (AVE)	Avg. Loadings	Variance Inflation Factor (VIF) Range
Performance Expectancy (PE)	0.930	0.690	0.83	1.835–3.454
Effort Expectancy (EE)	0.945	0.776	0.88	2.818–5.162
Social Influence (SI)	0.819	0.538	0.72	1.170–1.877
Facilitating Conditions (FC)	0.886	0.722	0.85	1.504–2.674
Artificial Intelligence Text Generators (AITGS)	0.862	0.513	0.71	1.385–1.899
Synchronous Learning Method (SLM)	0.834	0.505	0.70	1.195–2.039
Asynchronous Learning Method (ALM)	0.822	0.607	0.78	1.246–1.397
Learning Styles (LS)	0.832	0.555	074	1.204–1.807
Technology Dependency (TDP)	0.894	0.628	0.80	1.849–3.594
Critical Thinking (CTG)	0.931	0.553	0.76	1.665–3.914

As presented in Table 2, all constructs exhibit satisfactory internal consistency, with CR values exceeding the commonly accepted threshold of 0.70. The AVE values surpass 0.50 for all constructs, indicating adequate convergent validity. The average factor loadings are generally above 0.70, reflecting strong indicator contributions to their respective latent constructs. Furthermore, the VIF values remain below the critical cut-off of 5, confirming the absence of multicollinearity. These findings collectively support the robustness of the measurement model and its appropriateness for subsequent structural analysis.

In Table 3, the results of the discriminant validity assessment using the Fornell-Larcker criterion are presented. The square root of the AVE for each construct, shown on the diagonal, is compared against the inter-construct correlations. A summarized version is displayed in Table 4, while full results are available in Table A2.

Table 3. Summary of discriminant validity (Fornell-Larcker)

Construct	AVE Root
AITGS	0.716
ALM	0.779
CTG	0.743
EE	0.881
FC	0.850
LS	0.745
PE	0.830
SI	0.733
SML	0.711
TDP	0.793

As presented in Table 3, all constructs satisfy the Fornell-Larcker criterion. The square root of the AVE (displayed on the diagonal) is consistently greater than the inter-construct correlations in the corresponding rows and columns. For instance, the square root of the AVE for AITGS is 0.716, which is higher than its correlations with ALM (0.446), CTG (0.521), PE (0.612), and TDP (0.666). Likewise, PE has a square root of AVE of 0.830, exceeding its highest correlation value of 0.707 with EE. These results confirm that all constructs in the model are empirically distinct, demonstrating acceptable discriminant validity.

2) Structural model assessment

The results of the hypothesis testing are summarized in Table 4, which reports the path coefficients and significance levels for all proposed relationships within the structural model. To enhance interpretability, Fig. 1 provides a visual representation of these relationships, distinguishing significant paths with solid green lines and non-significant ones with dashed red lines. Full hypothesis testing results are presented in Table A3.

Table 4. Summary of path coefficient

Hypo theses	Path	Beta	t-value	*p*-value	Decision
H1	PE→AITGS	0.370	2.887	0.004	Accepted
H2	EE→AITGS	0.052	0.371	0.710	Rejected
H3	SI→AITGS	0.210	2.288	0.022	Accepted
H4	FC→AITGS	0.222	1.775	0.076	Rejected
H5	AITGS→LS	0.063	0.715	0.475	Rejected
H6	AITGS→TDP	0.518	6.099	0.000	Accepted
H7	AITGS→CTG	0.313	3.696	0.000	Accepted
H8	SLM x AITGS→LS	0.630	9.306	0.000	Accepted
H9	SLM x AITGS→TDP	−0.041	0.544	0.586	Rejected
H10	SLM x AITGS→CTG	0.324	3.494	0.000	Accepted
H11	ALM x AITGS→LS	0.095	0.922	0.356	Rejected
H12	ALM x AITGS→TDP	−0.061	0.778	0.437	Rejected
H13	ALM x AITGS→CTG	0.046	0.435	0.664	Rejected

According to the benchmarks for effect size established by Cohen (1988), where $\beta \approx 0.10$ is considered small, $\beta \approx 0.30$ is medium, and $\beta \geq 0.50$ is large, the structural model provides the following insights. In the context of H1, the medium-sized influence of PE on AI generator adoption is statistically significant (β = 0.370, t = 2.887, p = 0.004). This indicates that a one-unit increase in perceived usefulness corresponds to approximately a 37% rise in intention. H2's EE (β = 0.052, t = 0.371, p = 0.710) falls below the small-effect threshold and is not significant, suggesting that ease of use plays only a minimal role. H3, SI (β = 0.210, t = 2.288, p = 0.022), fulfills the criteria for a small effect and suggests that social influence increases adoption intent by approximately 21%. H4, FC (β = 0.222, t = 1.775, p = 0.076), despite approaching the small-effect mark, does not reach statistical significance, implying its practical contribution is modest under alpha level.

Turning to downstream outcomes, H5 shows that AI-generator use does not significantly alter LS (β = 0.063, t = 0.715, p = 0.475), as this coefficient remains well under 0.20. In contrast, H6 reveals a medium-to-large effect on TDP (β = 0.518, t = 6.099, p < 0.001), with each usage unit linked to a 52% increase in dependency. The H7 variable indicates a modestly positive effect on CTG, as indicated by the standardized beta coefficient of 0.313 and the t-statistic of 3.696, both of which are statistically significant at the p <0.001 level. This effect corresponds to an estimated 31% improvement in analytic skill.

The moderating role of SLM is evident in H8–H10: H8 demonstrates a medium-to-large enhancement of AI use on LS under SLM (β = 0.630, t = 9.306, p <0.001), and H10 exhibits a small-to-medium boost for CTG (β = 0.324, t = 3.494, p <0.001). In contrast, the interaction effect of H9 on TDP (β = –0.041, t = 0.544, p = 0.586) remains negligible. Lastly, none of the ALM (H11: β = 0.095, p = 0.356; H12: β = –0.061, p = 0.437; H13: β = 0.046, p = 0.664) reached the small-effect threshold or statistical significance. This finding indicates that non-real-time learning modalities do not meaningfully moderate AI-use outcomes.

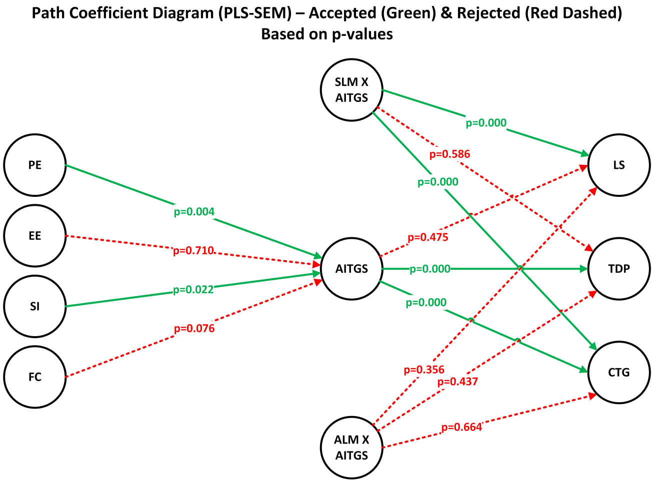

Fig. 1. Path diagram of structural model.

The hypothesis testing results reveal that PE (H1) and SI (H3) significantly affect the adoption of AITGs, while EE (H2) and FC (H4) do not. The use of AITGs has a significant positive impact on both TDP (H6) and CTG (H7), but not on LS (H5). SLM significantly moderates the effects of AITGs use on LS (H8) and CTG (H10), whereas its effect on TDP (H9) is not significant. All hypothesized moderating effects of ALM (H11–H13) were found to be insignificant.

B. Discussion

1) Performance expectancy and the use of AITGs

The result indicate that PE significantly influences accounting students' adoption of AITGs. Thus, H1 is Accepted. Students perceive AITGs as valuable tools for enhancing their learning efficiency, boosting productivity, and supporting academic goal achievement. The ability of AITGs to facilitate quicker comprehension, improve understanding, and streamline tasks reinforces their role as effective learning aids. This indicates that performance expectancy strongly predicts continued use of digital tools in education [10, 29]. Moreover, students reported a positive alignment between AITG-generated output and their expectations, further highlighting the growing integration of AI tools into modern learning environments. To encourage adoption, universities should emphasize these benefits when incorporating AITGs into their curriculum.

2) Effort expectancy and the use of AI text generators

On the other hand, EE was found to be non-significant, indicating that H2 is Rejected. This result indicates that ease of use does not play a crucial role in influencing AITGs adoption. Theoretically, effort expectancy reflects users' perceptions regarding how easy and effortless it is to use a particular technology. However, in this context, students—most of whom belong to Generation Z—are already highly familiar with digital tools and online platforms, reducing the relevance of ease of use as a determining factor. Rather than focusing on whether the tool is easy to operate, students may place greater emphasis on whether the technology adds academic value. AITGs are typically designed as user-friendly learning machines that do not require complex technical skills to operate. They are often used for basic search, explanation, or content generation tasks that align with routine academic activities. Thus, the primary barrier to adoption is not the complexity of the tool but rather the perceived value it provides [20, 30, 52].

3) Social influence and the use of AI text generators

Social Influence was found to be a significant predictor of AITG adoption, thus H3 Accepted. This reinforces the role of peer recommendations in shaping technology use. In this study, peer influence, particularly recommendations from friends and observed behaviors, played a greater role than external advertising in motivating students to adopt AITGs. Students were more inclined to try AITGs when encouraged by their peers, highlighting the social dynamics at play in technology adoption. Given this, universities can leverage student testimonials and AI-assisted collaborative learning environments to enhance engagement. These indicates that peer recommendations significantly drive students' adoption of new digital tools [20, 31]

4) Facilitating conditions and the use of AI text generators

In contrast, FC did not significantly affect AITGs adoption, indicating that H4 is Rejected. This suggests that the availability of resources such as compatible devices and internet access is not a primary factor influencing AITGs use among accounting students. Since access to digital tools is already well established, students may not perceive infrastructure as a barrier to adoption. FC has been found to have no significant effect on students' actual use of ChatGPT for academic purposes, likely because digital access is no longer a limiting factor in technology adoption [52, 53]. Given their high digital readiness, such infrastructure is already assumed. Instead, the decision to adopt AITGs appears to be driven more by personal motivation and perceived utility. This personal motivation may be triggered by curriculum structures that encourage self-directed learning, where students are often required to interpret materials, such as presentation slides, with minimal guidance. As members of Generation Z, students tend to respond to such learning demands by intuitively turning to AI tools to independently seek clarification and support.

5) AI text generators and learning styles

The study found that AITGs do not significantly influence learning styles, thus H5 is Rejected. This suggests that students' learning preferences remain stable despite the introduction of AITGs. Even with integration of AITGs, students continue to rely on established approaches such as group discussions, hands-on activities, and traditional lecture-based learning. Learning styles, including convergent and assimilative approaches, have been shown to remain consistent even when technology is incorporated into education [54]. This finding may also be attributed to the nature of AITG outputs, which predominantly consist of textual and numerical responses. Given that accounting education is heavily oriented toward textual analysis and quantitative reasoning. Additionally, while digital technologies contribute to more dynamic learning environments, meaningful changes often require shifts in teaching perspectives and the adoption of transformative learning approaches [55]. This reinforces the idea that technology supports learning processes but does not necessarily redefine them.

6) AI text generators and technology dependency

Conversely, AITGs usage significantly contributes to technology dependency, which supports the H6 Acceptance. This indicates that students are increasingly reliant on these tools for academic tasks and decision-making processes. The simplicity and convenience of AITGs may foster over-reliance, potentially hindering independent thinking and problem-solving abilities [42, 43]. This concern is particularly relevant in accounting, where automation can reduce hands-on experience and weaken the critical skills necessary for professional practice. The dual nature of AITGs is evident—they serve as valuable learning aids while also contributing to a growing dependency on technology. This finding highlights the need for a balanced approach in integrating AI tools into education, ensuring that they enhance learning without diminishing essential analytical capabilities

7) AI text generators and critical thinking skills

Furthermore, AITGs positively impact critical thinking, thus H7 accepted. Students demonstrated enhanced abilities in evaluating information critically, identifying logical fallacies, and considering multiple perspectives, suggesting that AITGs facilitate structured reasoning and problem-solving. These tools contribute to the development of key critical thinking dispostions, such as trust in one's analytical abilities, confidence in reasoning, open-mindedness, and maturity, all of which are essential for high-order thinking [56]. Additionally, AITGs have been recognized for their role in academic research and theory analysis, despite challenges related to personalization [57]. Integrating AI literacy into academic curricula has also been linked to improvements in students' critical thinking skills [58]. However, while AITGs provide structure guidance in reasoning, over-reliance on AITGs may limit deeper engagement with complex problems. To maximize their benefits, educators should promote structure AI integration, ensuring that AITGs enhance rather than replace critical thinking.

8) Synchronous learning, AITGs, and learning styles

The study reveals that the SLM enhances the way students integrate AITGs into their learning processes, leading to the acceptance of H8. In real-time learning environments, students engage more actively with AI-generated content, allowing them to refine their understanding through discussions and instructor-led explanations. The structured nature of synchronous learning fosters discipline and consistency, allowing students to navigate AITG-generated materials more effectively. Rather than fundamentally altering learning preferences, AITGs function as adaptive tools that complement existing study habits, reinforcing the idea that technology enhances rather than disrupts established learning behaviors [48, 50, 59]. This supports the argument that synchronous discussions create opportunities for students to critically engage with AI-generated content, refining their analytical skills in a way that aligns with constructivist theories of learning.

9) Synchronous learning, AITGs, and technology dependency

Despite its role in enhancing engagement, the SLM did not moderate the relationship between AITG use and technology dependency, leading to the rejection of H9. This suggests that structured learning environments do not significantly alter students' reliance on AI tools. This outcome may be explained by the inherent nature of synchronous learning, which involves real-time instruction, immediate feedback, and direct interaction with lecturers and peers. These features provide students with timely guidance and clarification, thereby reducing the perceived need to consult external tools such as AITGs during the learning process. As a result, students in synchronous settings may feel sufficiently supported through human interaction, diminishing the role of AITGs in shaping their technology dependency.

10) Synchronous learning, AITGs, and critical thinking skills

SLM also strengthens the role of AITGs in developing critical thinking, leading to the acceptance of H10. Real-time engagement in synchronous learning enables students to evaluate AI-generated content critically, challenge assumptions, and refine their reasoning through discussion. The immediate feedback provided in synchronous settings fosters deeper cognitive processing, allowing students to identify logical fallacies and consider multiple perspectives.

Moreover, SLM promotes collaborative learning, where students interact, debate, and construct knowledge together, rather than relying solely on AI-generated responses. This aligns with constructivist learning theories emphasizing that meaningful cognitive development occurs through active dialogue and reflection. With structured AI-supported discussions, students are encouraged to engage in higher-order thinking, structured reasoning, and problem-solving. Given these benefits, universities should consider integrating live AI-assisted discussions into curricula to maximize the potential of AITGs in enhancing students' analytical skills.

11) Asynchronous learning, AITGs, and learning styles

ALM did not moderate the effect of AITGs on learning styles, leading to the rejection of H11. While asynchronous learning provides flexibility, the lack of real-time engagement may limit its influence on how students interact with and adapt to AI-generated content. Learning styles, which tend to develop over time through structured experiences, may remain unchanged in self-paced settings where students have autonomy but less external guidance.

In this study, asynchronous learning was implemented through Guided Self Learning Class (GSLC) sessions, where students completed assignments and marked attendance via forum submissions. However, these forums primarily served administrative functions and lacked interactive elements or direct feedback from lecturers. As a result, students may not have engaged with AITGs in a manner that supports meaningful reflection or adaptation of their learning preferences.

Although asynchronous learning allows students to engage with materials at their own pace, the absence of real-time discussions may result in passive interaction with AITGs, where students treat them as static sources of information rather than tools for adaptive learning [60]. Without immediate feedback from lecturers, students are less likely to refine their learning strategies in response to AI-generated content. This highlights the importance of instructional design in asynchronous settings—while flexibility is beneficial, integrating structured reflection tasks or interactive discussions could help maximize the impact of AITGs on learning approaches.

12) Asynchronous learning, AITGs, and technology dependency

The study found that ALM did not moderate the relationship between AITG use and technology dependency, leading to the rejection of H12. This suggests that self-paced learning environments do not significantly alter students' reliance on AI tools. Without direct instructor support, students navigating asynchronous learning environments may turn to AITGs more frequently for quick solutions rather than as tools for deep analytical engagement. Unlike synchronous settings, where structured discussions and immediate feedback help shape learning behaviors, asynchronous learning allows students to engage with AITGs at their own pace, often without real-time guidance or peer interaction. The absence of structured guidance may contribute to greater reliance on AI-generated content, as students often prioritize efficiency over deeper cognitive processing [61]. While ALM fosters independent learning, it may also reinforce habitual AI usage without necessarily reducing dependency.

13) Asynchronous learning, AITGs, and critical thinking skills

The study further found that ALM did not moderate the relationship between AITG use and critical thinking, leading to the rejection of H13. Unlike synchronous learning, which fosters real-time discussions and collaborative problem-solving, asynchronous environments rely on students' self-regulation and motivation to engage critically with learning materials. The lack of immediate feedback may limit the depth of cognitive processing, as students are less likely to receive instant challenges to their perspectives or engage in structured debates [61].

Without interactive discussions, students may approach AITGs as convenient sources of information rather than tools for critical engagement. In the absence of structured guidance, the risk of passive learning increases, where students rely on AI-generated content without deeply analyzing or questioning it [60]. This aligns with findings that suggest self-paced learning often requires additional support mechanisms to foster deeper cognitive engagement. To enhance critical thinking in asynchronous settings, educators could incorporate AI-assisted peer review activities, guided reflection prompts, or interactive assignments that require students to critique AI-generated outputs actively. Future research should investigate how asynchronous platforms can be optimized to facilitate more dynamic and reflective learning experiences.

V. Conclusion

This study provides key insights into how AITGs in influencing cognitive engagement and learning behaviors among accounting students within higher education. The findings show that AITGs significantly enhance critical thinking skills and contribute to technology dependency, but do not significantly affect learning styles. This dual effect suggests that the while AITGs support analytical and evaluative thinking, they may also increase reliance on automated tools in decision-making.

The lack of impact on learning styles may reflect students' existing familiarity with digital tools and self-directed learning habits, particularly among Generation Z, who have long been immersed in technology. AITGs, therefore serve more as support tools than as drivers of learning transformation.

Synchronous learning method was found to strengthen the effect of AITGs on critical thinking, likely due to real-time interaction and instruction feedback that prompt students to engage critically with AI-generated content. However, it did not significantly moderate technology dependency, which may be shaped more by individual behavior and access than by teaching format.

Asynchronous learning method, while offering flexibility, did not show a notable moderating role. The lack of immediate interaction may reduce students' critical engagement with AITGs, highlighting the need for improved instructional design in such settings. Strategies like structured feedback, peer discussions, and scheduled check-ins may help close this gap.

These findings carry practical implications. Educators and institutions should design learning environments that encourage active engagement, critical thinking, and ethical AI use. Promoting AI literacy through reflective tasks, peer reviews, and scaffolded assignments can support responsible AITGs use. In asynchronous formats, built-in feedback loops and collaborative features can help sustain student engagements.

This study is limited to undergraduate accounting students, so the findings may not apply to other fields. Future research should include broader samples, explore long-term effects of AITG use, and consider other moderating factors such as instructor presence and curriculum design. Mixed-method approaches, including interviews or focus groups, may also reveal deeper insights beyond quantitative results.

Appendix

Table A1. Convergent validity

Variables	Indicators	Loadings	CR (rho_C)	AVE	VIF
PE	PE1	0.826	0.930	0.690	2.373
	PE2	0.840	-	-	2.612
	PE3	0.858	-	-	3.186
	PE4	0.874	-	-	3.454
	PE5	0.836	-	-	2.484
	PE6	0.742	-	-	1.835
EE	EE1	0.837	0.945	0.776	2.851
	EE2	0.911	-	-	4.211
	EE3	0.935	-	-	5.162
	EE4	0.904	-	-	3.663
	EE5	0.812	-	-	2.818
SI	SI1	0.627	0.819	0.538	1.358
	SI2	0.866	-	-	1.877
	SI3	0.565	-	-	1.170
	SI4	0.830	-	-	1.551
FC	FC1	0.849	0.886	0.722	2.168
	FC2	0.774	-	-	1.504
	FC3	0.920	-	-	2.674
AITGS	AITGS1	0.585	0.862	0.513	1.385
	AITGS2	0.736	-	-	1.624
	AITGS3	0.694	-	-	1.507
	AITGS4	0.678	-	-	1.518
	AITGS5	0.768	-	-	1.757

	AITGS6	0.814	-	-	1.899
SLM	SLM1	0.567	0.834	0.505	1.195
	SLM2	0.665	-	-	1.463
	SLM3	0.770	-	-	1.713
	SLM4	0.841	-	-	2.039
	SLM5	0.681	-	-	1.673
ALM	ALM1	0.787	0.822	0.607	1.344
	ALM2	0.732	-	-	1.246
	ALM3	0.817	-	-	1.397
LS	LS1	0.787	0.832	0.555	1.614
	LS2	0.708	-	-	1.408
	LS3	0.642	-	-	1.204
	LS4	0.830	-	-	1.807
TDP	TDP1	0.814	0.894	0.628	1.956
	TDP2	0.790	-	-	1.849
	TDP3	0.782	-	-	2.091
	TDP4	0.789	-	-	3.594
	TDP5	0.788	-	-	2.915
CTG	CTG1	0.753	0.931	0.553	2.423
	CTG2	0.703	-	-	2.928
	CTG3	0.751	-	-	3.369
	CTG4	0.691	-	-	2.420
	CTG5	0.590	-	-	1.665
	CTG6	0.655	-	-	2.308
	CTG7	0.821	-	-	2.863
	CTG8	0.818	-	-	3.484
	CTG9	0.750	-	-	3.675
	CTG10	0.825	-	-	3.914
	CTG11	0.784	-	-	3.431

The table provides the detailed convergent validity results for each construct.

Table A2. Discriminant validity

Variables	AITGS	ALM	CTG	EE	FC	LS	PE	SI	SML	TDP
AITGS	0.716	-	-	-	-	-	-	-	-	-
ALM	0.446	0.779	-	-	-	-	-	-	-	-
CTG	0.521	0.596	0.743	-	-	-	-	-	-	-
EC	0.539	0.404	0.552	0.881	-	-	-	-	-	-
FC	0.525	0.41	0.503	0.635	0.85	-	-	-	-	-
LS	0.248	0.415	0.532	0.357	0.23	0.745	-	-	-	-
PE	0.612	0.489	0.607	0.707	0.507	0.255	0.83	-	-	-
IS	0.481	0.49	0.39	0.4	0.393	0.221	0.441	0.733	-	-
SML	0.185	0.32	0.5	0.324	0.159	0.708	0.246	0.156	0.711	-
TDP	0.666	0.526	0.452	0.453	0.431	0.208	0.552	0.568	0.141	0.793

The diagonal values represent the square root of AVE, while the off-diagonal values represent inter-construct correlations.

Table A3. Path coefficient

Hypotheses	Path	Beta	Sample Mean (M)	Std Dev	t- value	*p*-value	LL 5 (%)	UL 95 (%)	Decision
H1	PE→AITGS	0.370	0.382	0.128	2.887	0.004	0.118,80	0.620,93	Accepted
H2	EE→AITGS	0.052	0.047	0.141	0.371	0.710	−0.223,35	0.327,81	Rejected
H3	SI→AITGS	0.210	0.211	0.092	2.288	0.022	0.030,05	0.389,85	Accepted
H4	FC→AITGS	0.222	0.222	0.125	1.775	0.076	−0.023,09	0.466,87	Rejected
H5	AITGS→LS	0.063	0.050	0.089	0.715	0.475	−0.110,50	0.237,44	Rejected
H6	AITGS→TDP	0.518	0.515	0.085	6.099	0.000	0.351,75	0.684,87	Accepted
H7	AITGS→CTG	0.313	0.313	0.085	3.696	0.000	0.147,00	0.478,99	Accepted
H8	SLM x AITGS→LS	0.630	0.642	0.068	9.306	0.000	0.497,14	0.762,42	Accepted
H9	SLM x AITGS→TDP	−0.041	−0.037	0.075	0.544	0.586	−0.188,09	0.106,34	Rejected
H10	SLM x AITGS→CTG	0.324	0.339	0.093	3.494	0.000	0.142,31	0.506,08	Accepted
H11	ALM x AITGS→LS	0.095	0.086	0.103	0.922	0.356	−0.106,63	0.296,14	Rejected
H12	ALM x AITGS→TDP	−0.061	−0.068	0.078	0.778	0.437	−0.213,30	0.092,07	Rejected
H13	ALM x AITGS→CTG	0.046	0.052	0.105	0.435	0.664	−0.160,75	0.252,38	Rejected

LL = Lower Limit, UL = Upper Limit of Confidence Interval. The table summarizes path coefficients and their statistical significance.

Conflict of Interest

The authors declare no conflict of interests.

Author Contributions

CK formulated the research objectives, designed the methodology, conducted the data collection and analysis, performed the literature review, and wrote the manuscript. SPH proposed the initial research topic, helped define the research problem, and provided academic supervision throughout the study; all authors had approved the final version.

Data Availability

Zenodo: "Dataset for: Analyzing the Impact of AI Text Generators on Learning Styles, Technological Dependency, and Critical Thinking among Accounting Students". https://zenodo.org/records/15526507. This project contains the following underlying data:

Dataset Paper Analyzing AITGs Impact on Accounting Students.xlsx.

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References

[1] N. Mungoli, "Revolutionizing industries: The impact of artificial intelligence technologies," *Journal of Electrical Electronics Engineering*, vol. 2, no. 3, pp. 206–210, 2023. doi: https://doi.org/10.33140/JEEE.02.03.03

[2] A. S. Priya, K. Monishkumar, and S. Sridhar, "Unveiling the realm of artificial intelligence: Exploring boundless innovation and endless potential," *IARJSET.*, vol. 11, no. 3, 2024. doi: https://doi.org/10.17148/IARJSET.2024.11359

[3] L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: A review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020. doi: https://doi.org/10.1109/ACCESS.2020.2988510

[4] J. Huang, S. Saleh, and Y. Liu, "A review on artificial intelligence in education," *Academic Journal of Interdisciplinary Studies*, vol. 10, no. 3, 206, 2021. doi: https://doi.org/10.36941/ajis-2021-0077

[5] D. A. Wood, M. P. Achhpilia, M. T. Adams *et al.*, "The ChatGPT artificial intelligence Chatbot: How well does it answer accounting assessment questions?" *Issues in Accounting Education*, vol. 38, no. 4, pp. 81–108, 2023. doi: https://doi.org/10.2308/ISSUES-2023-013

[6] D. J. Woo, H. Susanto, C. H. Yeung, K. Guo, and A. K. Y. Fung. "Exploring AI-generated text in student writing: How does AI help?" *Language Learning & Technology,* vol. 28, no. 2, pp. 183–209, 2023. doi:10.13140/RG.2.2.31475.20004

[7] M. A. AlAfnan, S. Dishari, M. Jovic, and K. Lomidze, "ChatGPT as an educational tool: Opportunities, challenges, and recommendations for communication, business writing, and composition courses," *Journal of Artificial Intelligence and Technology*, vol. 3, no. 2, 2023. doi: https://doi.org/10.37965/jait.2023.0184

[8] A. G. R. Castillo, G. J. S. Silva, J. P. F. Arocutipa *et al*., "Effect of Chat GPT on the digitized learning process of university students," *Journal of Namibian Studies: History Politics Culture*, vol. 33, pp. 1–15, 2023. doi: https://doi.org/10.59670/jns.v33i.411

[9] A. Essien, O. T. Bukoye, X. O'Dea, and M. Kremantzis, "The influence of AI text generators on critical thinking skills in UK business schools," *Studies in Higher Education*, vol. 49, no. 5, pp. 865–882, 2024. doi: https://doi.org/10.1080/03075079.2024.2316881

[10] J.-M. Romero-Rodríguez, M.-S. Ramírez-Montoya, M. Buenestado-Fernández, and F. Lara-Lara, "Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness," *Journal of New Approaches in Educational Research*, vol. 12, no. 2, pp. 323–339, 2023. doi: https://doi.org/10.7821/naer.2023.7.1458

[11] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: perceptions, benefits, and challenges in higher education," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, 43, 2023. doi: https://doi.org/10.1186/s41239-023-00411-8

[12] V. Venkatesh, "Adoption and use of AI tools: A research agenda grounded in UTAUT," *Annals of Operations Research*, vol. 308, pp. 641–652, 2022. doi: https://doi.org/10.1007/s10479-020-03918-9

[13] H. K. Simonsen, "AI text generators and text producers," in *Proc. 2022 International Conf. on Advanced Learning Technologies (ICALT)*, pp. 218–220, 2022. doi: https://doi.org/10.1109/ICALT55010.2022.00071

[14] E. N. Crothers, N. Japkowicz, and H. L. Viktor, "Machine-generated text: A comprehensive survey of threat models and detection methods," *IEEE Access*, vol. 11, pp. 70977–71002, 2023. doi: https://doi.org/10.1109/ACCESS.2023.3294090

[15] B. L. Frye. (December 2022). Should using an AI text generator to produce academic writing be plagiarism? *33 Fordham Intellectual Property, Media & Entertainment Law Journal 947 (2023)*. [Online]. Available: https://ssrn.com/abstract=4292283

[16] M. Cascella, J. Montomoli, V. Bellini, and E. Bignami, "Evaluating the feasibility of ChatGPT in healthcare: An analysis of multiple clinical and research scenarios," *Journal of Medical Systems*, vol. 47, no. 1, 33, 2023. doi: https://doi.org/10.1007/s10916-023-01925-4

[17] M. T. Dasborough, "Awe-inspiring advancements in AI: The impact of ChatGPT on the field of organizational behavior," *Journal of Organizational Behavior*, vol. 44, no. 2, pp. 177–179, 2023. doi: https://doi.org/10.1002/job.2695

[18] M. A. Elkot, E. Youssif, O. E. H. Elmahdi, M. AbdAlgane, and R. Ali, "Generative conversational AI: Active practices for fostering students with mild intellectual disabilities to improve English communication skills," *Contemporary Educational Technology*, vol. 17, no. 1, ep549, 2025. doi: https://doi.org/10.30935/cedtech/15688

[19] D. C. L. Tsai, A. Y. Q. Huang, O. H. T. Lu, and S. J. H. Yang, "Automatic question generation for repeated testing to improve student learning outcome," in *Proc. 2021 International Conf. on Advanced Learning Technologies (ICALT)*, pp. 339–341, 2021. doi: https://doi.org/10.1109/ICALT52272.2021.00108

[20] T. W. Kim and Q. Tan, "Repurposing text-generating AI into a thought-provoking writing tutor," arXiv Preprint, arXiv: 2304.10543, 2023. doi: 10.48550/arXiv.2304.10543

[21] X. (Joyce) Cheng, R. Dunn, T. Holt, K. Inger, J. G. Jenkins, J. Jones, J. Long, T. M. Loraas, M. Mathis, J. D. Stanley, and D. A. Wood, "Artificial intelligence's capabilities, limitations, and impact on accounting education: Investigating ChatGPT's performance on educational accounting cases," *SSRN Electronic Journal,* 2023. doi: https://doi.org/10.2139/ssrn.4431202

[22] R. Tandiono, "The impact of artificial intelligence on accounting education: A review of literature," *E3S Web of Conferences*, vol. 426, 02016, 2023. doi: https://doi.org/10.1051/e3sconf/202342602016

[23] I. Pedersen, "The rise of generative AI and enculturating AI writing in postsecondary education," *Frontiers in Artificial Intelligence*, vol. 6, 2023. doi: https://doi.org/10.3389/frai.2023.1259407

[24] M. Czerwinska, "Analysis of the use of the UTAUT model for modeling the information technology acceptance process," *Journal of Computer Sciences Institute*, vol. 17, pp. 417–420, 2020. doi: https://doi.org/10.35784/jcsi.2412

[25] A. M. Momani, "The unified theory of acceptance and use of technology," *International Journal of Sociotechnology and Knowledge Development*, vol. 12, no. 3, pp. 79–98, 2020. doi: https://doi.org/10.4018/IJSKD.2020070105

[26] L. Xue, A. M. Rashid, and S. Ouyang, "The Unified Theory of Acceptance and Use of Technology (UTAUT) in higher education: A systematic review," *Sage Open*, vol. 14, no. 1, 2024. doi: https://doi.org/10.1177/21582440241229570

[27] M. A. Hadi, I. A. Al-Baltah, and A. T. Zahary, "A survey on mobile payment applications and adopted theoretical models," *Sustainable Engineering and Innovation*, vol. 4, no. 2, pp. 112–126, 2022. doi: https://doi.org/10.37868/sei.v4i2.id163

[28] Venkatesh *et al*., "User acceptance of information technology: Toward a unified view," *MIS Quarterly*, vol. 27, no. 3, 425, 2003. doi: https://doi.org/10.2307/30036540

[29] Y. Li and M. Zhao, "A study on the influencing factors of continued intention to use MOOCs: UTAUT model and CCC moderating effect," *Frontiers in Psychology*, vol. 12, 2021. doi: https://doi.org/10.3389/fpsyg.2021.528259

[30] A. Strzelecki, "To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology," *Interactive Learning Environments*, vol. 32, no. 9, pp. 5142–5155, 2024. doi: https://doi.org/10.1080/10494820.2023.2209881

[31] I. Alvi, "College students' reception of social networking tools for learning in India: An extended UTAUT model," *Smart Learning Environments*, vol. 8, no. 1, 19, 2021. doi: https://doi.org/10.1186/s40561-021-00164-9

[32] D. Neupane, S. Pant, and P. Bhattarai, "Preferred learning techniques among bachelor's level students," *Nepal Journal of Multidisciplinary Research*, vol. 6, no. 2, pp. 145–154, 2023. doi: https://doi.org/10.3126/njmr.v6i2.57660

[33] H. Dong, X. Liu, and Z. Zhou, "Influential factors for gender differences in L2 learning," *Journal of Education, Humanities and Social Sciences*, vol. 8, pp. 947–955, 2023. doi: https://doi.org/10.54097/ehss.v8i.4385

[34] S. Nerita, J. Jamna, and S. Solfema, "Individual differences in the learning process and the factors that affect it," *Bioscientist : Jurnal Ilmiah Biologi*, vol. 10, no. 2, 1077, 2022. doi: https://doi.org/10.33394/bioscientist.v10i2.6333 (in Indonesian)

[35] J. Zhang, "Links between cognitive styles and learning strategies in second language acquisition," *Journal of Education, Humanities and Social Sciences*, vol. 8, pp. 327–333, 2023. doi: https://doi.org/10.54097/ehss.v8i.4269

[36] L. Zhao, "Different learning styles and second language teaching," in *Proc. the 2022 International Conf. on Creative Industry and Knowledge Economy (CIKE 2022),* 2022, pp. 384–387. doi: https://doi.org/10.2991/aebmr.k.220404.072

[37] B. D. Lund and T. Wang, "Chatting about ChatGPT: How may AI and GPT impact academia and libraries?" *Library Hi Tech News*, vol. 40, no. 3, pp. 26–29, 2023. doi: https://doi.org/10.1108/LHTN-01-2023-0009

[38] H. Allam, J. Dempere, V. Akre, D. Parakash, N. Mazher, and J. Ahamed, "Artificial intelligence in education: An argument of Chat-GPT use in education," in *Proc. 2023 9th International Conf. on Information Technology Trends (ITT)*, pp. 151–156, 2023. doi: https://doi.org/10.1109/ITT59889.2023.10184267

[39] A. A. Norman, A. H. Marzuki, F. Faith, S. Hamid, N. A. Ghani, S. D. Ravana, and N. I. Arshad, "Technology dependency and impact during COVID-19: A systematic literature review and open challenges," *IEEE Access*, vol. 11, pp. 40741–40760, 2023. doi: https://doi.org/10.1109/ACCESS.2023.3250770

[40] A. U. Mentsiev, M. V. Engel, A. M. Tsamaev, M. V. Abubakarov, and R. S.-E. Yushaeva, "The concept of digitalization and its impact on the modern economy," in *Proc. the International Scientific Conf. "Far East Con" (ISCFEC 2020)* 2020. doi: https://doi.org/10.2991/aebmr.k.200312.422

[41] S. Ghory and H. Ghafory, "The impact of modern technology in the teaching and learning process," *International Journal of Innovative Research and Scientific Studies*, vol. 4, no. 3, pp. 168–173, 2021. doi: https://doi.org/10.53894/ijirss.v4i3.73

[42] G. Thippanna, P. Jyothi, and P Krishnaiah "An extensive review of the benefits and drawbacks of AI tools," *World Journal of Advanced Research and Reviews*, vol. 20, no. 3, pp. 1668–1673, 2023. doi: https://doi.org/10.30574/wjarr.2023.20.3.2636

[43] A. Ardichvili, "The impact of artificial intelligence on expertise development: Implications for HRD," *Advances in Developing Human Resources*, vol. 24, no. 2, pp. 78–98, 2022. doi: https://doi.org/10.1177/15234223221077304

[44] O. F. Ahmad, D. Stoyanov, and L. B. Lovat, "Barriers and pitfalls for artificial intelligence in gastroenterology: Ethical and regulatory issues," *Techniques and Innovations in Gastrointestinal Endoscopy*, vol. 22, no. 2, pp. 80–84, 2020. doi: https://doi.org/10.1016/j.tgie.2019.150636

[45] P. Facione. "Critical thinking: A statement of expert consensus for purposes of educational assessment and instruction. research findings and recommendations," *Research Findings and Recommendations*, 1990.

[46] N. E. A. Latif, F. M. Yusuf, N. M. Tarmezi, S. Z. Rosly, and Z. N. Zainuddin, "The application of critical thinking in accounting education: A literature review," *International Journal of Higher Education*, vol. 8, no. 3, 57, 2018. doi: https://doi.org/10.5430/ijhe.v8n3p57

[47] S. K. Wolcott and M. J. Sargent, "Critical thinking in accounting education: Status and call to action," *Journal of Accounting Education*, vol. 56, 100731, 2021. doi: https://doi.org/10.1016/j.jaccedu.2021.100731

[48] C. Gaul and M. K. Kim, "Learner participation regulation supported by long-term peer moderation and participation feedback during asynchronous discussions," *Journal of Computers in Education*, vol. 7, no. 3, pp. 295–331, 2020. doi: https://doi.org/10.1007/s40692-020-00158-5

[49] J. K. V. Akkeren and J.-A. Tarr, "The application of experiential learning for forensic accounting students: the Mock trial," *Accounting Education*, vol. 31, no. 1, pp. 39–66, 2022. doi: https://doi.org/10.1080/09639284.2021.1960573

[50] K. Seo, J. Tang, I. Roll, S. Fels, and D. Yoon, "The impact of artificial intelligence on learner–instructor interaction in online learning," *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, 54, 2021. doi: https://doi.org/10.1186/s41239-021-00292-9

[51] Q. Wang, Y. Wen, and C. L. Quek, "Engaging learners in synchronous online learning," *Education and Information Technologies*, vol. 28, no. 4, pp. 4429–4452, 2023. doi: https://doi.org/10.1007/s10639-022-11393-x

[52] A. E. E. Sobaih, I. A. Elshaer, and A. M. Hasanein, "Examining students' acceptance and use of ChatGPT in Saudi Arabian higher education," *European Journal of Investigation in Health, Psychology and Education*, vol. 14, no. 3, pp. 709–721, 2024. doi: https://doi.org/10.3390/ejihpe14030047

[53] T. Budhathoki, A. Zirar, E. T. Njoya, and A. Timsina, "ChatGPT adoption and anxiety: A cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT)," *Studies in Higher Education*, vol. 49, no. 5, pp. 831–846, 2024. doi: https://doi.org/10.1080/03075079.2024.2333937

[54] S. Bayona-Oré, "Student learning styles in information technology," *WSEAS Transactions on Computer Research*, vol. 11, pp. 385–392, 2023. doi: https://doi.org/10.37394/232018.2023.11.35

[55] C. Blundell, K.-T. Lee, and S. Nykvist, "Moving beyond enhancing pedagogies with digital technologies: Frames of reference, habits of mind and transformative learning," *Journal of Research on Technology in Education*, vol. 52, no. 2, pp. 178–196, 2020. doi: https://doi.org/10.1080/15391523.2020.1726235

[56] Muthmainnah, P. M. I. Seraj, and I. Oteir, "Playing with AI to investigate human-computer interaction technology and improving critical thinking skills to pursue 21st century age," *Education Research International*, 2022, 6468995, 2022. doi: https://doi.org/10.1155/2022/6468995

[57] Darwin, D. Rusdin, N. Mukminatien, N. Suryati, E. D. Laksmi, and Marzuki, "Critical thinking in the AI era: An exploration of EFL students' perceptions, benefits, and limitations," *Cogent Education*, vol. 11, no. 1, 2024. doi: https://doi.org/10.1080/2331186X.2023.2290342

[58] Y. Walter, "Embracing the future of artificial intelligence in the classroom: The relevance of AI literacy, prompt engineering, and critical thinking in modern education," *International Journal of Educational Technology in Higher Education*, vol. 21, no. 1, 15, 2024. doi: https://doi.org/10.1186/s41239-024-00448-3

[59] H. Frick, J. Birt, and J. Waters, "Enhancing student engagement in large management accounting lectures," *Accounting & Finance*, vol. 60, no. 1, pp. 271–298, 2020. doi: https://doi.org/10.1111/acfi.12318

[60] S. Fabriz, J. Mendzheritskaya, and S. Stehle, "Impact of synchronous and asynchronous settings of online teaching and learning in higher education on students' learning experience during COVID-19," *Frontiers in Psychology*, vol. 12, 2021. doi: https://doi.org/10.3389/fpsyg.2021.733554

[61] J. Secker, S. Reimers, and G. Foley, "From face-to-face to remote learning: What can we learn from student experiences of pre-recorded lectures in the pandemic?" in *Proc. 16th International Technology, Education and Development Conf.*, 2022, pp. 1737–1743. doi: https://doi.org/10.21125/inted.2022.0520