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Generative AI in Higher Education: Investigating How Perceived Usefulness and Usage Patterns Influence Student Engagement and Academic Performance

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Abstract. This study examines the influence of generative Artificial Intelligence (AI) tools on student learning outcomes in higher education. A questionnaire developed using two validated instruments (perceived usefulness of generative AI tools among students and the level of interest of students' interaction with study materials after using generative AI tools) was used to collect primary data from 208 students across four institutions. The collected data were analyzed using descriptive statistics, inferential statistical methods, and Partial Least Squares Structural Equation Modeling (PLS-SEM). The outcome of the analysis highlights the ability of generative AI to enhance academic engagement, intellectual curiosity, and personalized learning experiences. Key findings include the high perceived usefulness of generative AI in understanding complex topics and connecting coursework to real-world applications. Also, generative AI has the potential to support active knowledge construction and cognitive development, offering actionable insights for educators and policymakers. Challenges such as limited technical training for academics and data privacy concerns are identified as factors that reduce the positive impact of generative AI in student learning outcomes. Conclusively, generative AI could be used to enhance learning outcomes and streamline educational processes.

Keywords: Generative AI; Higher Education; Technology Integration; Cognition and Learning Outcomes; Perceived Usefulness

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1. Introduction

The educational community has taken notice of Artificial Intelligence (AI) because of its potential to revolutionize teaching and learning. Following thirty years of research, the widespread adoption of AI technologies in classrooms has accelerated due to developments in computing and connectivity (Ouyang et al., 2022). The integration of AI into educational frameworks is growing due to its ability to provide personalized instruction, automate administrative tasks, and offer immediate feedback (Zawacki-Richter et al., 2019). As a subset of AI, generative AI improves student learning through the production of study materials, content creation, learning experience personalization, and grading support (Brown et al., 2024; Zawacki-Richter et al., 2019).

Personalized content recommendations, adaptive feedback mechanisms, AI-powered data representation tools, and interactive learning resources have been implemented across all stages of the self-regulatory process, especially in higher education settings, increasing students' autonomy in their learning journey (Lima et al., 2024). While AI offers promising enhancements to education, its integration also presents challenges. This study evaluates the impact of AI on learning outcomes in higher education, balancing potential advantages with existing challenges.

Although research on the benefits of AI has been conducted, little is known about how these technologies affect pedagogical practices and student engagement in a variety of contexts, particularly South African higher education. By filling in these gaps, this study adds to the larger field of AI in education, highlighting its unique context and implications. The study investigates the impact of generative AI on student learning outcomes from the perspective of a developing country's higher education system and its unique characteristics.

The main research question guiding this study is: **What is the impact of integrating generative Artificial Intelligence (AI) on student learning outcomes in South African higher education?** The paper is structured as follows: First, the theoretical framework underpinning the study was discussed. Second, relevant extant literature on AI in higher education was reviewed. Then, the methodology used in the study, followed by the findings, discussion, and conclusion were presented.

1.1 Theoretical Framework

This study draws upon several interrelated theories, including constructivism (Piaget, 2013), cognitive development, and Eisner's learning outcomes framework (Eisner, 1993), to provide a comprehensive lens through which the effects of AI technologies on education are examined. Constructivism posits that learners actively construct knowledge through their experiences and interactions with their environment. The theory, whose foundation was articulated by key figures such as Piaget (2013) and Vygotsky (2004), emphasises the importance of personalised learning experiences that cater to individual student needs. In the context of AI, generative tools can create tailored educational content that adapts to various learning styles, thereby enhancing student engagement and understanding. By aligning our research with constructivist principles, we can better analyse how AI facilitates active learning and knowledge construction, ultimately leading to improved learning outcomes (O'Connor, 2022).

The Cognitive development theory further supports the study by highlighting the role of mental processes in learning. This perspective allows for the exploration of how AI tools can stimulate cognitive growth through adaptive learning tasks that promote critical thinking and problem-solving skills. The study adapted questions from two validated instruments, which employed the cognitive theory in their development (Liang et al., 2023; Yilmaz et al., 2024).

Eisner (1993) defines learning outcomes as the results of a learner's engagement in the educational process, which includes both intentional and incidental effects. Kuh and Hu (2001) characterized a learning outcome as a student's capacity to exhibit proficiency in knowledge, abilities, and values upon the completion of a training module or an entire program. This comprehensive perspective on learning outcomes enables us to assess the impact of artificial intelligence (AI) on various aspects of student learning, including knowledge acquisition, retention, and application.

Eisner (1993) also discusses the importance of different forms of representation in learning. In this context, AI can provide diverse forms of content representation such as visual, auditory, and interactive simulations. These diverse forms cater to different learning styles, improving student engagement and positively impacting student learning outcomes. Furthermore, Eisner (1993) highlights the political nature of education and the need for diverse forms of representation. AI has the potential to democratize education by providing equal access to high-quality learning resources and personalized support.

This could potentially reduce educational inequalities, making higher education more accessible and beneficial for all students (Zawacki-Richter et al., 2019). Thus, the principles outlined in Eisner's paper provide a valuable framework for understanding the impact of AI on student learning outcomes in higher education. By employing these theoretical underpinnings, the rigour of the research is enhanced, and the results contribute valuable insights into the effective integration of AI technologies in higher education.

2. Literature Review

2.1 Generative AI in Higher Education

Collins et al. (2021) describe AI as computers that execute cognitive tasks typically associated with human minds, especially learning and problem-solving. The authors emphasise that AI is not a single technology but an umbrella term encompassing a variety of technologies and methods, including machine learning, natural language processing, data mining, neural networks, and algorithms. Generative AI refers to a subset of artificial intelligence that leverages machine learning techniques to generate data that resembles the input data it is trained on (Goodfellow et al., 2014. The integration of artificial intelligence in educational systems holds significant potential to address critical challenges within the field of higher education, potentially accelerating progress towards the achievement of Sustainable Development Goal 4 (SDG 4) (Balachandran & Rabbiraj, 2024). While various forms of AI have been applied in educational settings, generative AI stands out for its unique ability to create new content. This capability makes it particularly useful in educational settings, where it can generate study materials, provide personalised learning experiences, and even assist in grading assignments (Bates et al., 2020).

Machine learning AI, for instance, focuses on developing algorithms that enable machines to learn from data without being explicitly programmed. While it can be used for tasks such as predictive modelling and data analysis, it cannot generate new content like generative AI (Bates et al., 2020). Similarly, natural language processing AI is used for tasks such as language translation and text summarization, but it cannot create new content. Rule-based AI uses pre-defined rules to make decisions and perform tasks, but it lacks the creative capabilities of generative AI.

Hybrid AI combines multiple AI techniques, but it cannot generate new content like generative AI (Crompton & Burke,2023). Generative AI has a wide range of applications across various domains. In the creative industry, it is used to generate new works of art, music, and design (Elgammal et al., 2017) In healthcare, it is used to generate synthetic data for training machine learning models (Beaulieu-Jones et al., 2017). In natural language processing, it is used to generate human-like text, enabling more natural interactions between humans and AI (Radford et al., 2019).

In the education sector, generative AI can provide interactive and adaptive learning environments that cater to different learning styles and abilities. Applied with forethought, AI tools can enable personalized learning and foster critical thinking, transforming educators from knowledge transmitters to guides, and providing interactive learning environments that can improve student engagement and performance (Elgammal et al., 2017). Generative AI has been particularly influential in this regard. Generative AI can also assist in grading assessments and other administrative tasks, freeing educators to focus on developing curriculum and providing quality instruction (Crompton and Burke, 2023).

The authors suggest that AI has a positive impact on the learning experience by facilitating the acquisition of new knowledge and skills. AI algorithm models can extract and analyse educational data from higher education system databases to gain insights into course status and student learning performance. This analysis can help administrators and decision-makers to make necessary adjustments to courses (Bates et al., 2020; Zawacki-Richter et al., 2019).

According to Slimi (2023), AI affects not only teaching and learning processes, it also affects assessment and grading procedures. AI tools like Turnitin can rapidly compare assignments and research projects against a vast database of resources, quickly identifying potential plagiarism. Additionally, AI can use online rubrics and grading forms to evaluate assignments based on predefined criteria, automatically generating final grades (Crompton & Burke, 2023). One significant benefit of AI in education is its ability to provide students with immediate and constructive feedback. Automated grading systems powered by AI algorithms can assess and provide feedback on assignments, quizzes, and exams promptly, enabling students to understand their strengths and weaknesses in real-time. This timely feedback facilitates self-reflection and enables students to make necessary improvements, leading to enhanced learning outcomes (Holmes &Tuomi, 2022).

However, the use of generative AI has its own unique set of challenges (Chan, 2023). Among the identified challenges are the risk of over-reliance on AI and the potential loss of critical thinking and problem-solving skills (Chan, 2023). The potential for misuse and abuse is another concern (Chan, 2023). Furthermore, the effectiveness of these tools can be influenced by a variety of factors, including the quality of the AI algorithms, the nature of the data input on the AI, the design of the user interface, and the level of support provided to the users (Xu, 2023).

There are also concerns about the potential negative impact of AI on learning outcomes. This is because AI systems can provide quick answers without encouraging students to engage in deeper analysis and reflection (Seo et al., 2021). AI-powered grading systems may also perpetuate biases and inaccuracies if not properly designed and tested, which could negatively affect student learning outcomes (Crompton & Burke, 2023; Ouyang et al., 2022). Furthermore, the integration of AI in education raises questions about the role of human instructors. While AI can automate routine tasks, human instructors can help students develop essential skills like communication, teamwork, and creativity, which are difficult to replicate with AI alone (Luan et al., 2020). Research suggests that the use of AI tools can increase student engagement and interest in learning (Blikstein and Worsley, 2016).

However, this may depend on the nature of the tasks or activities, the student's prior experience with AI, and their attitudes towards technology (Eynon, 2013). Despite the transformative potential of AI in higher education, ethical issues, data privacy, and bias pose significant limitations. Ethical concerns arise when AI systems inadvertently perpetuate inequities, especially among marginalized student groups Okewu et al., 2021. Questions of responsibility and accountability for AI-driven outcomes, such as grading systems or personalized learning pathways, can have profound consequences for students' futures, necessitating clear protocols and informed consent regarding AI's role in education. Data privacy also presents significant challenges, as institutions collect vast amounts of sensitive student data.

Ensuring compliance with data protection regulations, such as GDPR, and safeguarding against misuse require robust policies and transparent practices. Additionally, biases in AI algorithms, stemming from imbalanced or incomplete training data, risk producing unfair or exclusionary results, particularly affecting rural or underserved communities (Slimi & Carballido, 2023). These biases can exacerbate existing educational inequalities, underlining the need for rigorous validation and critical evaluation of AI tools. Addressing these issues through ethical guidelines, stakeholder engagement, and contextualized AI deployment is essential to harness AI's potential while safeguarding equity, privacy, and trust in education systems.

Luckin and Cukurova, (2019) emphasise that for AI to effectively enhance education, it is crucial to strengthen the collaboration between AI developers and experts in learning sciences. The authors contend that without this partnership, AI may reinforce ineffective teaching methods and misconceptions about learning. In its current state, generative AI helps equip students with foundational skills like comprehension and understanding, however, this does not foster higher-order skills such as critical thinking, problem-solving, creativity, and knowledge management in students (Islam et al., 2022; Xu, 2023).

The impact of AI systems on learner-instructor interaction in online learning is still elusive (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). While AI systems have been positively recognized for improving the quantity and quality of communication, providing just-in-time, personalised support for large-scale settings, and improving the feeling of connection, there are concerns about responsibility, agency, depth of engagement, ethics and surveillance issues (Seo et al., 2021).

3. Methodology

The study employed a quantitative research design to investigate the effects of AI integration in higher education on student learning outcomes. The primary data collection method was a questionnaire, which was designed to measure students' learning outcomes after using generative AI tools. The questionnaire was developed using two validated instruments that were identified through a comprehensive literature search on the Web of Science database (Liang et al., 2023; Yilmaz et al., 2024). The search strings used to identify these instruments are provided as an appendix. These instruments were selected because they closely aligned with the research questions of this study and enabled the accurate measurement of the constructs under investigation.

The first instrument focused on measuring the perceived usefulness of generative AI in helping students immerse themselves in their study material. It included Likert scale questions that probed into students' beliefs about the extent to which generative AI tools enhanced their understanding of study material, made studying more engaging, and improved their overall learning outcomes. The second instrument was designed to measure the level of interest students had in interacting with the study materials after using generative AI tools.

It encompassed elements such as the frequency of use, self-efficacy belief, cognitive engagement, learning achievement, and overall satisfaction. By combining constructs from these two instruments, we developed a comprehensive questionnaire that accurately measures the elements related to our research question. This approach ensured that we captured a holistic view of the students' experiences and perceptions of using generative AI tools in their learning process. Before administering the questionnaire, it was pilot tested with a small group of students to ensure the clarity and relevance of the questions. The feedback from the pilot test was used to refine the questionnaire before it was distributed to the larger student population. The data collected from the questionnaire were then analysed using descriptive statistics (e.g., means, standard deviations) and inferential statistical methods, specifically t-tests and ANOVA, to determine the impact of AI integration on student learning outcomes. This rigorous methodology ensured the validity and reliability of the findings, contributing to the robustness of the study. The demographics of the respondents are in Table 1. The findings of the empirical data collection are presented below the demographic table.

4. Results and Discussion

4.1 Effects of Generative AI Integration in Higher Education on Students' Learning Outcomes

Table 1 shows the demographic information on the respondents to the administered questionnaire while Table 2 reflects the outcome of the statistical analysis of elements/constructs related to the research question

Table 1: Demographics information

Characteristics	Item	Frequency	Percent
Age	18-24	116	55.8
	25-30	88	42.3
	31-40	4	1.9
Sex	Male	128	61.5
	Female	80	38.5
Level of Education	Secondary school	4	1.9
	Diploma/Certificate	32	15.4
	Bachelor's degree	170	81.7
	Master's degree	2	1
Location	Rural	76	36.5
	Suburban	24	11.5
	Urban	108	51.9
AI Familiarity	Not at all familiar	10	4.8
	Slightly familiar	96	46.2
	Moderately familiar	34	16.3
	Very familiar	54	26
	Extremely familiar	14	6.7
AI Training	No, never	70	33.7
	No, but planning to	86	41.3
	Yes, less than 6 months	46	22.1
	Yes, 6 months – 1 year	4	1.9
	Yes, more than 1 year	2	1
Economic status	Lower class	32	15.4
	Middle class	142	68.3
	Upper class	34	16.3

Table 2: Mean and standard deviations

Construct	Item	Mean	SD
FREQ	FREQ2	3.029	1.133
	FREQ1	2.654	1.093
	FREQ3	2.702	1.067
	FREQ4	2.115	1.015
USEF	USEF2	3.894	0.856
	USEF6	3.808	0.902
	USEF5	3.769	0.789
	USEF3	3.769	0.893
	USEF4	3.712	0.876
	USEF9	3.49	1.228
	USEF8	3.192	1.204
	USEF7	3.183	1.169
	USEF1	2.644	1.002
ENGAGE	ENGAG1	3.663	0.979
	ENGAG3	3.663	0.782
	ENGAG2	3.702	0.889
	ENGAG5	3.308	1.22
	ENGAG4	3.25	1.01
INTERE	INTERE3	3.808	0.993
	INTERE5	3.76	0.968
	INTERE4	3.683	0.935
	INTERE1	3.452	1.048
	INTERE2	3.25	1.01
PERFORM	PERFORM2	3.952	0.766
	PERFORM1	3.827	0.873
	PERFORM5	3.721	0.816
	PERFORM4	3.5	1.212
	PERFORM3	3.077	1.152
COGNTV	COGNTV3	3.75	0.808
	COGNTV6	3.913	0.869
	COGNTV1	3.644	0.952
	COGNTV2	3.288	1.152
	COGNTV5	3.279	1.026
	COGNTV4	3.077	1.056
EFFICACY	EFFICACY1	3.25	0.94
	EFFICACY5	3.212	1.056
	EFFICACY3	3.212	0.95
	EFFICACY2	3.135	1.05
	EFFICACY4	2.99	0.968

4.1.1 Frequency of Use (FREQ)

The "Frequency of Use" construct measures how frequently individuals interact with generative AI tools across various academic tasks. From the data, the average use frequency spans moderately across tasks such as generating ideas, creating visual content, and data analysis. Among these, generating ideas for essays or projects (FREQ2) sees the highest frequency, indicating that students commonly rely on AI tools to brainstorm and enhance their creative processes. The least frequent use is observed in employing generative AI tools for data analysis (FREQ4), reflecting a lower inclination or opportunity to leverage these tools for research-based tasks.

4.1.2 Usefulness and Impact (USEF)

This construct evaluates the perceived usefulness and impact of generative AI tools on academic learning outcomes. Students overwhelmingly agree that AI tools have significantly enhanced their understanding of course material (USEF2) and had a positive impact on overall learning outcomes (USEF3). Generative AI is also perceived to stimulate intellectual curiosity (USEF4) and deepen engagement with course topics (USEF5). Furthermore, students acknowledge the role of AI tools in fostering connections between coursework and real-world applications (USEF6). However, challenges remain in how these tools contribute to solving complex problems (USEF7) and promoting active class participation (USEF8).

4.1.3 Engagement (ENGAGE)

"Engagement" examines how generative AI tools foster students' involvement in their studies and boost their confidence in their academic abilities. The use of AI tools has been strongly associated with better understanding of study materials (ENGAGE1) and improved learning outcomes (ENGAGE2). Students report feeling more confident in their ability to participate in discussions (ENGAGE4) and perform academically (ENGAGE5). However, the construct reveals variability, with some students expressing that AI tools have only moderately influenced their active engagement during class activities, suggesting room for improvement in the integration of AI into collaborative and participatory learning.

4.1.4 Interest and Curiosity (INTERE)

The "Interest" construct examines whether generative AI tools increase students' curiosity and make academic tasks more engaging. The findings reveal that students are generally more interested in their study materials after using these tools (INTERE1) and find tasks such as assignments and projects more enjoyable (INTERE3). Additionally, generative AI is reported to encourage further exploration of topics beyond coursework requirements (INTERE5). Despite these positive perceptions, the data indicate moderate variability in how AI tools inspire sustained curiosity and learning interest across different individuals.

4.1.5 Performance and Cognitive Impact (PERFORM and COGNTV)

The "Performance" and "Cognitive Impact" constructs jointly reflect the influence of generative AI on academic achievement and intellectual engagement. Students generally agree that AI tools have improved their understanding of subjects (PERFORM1) and enhanced their ability to complete assignments (PERFORM2). Cognitive aspects, such as stimulating intellectual curiosity (COGNTV1) and making connections between theoretical knowledge and real-world applications (COGNTV3), are also positively influenced. However, challenges persist in areas such as solving complex problems (COGNTV4) and achieving higher grades (PERFORM3). The findings suggest that while generative AI significantly supports performance, its impact on critical thinking and advanced problem-solving needs further enhancement.

4.2 Summary of Statistics Across Constructs

Table 3 shows the summary of the results of the statistical analysis across constructs.

Table 3: Summary of statistics across constructs

Construct	Item	Low (%)	Neutral (%)	High (%)	Mean	SD
Frequency (FREQ)	FREQ2	25	44.23	30.77	3.029	1.133
	FREQ1	48.08	26.92	25	2.654	1.093
	FREQ3	36.54	44.23	19.23	2.702	1.067
	FREQ4	64.42	25.96	9.62	2.115	1.015
Usefulness (USEF)	USEF2	4.81	19.23	75.96	3.894	0.856
	USEF6	6.73	20.19	73.08	3.808	0.902
	USEF5	2.89	27.88	69.23	3.769	0.789
	USEF8	29.81	26.92	43.27	3.192	1.204
Engagement (ENGAGE)	ENGAG1	7.69	26.92	65.39	3.663	0.979
	ENGAG2	7.69	29.81	62.5	3.702	0.889
	ENGAG5	26.92	31.73	41.35	3.308	1.22
Interest (INTERE)	INTERE3	6.73	23.08	70.19	3.808	0.993
	INTERE5	7.69	24.04	68.27	3.76	0.968
	INTERE1	18.27	25	56.73	3.452	1.048
Performance (PERFORM)	PERFORM2	3.85	14.42	81.73	3.952	0.766
	PERFORM1	6.73	19.23	74.04	3.827	0.873
	PERFORM4	20.19	26.92	52.88	3.5	1.212
Cognitive (COGNTV)	COGNTV6	5.77	22.12	72.12	3.913	0.869
	COGNTV3	5.77	22.12	72.12	3.75	0.808
	COGNTV4	30.77	34.62	34.62	3.077	1.056
Efficacy (EFFICACY)	EFFICACY1	23.08	31.73	45.19	3.25	0.94
	EFFICACY5	28.85	27.89	43.27	3.212	1.056
	EFFICACY3	25.96	31.73	42.31	3.212	0.95
	EFFICACY2	26.92	37.5	35.58	3.135	1.05
	EFFICACY4	30.77	41.35	27.89	2.99	0.968

The study evaluates various constructs, including Frequency of Use (FREQ), Perceived Usefulness (USEF), Engagement (ENGAGE), Interest (INTERE), Academic Performance (PERFORM), Cognitive Engagement (COGNTV), and Self-Efficacy Beliefs (EFFICACY), based on respondents' Likert scale ratings. Results indicate varied high response rates, with Frequency showing the highest agreement (30.77%) for generating ideas (FREQ2) and the lowest for data analysis (FREQ4, 9.62%). Similarly, Perceived Usefulness had strong positive responses, with notable agreement on improving course understanding (USEF2, 75.96%) and engaging with real-world topics (USEF6, 73.08%).

For Engagement and Interest, high responses suggest positive academic experiences associated with the use of generative AI. Engagement metrics revealed increased interaction with study materials (ENGAG1, 65.39%) and improved learning outcomes (ENGAG2, 62.50%). Similarly, Interest highlighted the ability of AI tools to make assignments enjoyable (INTERE3, 70.19%) and foster exploration beyond required topics (INTERE5, 68.27%). These results underscore the role of AI in enhancing both curiosity and active participation among students.

Academic Performance and **Cognitive Engagement** also showed significant positive impacts. Respondents reported improved task completion (PERFORM2, 81.73%) and better subject understanding (PERFORM1, 74.04%). **Cognitive Engagement** findings reflected the usefulness of AI in connecting coursework to real-world applications (COGNTV3, 72.12%) and enhancing intellectual curiosity (COGNTV6, 72.12%). In terms of **Self-Efficacy**, confidence in using AI tools was moderate, with the highest agreement (EFFICACY1, 45.19%) observed in effective tool usage. These insights collectively demonstrate the multi-faceted benefits of generative AI tools in academic settings, from improving performance to fostering deeper engagement and confidence.

4.2.1 Summary of results

The socio-economic analysis reveals a diverse student population primarily consisting of young adults aged 18-24, with a higher representation of males (61.5%) compared to females (38.5%). Most respondents hold a bachelor's degree and reside in urban areas, indicating a well-educated and predominantly urban demographic. Familiarity with AI varies, with a significant portion of students being slightly familiar (46.2%) with AI technologies, yet many lack formal training (41.3%) and plan to receive it in the future. This highlights the need for enhanced AI training and education to bridge the familiarity gap.

The frequency of AI usage among students shows varied engagement, with most students using AI tools occasionally for assignments and projects. For example, AI tools are occasionally used for generating ideas for essays and visual content for presentations, while data analysis remains a less frequent application. This suggests that while students recognize the potential of AI tools for creative and presentation tasks, their usage for analytical purposes is not as widespread, highlighting an area for potential growth in AI integration.

Students perceive AI tools as incredibly useful in enhancing their learning outcomes. The highest perceived usefulness is in understanding course material and encouraging deeper exploration of subjects. This is evidenced by high agreement levels for these aspects, indicating that AI tools are valuable in making complex topics more comprehensible and stimulating intellectual curiosity among students. Such tools appear to play a crucial role in facilitating a deeper understanding of academic content.

The engagement metrics indicate that AI tools have a positive impact on students' engagement with study materials and overall learning outcomes. Many students agree or strongly agree that AI tools help them understand study materials better and improve their learning outcomes. The confidence boost in academic abilities further underscores the motivational effect of AI integration, suggesting that students feel more capable and supported in their academic endeavours when utilizing these technologies.

Interest levels in assignments and tasks have increased significantly due to the integration of AI. A significant portion of students express high levels of interest in assignments and ongoing engagement post-AI use. This heightened interest likely translates to improved motivation and enthusiasm towards academic work, indicating that AI tools can make learning experiences more engaging and enjoyable for students.

Academic performance, particularly in terms of assignment completion and overall academic performance, shows a positive trend with the use of AI. Students agree that AI tools help them complete assignments more efficiently and enhance their overall academic performance. This suggests that AI tools not only facilitate understanding and engagement but also contribute to tangible improvements in academic success, making them valuable assets in higher education.

Lastly, cognitive engagement and self-efficacy are positively influenced by AI tools. Students report that AI tools stimulate their intellectual curiosity and help them apply knowledge to real-world contexts. Confidence in using AI tools effectively and enhancing learning outcomes is also high, although some students still experience technical challenges. This suggests that while AI tools are generally well-received, ongoing support and training are essential to maximize their benefits and address any technical difficulties students may encounter.

Based on the findings, we submit that the integration of generative AI in higher education significantly enhances students' learning outcomes by increasing engagement, interest, academic performance, and self-efficacy, while also highlighting the need for improved training and support to fully realize the potential of AI technologies. To further test the hypothesis, we used a PLS-SEM approach to validate and confirm the findings. The result is presented in Table 4

4.3 Effects of Generative AI Integration in Higher Education on Students' Learning Outcomes: A PLS-SEM Approach

The result of the PLS-SEM analysis of the effects of generative AI intergration in higher education on students learning outcome is shown on Table 4.

Table 4: A PLS-SEM approach

Construct	High Frequency or Positive Responses (%)	Key Observations
Frequency of Use (FREQ)	Generating ideas (FREQ2) frequently used by 30.77% (Frequently + Very Frequently), while data analysis (FREQ4) lowest at 9.62%.	Students use generative AI tools more for creative tasks than for research or technical analysis.
-+]Perceived Usefulness (USEF)	High agreement (Agree + Always) observed in improving course understanding (USEF2: 75.96%) and engagement with real-world topics (USEF6: 73.08%).	Students find AI tools highly beneficial for academic understanding, but less impactful on active participation (USEF8: 43.27%).
Engagement (ENGAGE)	Strong agreement on improved learning outcomes (ENGAG2: 62.50%) and study materials engagement (ENGAG1: 65.38%).	Generative AI tools have a positive influence on comprehension and confidence, although they are less effective in fostering interactive engagement.
Interest (INTERE)	High interest in making tasks enjoyable (INTERE3: 70.19%) and fostering topic exploration (INTERE5: 68.27%).	AI tools increase interest and curiosity, particularly for tasks that involve creative or exploratory activities.
Academic Performance (PERFORM)	Significant agreement on task completion improvement (PERFORM2: 81.73%) and subject understanding (PERFORM1: 74.04%).	Generative AI enhances academic performance but is slightly less effective in improving critical thinking for advanced tasks (PERFORM3: 36.54%).
Cognitive Engagement (COGNTV)	Strong agreement on connecting coursework to real-world applications (COGNTV3: 72.12%) and understanding enhancement (COGNTV1: 67.31%).	Students perceive AI tools as valuable for both intellectual engagement and practical application, with moderate variability in their critical problem-solving abilities.
Self-Efficacy Beliefs (EFFICACY)	High confidence in using AI tools for academic tasks was observed at a moderate level (EFFICACY1: 45.19%; EFFICACY3: 42.31%).	Generative AI tools modestly improve students' confidence in their academic abilities, with variability across individuals.

This table summarizes the key patterns and observations across constructs, highlighting strengths and areas for improvement in the use of generative AI and its impact on student learning outcomes.

4.4 Multicollinearity Assessment Report

Table 5 presents the assessment of collinearity issues among the indicators by displaying the Variance Inflation Factor (VIF) values.

Table 5: Collinearity issue assessment

Indicators	VIF<5	Indicators	VIF<5
COGNTV1	1.498	FREQ4	2.199
COGNTV2	1.531	INTERE2	1.402
COGNTV4	1.777	INTERE3	1.873
COGNTV5	1.759	INTERE4	1.490
EFFICACY1	2.116	INTERE5	1.982
EFFICACY2	3.180	PERFORM1	2.119
EFFICACY3	2.515	PERFORM2	1.690
EFFICACY4	3.303	PERFORM3	1.704
EFFICACY5	2.667	PERFORM4	1.538
ENGAG1	2.464	PERFORM5	1.725
ENGAG2	2.203	USEF1	2.387
ENGAG4	2.064	USEF2	3.143
ENGAG5	2.181	USEF3	1.930
FREQ1	2.956	USEF4	2.131
FREQ2	3.793	USEF5	2.176
FREQ3	3.531	USEF6	2.059

To ensure the robustness of the regression model and avoid the issues associated with multicollinearity, a Variance Inflation Factor (VIF) analysis was conducted. The results demonstrate that all indicators fall within the acceptable threshold of VIF < 5, indicating no significant multicollinearity among the variables. All the Variance Inflation Factor (VIF) values are below the threshold of 5, indicating no significant multicollinearity problems. The VIF values for the Cognitive Engagement (COGNTV) indicators range from 1.498 to 1.777, suggesting that these indicators do not exhibit problematic collinearity. Similarly, the Self-Efficacy Beliefs (EFFICACY) indicators have VIF values ranging from 2.116 to 3.303, indicating acceptable levels of collinearity.

Cognitive Engagement (COGNTV): Indicators such as COGNTV1, COGNTV2, COGNTV4, and COGNTV5 exhibit VIF values ranging from 1.498 to 1.777. These values confirm minimal multicollinearity and reflect the distinct contributions of cognitive engagement variables to the analysis.

Self-Efficacy Beliefs (EFFICACY): VIF values for EFFICACY indicators range from 2.116 to 3.303. While EFFICACY4 showed the highest VIF, it remains well within the acceptable range, affirming its independence from other variables. Engagement with Study Materials (ENGAGE): VIF values for ENGAGE indicators range from 2.064 to 2.464, indicating moderate but acceptable correlations among these indicators.

Frequency of GAI Usage (FREQ): Indicators FREQ1 to FREQ4 displayed VIF values ranging from 2.199 to 3.793. Notably, FREQ2 and FREQ3 have higher VIF values within the construct but remain below the threshold, ensuring the validity of their inclusion. Interest Level (INTERE): INTERE indicators show VIF values ranging from 1.402 to 1.982. These results confirm a lack of multicollinearity and underscore the reliability of the variables representing interest in GAI usage.

Perceived Usefulness (USEF): The USEF indicators have VIF values ranging from 1.930 to 3.143. USEF2 exhibits the highest value within this construct but does not signal concerns about multicollinearity. Academic Performance (PERFORM): Indicators PERFORM1 through PERFORM5 present VIF values ranging from 1.538 to 2.119, ensuring the independence of these variables in measuring academic outcomes. The VIF analysis confirms the independence of all constructs and their respective indicators. These findings validate the inclusion of the selected variables in the regression model, supporting the integrity of subsequent analyses.

Indicators with outer loadings below 0.7 were removed because of weaker relationships with their respective constructs. Specifically, the following indicators were eliminated: COGNTV3 (0.676), COGNTV6 (0.601), ENGAG2 (0.54), ENGAG3 (0.686), INTERE1 (0.662), USEF7 (0.684), USEF8 (0.612), and USEF9 (0.601). This removal can generally enhance the model's performance. The constructs are assessed to ensure that they meet the thresholds for reliability and validity, which are Cronbach's Alpha greater than 0.6 and Composite Reliability greater than 0.7, with item loadings greater than or equal to 0.7.

The construct of Cognitive Engagement (COGNTV) demonstrated a Cronbach's Alpha of 0.803 and a Composite Reliability of 0.805, indicating strong internal consistency and reliability. The items retained for this construct, with their outer loadings, are COGNTV1 (0.757), COGNTV2 (0.791), COGNTV4 (0.815), and COGNTV5 (0.806). These values indicate that the indicators are reliable measures of cognitive engagement within the study context. Self-Efficacy Beliefs (EFFICACY) showed high reliability, with a Cronbach's Alpha of 0.900 and a Composite Reliability of 0.907. The items included for this construct are EFFICACY1 (0.782), EFFICACY2 (0.859), EFFICACY3 (0.847), EFFICACY4 (0.870), and EFFICACY5 (0.866). These outer loadings indicate that each item makes a robust contribution to the overall construct, confirming the high internal consistency and reliability of the self-efficacy measures.

The Engagement with Study Materials (ENGAGE) construct had a Cronbach's Alpha of 0.821 and Composite Reliability of 0.828, reflecting satisfactory internal consistency. The retained items are ENGAG1 (0.827), ENGAG2 (0.755), ENGAG4 (0.809), and ENGAG5 (0.832). These loadings indicate that the indicators are reliable in measuring student engagement with their study materials. The construct for the Frequency of Generative AI Usage (FREQ) reported very high reliability, with a Cronbach's Alpha of 0.912 and Composite Reliability of 0.958.

The items and their loadings are FREQ1 (0.912), FREQ2 (0.929), FREQ3 (0.900), and FREQ4 (0.805). These high outer loadings show that the indicators are strong measures of how frequently students use generative AI tools. Perceived Usefulness of GAI Tools in Enhancing Learning (USEF) also demonstrated strong reliability, with a Cronbach's Alpha of 0.884 and Composite Reliability of 0.899.

The items included are USEF1 (0.751), USEF2 (0.849), USEF3 (0.730), USEF4 (0.791), USEF5 (0.818), and USEF6 (0.823). These loadings confirm that the indicators are reliable and contribute significantly to measuring the perceived usefulness of generative AI tools in enhancing learning.

4.5 Result of Convergent Validity Tests

Table 6 summarizes the convergent validity tests for various constructs by presenting their Average Variance Extracted (AVE) values.

Table 6: Convergent validity tests

Constructs	AVE >0.5
COGNTV	0.629
EFFICACY	0.715
ENGAG	0.650
FREQ	0.788
INTERE	0.623
PERFORM	0.598
USEF	0.632

All the Average Variance Extracted (AVE) values exceed the threshold of 0.5, indicating good convergent validity. Specifically, the constructs and their AVE values are: Cognitive Engagement (COGNTV) at 0.629, Self-Efficacy Beliefs (EFFICACY) at 0.715, Engagement with Study Materials (ENGAG) at 0.650, Frequency of GAI Usage (FREQ) at 0.788, Level of Interest (INTERE) at 0.623, Academic Performance (PERFORM) at 0.598, and Perceived Usefulness of GAI Tools in Enhancing Learning (USEF) at 0.632. These values confirm that the constructs explain a substantial portion of the variance of their indicators, supporting their convergent validity.

For the other constructs, the Engagement with Study Materials (ENGAGE) indicators have VIF values ranging from 2.064 to 2.464, and the Frequency of GAI Usage (FREQ) indicators have higher VIF values ranging from 2.199 to 3.793, but still within acceptable limits. The Level of Interest (INTERE) indicators show VIF values between 1.402 and 1.982, while the Academic Performance (PERFORM) indicators range from 1.538 to 2.119. Lastly, the Perceived Usefulness of GAI Tools in Enhancing Learning (USEF) indicators have VIF values from 1.930 to 3.143. Overall, the VIF values across all constructs are below 5, confirming that collinearity is not a concern in this model.

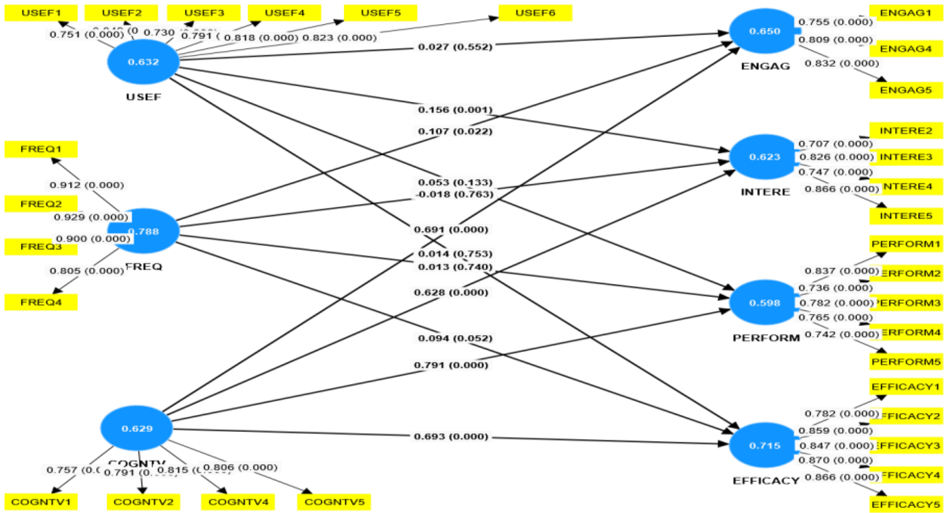

Figure 1: Path coefficient

4.6 Discriminant Validity Analysis Using HTMT

The discriminant validity of the constructs was assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations and the result is presented in Table 7.

Table 7: Discriminant validity analysis using HTMT

Constructs	Heterotrait-monotrait ratio (HTMT)
EFFICACY <-> COGNTV	0.844
ENGAG <-> COGNTV	0.892
ENGAG <-> EFFICACY	0.660
FREQ <-> COGNTV	0.373
FREQ <-> EFFICACY	0.346
FREQ <-> ENGAG	0.372
INTERE <-> COGNTV	0.800
INTERE <-> EFFICACY	0.679
INTERE <-> ENGAG	0.789
INTERE <-> FREQ	0.231
PERFORM <-> COGNTV	0.967
PERFORM <-> EFFICACY	0.827
PERFORM <-> ENGAG	0.810
PERFORM <-> FREQ	0.310
PERFORM <-> INTERE	0.792
USEF <-> COGNTV	0.236
USEF <-> EFFICACY	0.188
USEF <-> ENGAG	0.219
USEF <-> FREQ	0.168
USEF <-> INTERE	0.331
USEF <-> PERFORM	0.240

According to established thresholds, HTMT values below 0.85 indicate sufficient discriminant validity, while values above 0.90 may signal concerns about the distinctiveness of constructs. Most of the construct pairings in the model meet these criteria, but there are a few instances that require further consideration. The construct pairings EFFICACY and COGNTV (HTMT = 0.844), INTERE and COGNTV (HTMT = 0.8), and ENGAG and COGNTV (HTMT = 0.892) exhibit HTMT values near or below 0.85. This suggests that while these constructs are closely related, they retain sufficient discriminant validity. However, the pairing PERFORM and COGNTV (HTMT = 0.967) exceeds the upper threshold, indicating potential overlap between these constructs and necessitating further refinement or theoretical justification.

The relationships involving USEF consistently display low HTMT values (ranging from 0.168 to 0.331), highlighting a clear distinction between USEF and other constructs, such as COGNTV, EFFICACY, ENGAG, FREQ, and PERFORM. This confirms that USEF maintains strong discriminant validity relative to the other constructs in the model, underscoring its unique contribution. The pairings involving FREQ also demonstrate low HTMT values, such as FREQ and COGNTV (0.373) and FREQ and EFFICACY (0.346).

These results provide additional support for the discriminant validity of FREQ in the model. Furthermore, its pairing with INTERE (HTMT = 0.231) shows the constructs are sufficiently distinct, despite being moderately related. In summary, the discriminant validity of most constructs in the model is supported, with HTMT values generally falling within acceptable thresholds. However, the high HTMT value for PERFORM and COGNTV suggests that these constructs may overlap and require theoretical clarification or refinement. Overall, the results confirm the structural integrity of the model while pointing out areas for improvement.

4.7 Discriminant Validity Analysis Using Fornell-Larcker Criterion

The discriminant validity of the constructs was assessed using the Fornell-Larcker Criterion and the result is presented in Table 8.

Table 8: Discriminant validity analysis using Fornell-Larcker criterion

Constructs	COGNTV	EFFICACY	ENGAG	FREQ	INTERE	PERFORM	USEF
COGNTV	0.793						
EFFICACY	0.727	0.846					
ENGAG	0.732	0.574	0.807				
FREQ	0.336	0.329	0.343	0.888			
INTERE	0.655	0.579	0.643	0.217	0.789		
PERFORM	0.807	0.729	0.674	0.287	0.653	0.773	
USEF	0.209	0.172	0.187	0.150	0.284	0.220	0.795

The Fornell-Larcker criterion was applied to assess discriminant validity by comparing the square root of the average variance extracted (AVE) of each construct with its correlations with other constructs. The diagonal values represent the square root of the AVE, and they are expected to be higher than the off-diagonal correlations for the corresponding construct. In this analysis, the square root of AVE for all constructs—COGNTV (0.793), EFFICACY (0.846), ENGAG (0.807), FREQ (0.888), INTERE (0.789), PERFORM (0.773), and USEF (0.795)—exceeds the respective inter-construct correlations, confirming sufficient discriminant validity. The correlations among constructs indicate varying levels of association.

Constructs such as COGNTV and EFFICACY ($r = 0.727$) and COGNTV and PERFORM ($r = 0.807$) show strong relationships, suggesting a high degree of relatedness while still maintaining their distinctiveness, as indicated by the Fornell-Larcker criterion. On the other hand, constructs like USEF demonstrate low correlations with others, such as COGNTV (0.209) and EFFICACY (0.172), indicating clear separation and strong discriminant validity for USEF. The results from the Fornell-Larcker analysis confirm that the constructs in the model possess adequate discriminant validity, with the square root of AVE for each construct consistently surpassing the correlations with other constructs. These findings support the distinctiveness of the constructs while acknowledging the theoretical relationships among them.

4.7.1 Summary of hypotheses and loadings analysis

This study examined the significance of the relationships between latent constructs and their indicators, as represented by outer loadings. Hypotheses were formulated to test whether indicators significantly contribute to their respective latent constructs, including Cognitive Engagement, Self-Efficacy, Engagement, Frequency of Use, Interest, Performance, and Usefulness. Each hypothesis contrasts a null statement of no significant relationship with an alternative that posits a significant association. The hypotheses aim to validate the reliability and importance of the indicators in measuring the constructs.

The outer loadings indicate the strength of relationships between indicators and their latent constructs. A threshold of 0.7 was used to determine the validity of the indicator, with values above this threshold considered strong contributors. Most indicators demonstrated strong loadings, such as FREQ2(0.9290) and EFFICACY4 (0.8700), which reinforce their role as reliable measures. Moderate loadings, such as COGNTV1 (0.7570) and USEF3 (0.7300), were also acceptable within the model's reflective measurement approach. Indicators with low loadings were removed to improve model validity and reliability.

This ensures that only indicators with sufficient explanatory power and relevance remain, strengthening the model's overall structure. By focusing on significant relationships, the analysis enhances construct validity and ensures the development of robust measurement scales. The results confirm that the retained indicators exhibit high and consistent loadings, which support the convergent validity of the constructs. This means the indicators effectively represent their underlying latent constructs. The consistent pattern of significant loadings also validates the measurement model for further structural and predictive analyses.

In conclusion, the findings demonstrate the reliability of the measurement model and the robustness of the constructs. The removal of weak indicators and the presence of strong loadings across constructs affirm the validity of the relationships tested. This provides a strong foundation for subsequent stages of analysis, such as testing theoretical relationships and hypotheses within the structural model. The structural model evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM) was analyzed to determine the relationships between latent constructs and their respective indicators, as well as the strength of inter-construct relationships.

Constructs and Indicator Reliability: The model consists of seven latent constructs: USEF, FREQ, ENGAG, INTERE, PERFORM, EFFICACY, and COGNTV. Each construct is measured using multiple indicators, with outer loadings used to assess their reliability. Most of the indicators demonstrated strong outer loadings above 0.7, indicating that they are reliable measures of their respective constructs. For instance, the indicators for USEF (e.g., USEF1, USEF2) recorded loadings between 0.730 and 0.849, while the indicators for FREQ showed even higher loadings, ranging from 0.805 to 0.929. However, a few indicators, such as USEF6 (loading = 0.187), exhibited lower contributions but remained within an acceptable range for inclusion.

Explained Variance of Constructs: The R^2 values for the latent constructs indicate the extent to which their variance is explained by the independent variables in the model. USEF recorded an R^2 value of 0.632, implying that 63.2% of the variance in the construct is explained by its predictors. Similarly, the R^2 values for other constructs, such as FREQ (0.788), ENGAG (0.650), and INTERE (0.623), demonstrate moderate to high explanatory power. These values highlight the model's strength in capturing the variance within the dependent constructs.

Strength of Relationships Between Constructs: The structural model’s path coefficients quantify the relationships between constructs. Significant relationships were observed, such as the influence of ENGAG on USEF (path coefficient = 0.284) and FREQ on INTERE (path coefficient = 0.343). These coefficients indicate the strength and direction of the hypothesized influences within the model. Constructs like FREQ showed substantial contributions to explaining variance in other constructs, aligning with theoretical expectations.

Indicator Contributions to Constructs: The indicators consistently demonstrated high contributions to their respective constructs. For example, COGNTV indicators such as COGNTV4 and COGNTV5 recorded loadings of 0.815 and 0.806, respectively, indicating their strong reflection of the construct. Similarly, the indicators for EFFICACY (e.g., EFFICACY4 and EFFICACY5) had outer loadings exceeding 0.86, underscoring their significant contributions. These results affirm the reliability of the measurement model and its alignment with theoretical constructs.

Model Evaluation: The model demonstrates robust reliability and validity, supported by high outer loadings, significant path coefficients, and moderate to high R^2 values. The findings indicate that the selected indicators are strong measures of their respective constructs, while the relationships between constructs are consistent with theoretical assumptions. The results validate the hypothesized model, providing valuable insights into the interactions between the constructs and their practical implications within the research framework. This analysis provides a comprehensive understanding of the structural model without relying on a visual representation, ensuring clarity and coherence in the report.

4.8 Test of Significance for Outer Loading

Table 9 presents the test of significance for outer loadings, showing the original sample values (O), sample means (M), standard deviations (Std.dev), T statistics, and P values for each indicator.

Table 9: Test of significance for outer loadings

Indicators	Original sample (O)	Sample mean (M)	Std.dev	T statistics	P values
COGNTV1 <- COGNTV	0.757	0.757	0.037	20.710	0.000
COGNTV2 <- COGNTV	0.791	0.791	0.033	23.933	0.000
COGNTV4 <- COGNTV	0.815	0.814	0.025	32.354	0.000
COGNTV5 <- COGNTV	0.806	0.804	0.034	24.039	0.000
EFFICACY1 <- EFFICACY	0.782	0.779	0.042	18.661	0.000
EFFICACY2 <- EFFICACY	0.859	0.859	0.021	41.744	0.000
EFFICACY3 <- EFFICACY	0.847	0.847	0.025	34.377	0.000
EFFICACY4 <- EFFICACY	0.870	0.870	0.022	39.057	0.000
EFFICACY5 <- EFFICACY	0.866	0.865	0.022	39.112	0.000
ENGAG1 <- ENGAG	0.827	0.826	0.028	29.344	0.000
ENGAG2 <- ENGAG	0.755	0.753	0.048	15.875	0.000
ENGAG4 <- ENGAG	0.809	0.810	0.026	31.496	0.000
ENGAG5 <- ENGAG	0.832	0.832	0.019	44.790	0.000
FREQ1 <- FREQ	0.912	0.912	0.017	54.808	0.000
FREQ2 <- FREQ	0.929	0.929	0.016	57.641	0.000
FREQ3 <- FREQ	0.900	0.897	0.020	44.185	0.000
FREQ4 <- FREQ	0.805	0.801	0.039	20.480	0.000
INTERE2 <- INTERE	0.707	0.704	0.052	13.667	0.000
INTERE3 <- INTERE	0.826	0.824	0.033	25.308	0.000
INTERE4 <- INTERE	0.747	0.744	0.060	12.486	0.000
INTERE5 <- INTERE	0.866	0.866	0.020	42.805	0.000
PERFORM1 <- PERFORM	0.837	0.836	0.024	35.455	0.000
PERFORM2 <- PERFORM	0.736	0.736	0.041	17.980	0.000
PERFORM3 <- PERFORM	0.782	0.781	0.030	26.054	0.000
PERFORM4 <- PERFORM	0.765	0.765	0.031	24.585	0.000
PERFORM5 <- PERFORM	0.742	0.738	0.048	15.599	0.000
USEF1 <- USEF	0.751	0.740	0.076	9.914	0.000
USEF2 <- USEF	0.849	0.838	0.054	15.814	0.000
USEF3 <- USEF	0.730	0.722	0.067	10.900	0.000
USEF4 <- USEF	0.791	0.787	0.048	16.367	0.000
USEF5 <- USEF	0.818	0.814	0.039	20.887	0.000
USEF6 <- USEF	0.823	0.821	0.038	21.750	0.000

Table 9 presents the test of significance for outer loadings, showing the original sample values (O), sample means (M), standard deviations (Std.dev), T statistics, and P values for each indicator. The Cognitive Engagement (COGNTV) indicators exhibit strong and significant outer loadings, with values ranging from 0.757 to 0.815. The T statistics for these indicators are high, ranging from 20.710 to 32.354, and all P values are 0.000, indicating that the loadings are highly significant.

The Self-Efficacy Beliefs (EFFICACY) indicators also exhibit robust and significant outer loadings, with values ranging from 0.782 to 0.870. The T statistics for these indicators are particularly high, with the lowest being 18.661 and the highest at 41.744, all with P values of 0.000. The Engagement with Study Materials (ENGAG) indicators have outer loadings ranging from 0.755 to 0.832, with T statistics between 15.875 and 44.790, also indicating significant loadings with P values of 0.000.

The Frequency of GAI Usage (FREQ) indicators exhibit extremely high outer loadings, ranging from 0.805 to 0.929, with T statistics varying from 20.480 to 57.641, all of which are significant with P values of 0.000. The Level of Interest (INTERE) indicators have outer loadings between 0.707 and 0.866, with T statistics from 12.486 to 42.805, confirming their significance with P values of 0.000. Lastly, the Academic Performance (PERFORM) and Perceived Usefulness of GAI Tools in Enhancing Learning (USEF) indicators also show significant outer loadings, with T statistics ranging from 9.914 to 35.455 and P values of 0.000, indicating strong reliability and validity across all constructs.

4.8.1 Summary of findings

The findings from the PLS-SEM analysis reveal significant and reliable outer loadings across all constructs, suggesting robust indicator reliability and internal consistency. Indicators for Cognitive Engagement (COGNTV) such as COGNTV1, COGNTV2, COGNTV4, and COGNTV5 exhibit high outer loadings, ranging from 0.757 to 0.815, with corresponding high T statistics, all of which are significant at P values of 0.000.

This indicates staunch support for the measured constructs and confirms the validity of the indicators in measuring cognitive engagement effectively. Self-Efficacy Beliefs (EFFICACY) indicators, including EFFICACY1 to EFFICACY5, exhibit even higher outer loadings, ranging from 0.782 to 0.870, and exceptionally high T-statistics, with all P-values at 0.000. Similarly, the Engagement with Study Materials (ENGAG) and Frequency of GAI Usage (FREQ) constructs show strong and significant outer loadings, with ENGAG indicators ranging from 0.755 to 0.832 and FREQ indicators from 0.805 to 0.929. These findings underscore the reliability and convergent validity of the constructs, confirming that the indicators effectively measure their respective latent variables.

The analysis of the Level of Interest (INTERE), Academic Performance (PERFORM), and Perceived Usefulness of GAI Tools in Enhancing Learning (USEF) constructs further validates the model. INTERE indicators range from 0.707 to 0.866, PERFORM indicators from 0.736 to 0.837, and USEF indicators from

0.730 to 0.849, all with significant T statistics and P values of 0.000. This comprehensive assessment confirms that the model exhibits strong internal consistency, reliability, and validity, making it a robust framework for understanding the relationships among the constructs in the context of cognitive engagement, self-efficacy, engagement with study materials, frequency of GAI usage, level of interest, academic performance, and perceived usefulness of GAI tools in enhancing learning.

5. Theoretical implications

The integration of AI in education has significant theoretical implications, particularly in relation to constructivist learning theories. By facilitating personalized learning experiences, AI tools align with the principles of constructivism, which posits that learners actively construct knowledge through interaction with their environment. This study underscores the importance of adapting educational practices to leverage AI's capabilities in fostering active learning and cognitive development. Furthermore, the findings contribute to existing educational theories by illustrating how AI can enhance cognitive processes such as critical thinking and problem-solving, thereby enriching the theoretical framework surrounding learning outcomes in higher education.

6. Practical implications

From a practical standpoint, this research highlights the necessity for educators and policymakers to thoughtfully integrate AI technologies into teaching practices. The findings suggest that while AI can enhance student engagement and learning outcomes, it also requires comprehensive teacher training and awareness of potential challenges, such as data privacy concerns. Educators must be equipped not only to utilize AI tools effectively but also to critically assess their impact on student learning. Additionally, institutions should consider developing tailored AI applications that address specific educational needs, ensuring that technology serves as a facilitator rather than a replacement for traditional teaching methods.

7. Research limitations

This study acknowledges several limitations that may affect the generalizability of its findings. First, the research is based on data collected from a limited number of educational institutions within a specific geographical context (South Africa), which may not reflect broader trends in AI integration across diverse educational settings. Second, while the study employs robust analytical methods, the rapidly evolving nature of AI technologies means that findings may become outdated as new tools and applications emerge.

Future research should aim to conduct longitudinal studies to assess the long-term impacts of AI on student learning outcomes and explore its effects in various educational contexts.Moreover, the proposed solutions, including personalized AI-driven learning tools, adaptive feedback mechanisms, and interdisciplinary collaboration between educators and technologists, have universal applicability. These approaches align with global trends in AI integration, offering insights that can be adapted to varying cultural, institutional, and technological contexts.

8. Conclusion and Recommendation

8.1 Conclusion

This study provides valuable insights into generative AI's potential to enhance learning outcomes and streamline educational processes. Using PLS-SEM, we rigorously analysed data to identify key factors influencing AI integration in education. Our findings highlight significant benefits but also underscore the need for careful management of challenges like data privacy and teacher training. The study contributes to existing knowledge by offering a comprehensive analysis and actionable recommendations for educators and policymakers.

Recommendations include strategic interventions like enhanced training, adaptive AI tools, robust ethical frameworks and longitudinal studies to assess sustained impacts and inform solutions tailored to diverse educational contexts. Future research should focus on leveraging advancements in AI, such as natural language processing and predictive analytics, to promote personalized learning experiences. Integrating AI with emerging technologies like AR and VR also warrants further investigation.

Interdisciplinary collaboration among technologists, educators, and policymakers is crucial for aligning AI developments with pedagogical goals and ethical standards. By prioritizing these areas, higher education can harness AI's transformative potential globally. Future studies should explore longitudinal impacts of AI on education and develop tailored tools addressing specific educational needs. While focused on South African higher education, our findings have broader relevance for regions facing similar challenges in developing nations with under-resourced educational systems.

8.2 Recommendations

Based on the findings from the PLS-SEM analysis, it is recommended that educational institutions focus on enhancing high-impact indicators to improve cognitive engagement, self-efficacy, and academic performance. Indicators such as COGNTV4, EFFICACY4, and FREQ2 demonstrated exceptionally high outer loadings and significance, suggesting that interventions should prioritise activities and resources that enhance these specific aspects. For instance, integrating interactive and challenging cognitive tasks can significantly improve student engagement, while providing support to boost self-efficacy can enhance students' confidence and performance. Engagement with study materials also showed strong reliability, indicating the importance of developing and incorporating engaging, diverse, and interactive study materials and learning tools. Educators should leverage regular feedback and adaptive learning technologies to maintain high engagement levels. By creating a learning environment that is both stimulating and supportive, students are more likely to stay motivated and perform well academically. The high loadings for the Frequency of GAI Usage (FREQ) and Perceived Usefulness (USEF) highlight the positive impact of generative AI tools on student learning. Institutions should ensure the availability and proper training for these tools, encouraging their integration into daily learning activities. Collecting regular feedback on the effectiveness of these tools and making necessary adjustments will further enhance their impact on learning outcomes. By leveraging GAI tools effectively, educational institutions can create a more supportive, engaging, and effective learning environment that maximizes the benefits of technology in education.

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Appendix

FREQ1-How frequently do you use generative AI tools to assist with assignments?

FREQ2-How often do you use generative AI tools for generating ideas for essays or projects?

FREQ3-How often do you use generative AI tools for creating visual content (like graphs, diagrams) for your presentations?

FREQ4-How frequently do you use generative AI tools for data analysis for your research?

USEF1-How frequently do you use generative AI tools for data analysis for your research?

USEF2-To what extent do you agree that Generative AI tools have helped improve your understanding of course material?

USEF3-To what extent do you agree that using Generative AI tools has positively impacted your overall learning outcomes?

USEF4-To what extent do you agree that the use of generative AI in your coursework stimulates your intellectual curiosity?

USEF5-How often does the use of generative AI in your studies encourage you to explore topics in more depth than required?

USEF6-How much do you agree that generative AI helps you to make connections between your coursework and real-world application?

USEF7-To what degree does the use of generative AI in your coursework challenge you to solve complex problems?

USEF8-How often does the use of generative AI in your studies motivate you to participate more actively in class discussions?

USEF9-How often does the use of generative AI in your studies motivate you to participate more actively in class discussions?

ENGAGE1-To what extent do you agree that the use of generative AI helps you understand your study material better?

ENGAGE2-To what extent do you agree that the use of generative AI improves your overall learning outcomes?

ENGAGE3-To what extent do you agree that the use of generative AI in your coursework has increased your confidence in understanding the subject matter?

ENGAGE4-How often has the use of generative AI in your studies made you feel more confident in participating in class discussions?

ENGAGE5-To what extent do you agree that generative AI has enhanced your confidence in your overall academic abilities?

INTERE1-How interested are you in learning activities after interacting with generative AI tools?

INTERE2-To what extent has the use of generative AI tools increased your interest in your study materials?

INTERE3-How much do you agree that generative AI tools make your assignments, tasks, or summative activities more interesting?

INTERE4-Do you find yourself more engaged with your study materials after using generative AI tools?

INTERE5-To what extent do you agree that the use of generative AI tools has increased your interest in further learning and exploration?

where

PERFORM1-To what extent do you agree that the use of generative AI in your coursework has improved your understanding of the subject matter?

PERFORM2-Do you agree that generative AI has helped you to complete assignments more effectively?

PERFORM3-To what degree has the use of generative AI in your coursework helped you to achieve better grades?

PERFORM4-How often has the use of generative AI in your studies helped you to prepare more thoroughly for exams?

PERFORM5-Do you agree that generative AI has enhanced your overall academic performance?

COGNTV1-Do you agree that the use of generative AI in your coursework stimulates your intellectual curiosity?

COGNTV2-How often does the use of generative AI in your studies encourage you to explore topics in more depth than required?

COGNTV3-Do you agree that generative AI helps you to make connections between your coursework and real-world applications?

COGNTV4-To what degree does the use of generative AI in your coursework challenge you to solve complex problems?

COGNTV5-How often does the use of generative AI in your studies motivate you to participate more actively in class discussions?

COGNTV6-Overall, how satisfied are you with the impact of generative AI tools on your learning experience?

EFFICACY1-How confident are you in your ability to use generative AI tools effectively in your studies?

EFFICACY2-To what extent do you believe that you can handle any technical issues that might arise while using generative AI tools?

EFFICACY3-How confident are you in your ability to use generative AI tools to enhance your learning outcomes?

EFFICACY4-To what extent do you believe that you can handle any technical issues that might arise while using generative AI tools?

EFFICACY5-How confident are you in your ability to use generative AI tools to enhance your learning outcomes?