

The Effect of Generative AI Usage on Academic Engagement: A Mixed-Methods Case Study at a College of Education in Ghana

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ABSTRACT

The study was conducted to investigate the impact of the usage of generative AI on the academic engagement of students in a selected college of education in Ghana. The study seeks to explore and provide insights on the relationship between the use of generative AI in learning and students' academic engagement. This approach was selected because it offers a more comprehensive understanding of the relationship between generative AI use and students' academic engagement. A sequential-explanatory mixed-method research design is applied in the study to provide in-depth enlightenment, discussion, investigation, and thorough understanding of the generative AI frequently used by students and how it affects their academic engagement. This approach was selected because it offers a more comprehensive understanding of the relationship between generative AI use and students' academic engagement. Ninety-eight (98) respondents served as participants for the quantitative phase of the study, and twelve (15) interviewees for the qualitative phase. The respondents were selected using convenience sampling, a non-probability sampling technique. The instrument for the quantitative data was a survey questionnaire to examine the type of generative AI mostly used by students and also assess the effect of generative AI on students' academic engagement. The interview guide, on the other hand, was used to gather qualitative data to obtain rich data that could not be explored using only the quantitative data.

Findings showed that use of generative AI has positively affected students' academic engagement and it improved their learning environment. On the other hand, generative AI has been a great aid in enhancing students' learning and engagement. Using Pearson R-Correlation, the researcher found that there is a significant high positive correlation between use of generative AI and students' academic engagement ($r(98) = 0.785, p < 0.00001$).

INTRODUCTION

Background

The use of Artificial Intelligence (AI) in education has attracted considerable attention in recent years, with researchers highlighting its transformative effects on teaching and learning (Okoye & Mante, 2024). (GenAI), a branch of artificial intelligence that focuses on machine-generated content, has significant potential for delivering personalized and context-aware learning experiences, particularly in out-of-classroom settings. (Norman & Fraenkel, 2000).

GenAI tools refer to students' usage of generative AI technologies to support personalized learning, receive instant feedback, and access adaptive content (Bulawan, 2023). Generative AI helps students simplify academic

tasks, fostering collaboration and promoting critical thinking education. It enables deeper engagement with content by automating routine tasks and offering adaptive learning, contributing to enhanced AA, particularly in achieving SDG4 (Baidoo-Anu & Owusu Ansah, 2023; Bulawan, 2023).

Generative AI applies transformer-based deep learning architectures to produce novel content such as text, images, and audio, exemplified by tools like ChatGPT, Microsoft Copilot, and Canva (Vaswani et al., 2017; Lim et al., 2023).

Globally, generative AI tools have been adopted in higher education, reshaping learning behaviors. Students perceive GenAI as an accessible tutor, available anytime, while institutions continue to grapple with challenges such as academic dishonesty (Liu, 2024; Oravec, 2023). In some contexts, authorities have even banned ChatGPT, citing fears of plagiarism and reduced critical thinking (Estrellado, 2023; Johnson, 2023). Meanwhile, other studies have revealed the benefits of responsible use, such as improved writing, learning engagement, and personalized learning opportunities (Bulawan, 2023; Lim, 2023; Sok & Heng, 2023).

Statement of the Problem

The growing integration of artificial intelligence (AI) and machine learning in education offers opportunities to personalize and enhance learning experiences; however, their full potential and limitations remain insufficiently understood. Although generative AI promotes efficiency, creativity, and active learning, it also presents challenges such as dependency, plagiarism, and diminished student initiative (Hagendorff, 2020; Halaweh, 2023; Rodrigues, 2024). In Ghanaian Colleges of Education, students increasingly utilize tools like ChatGPT, Quillbot, and Grammarly to support academic tasks (Bulawan, 2023), yet little empirical research has examined how such use influences student engagement.

To fill this gap, the present study investigates the impact of generative AI usage on students' academic engagement and explores its relationship with academic achievement. Insights from this research will guide educators, policymakers, and curriculum developers in promoting the responsible integration of AI technologies while preserving meaningful student engagement.

To what extent does the use of generative AI influence the academic engagement of students, and how do students perceive and describe their experiences of engagement when using generative AI in their learning?

What is the relationship between the use of generative AI and students' academic engagement, and how do students explain their experiences and perspectives of this relationship in their learning?

LITERATURE REVIEW

It is fascinating to see how technology continues to shape the educational landscape, isn't it? Liang et al. (2023) posited that although the emergence and increasing utilization of GenAI are recent developments, scholars have long been intrigued by the probable applications of AI in education. Earlier research has demonstrated how leveraging AI can enhance assessment feedback and streamline administrative tasks (Crompton & Bruke, 2023; Popenici & Kerr, 2017; Brown et al., 1978; Garito, 1991). Both Liang (2023) and Yang et al., (2024) emphasize how generative artificial intelligence (GenAI) improves student learning engagement and accomplishment. Hidayat-ur-Rehman (2024) investigates the association between students' engagement in a GenAI atmosphere through smartphone usage, formal digital learning activity, and digital skills. Taken together, these findings further demonstrate GenAI's effectiveness in enhancing student learning and engagement and extend the scope of GenAI in many learning contexts.

GenAI is a special and powerful case of artificial intelligence. Hashmi & Bal (2024) describe generative artificial intelligence (GenAI) as a machine learning tool that generates new text, video, and image content (page 5/28); its prevalence has risen sharply in recent years. Like having a digital tutor who knows the preferences and adapts accordingly, GenAI tailors' content to individual learners, provides swift feedback, and generates thought-provoking prompts for formative assessments and interactive theory beyond humans, thus human-to-machine scenarios (Liang et al., 2023). GenAI could be more interactive compared with the traditional types of

learning resources, such as textbooks and exercises, and could promote students' engagement, which may be attributable to the reward mechanism.

Motivation to learn with AI

The potential of AI to transform education has been widely acknowledged. As highlighted in a recent systematic review of AI in education by Chiu (2023a), AI technologies are demonstrating their capacity to reshape teaching and learning. AI technologies such as chatbots, intelligent tutoring systems, and automatic grading systems are increasingly used in schools (Chiu et al., 2023b; Yim & Su, 2024). For example, chatbots could facilitate personalized learning based on students' competence, intelligent tutoring systems could offer timely feedback on students' inquiries, and automatic grading systems could provide detailed and effective grading (Vázquez-Cano et al., 2021). These advancements represent a significant stride toward a technologically advanced and efficient educational environment. However, the question of the extent to which university students are motivated to interact with and apply AI technologies in their learning process remains underexplored. Students may demonstrate different types of motivation to interact and learn with AI technologies (Scherer & Siddiq, 2019). Some may be largely inspired by inherent interest in and the enjoyment of learning with AI, whereas others might be motivated by external factors such as the pressure to avoid lagging behind others or the benefits of learning with AI. In general, those with higher autonomous motivation to use AI in learning are likely to devote more time to using, engage more with, and benefit more from AI technologies (Al Shamsi et al., 2022; Esiyok et al., 2025; Kelly et al., 2023; Lai et al., 2023).

Impact of AI on Teaching and Learning Processes

The use of GenAI is increasingly growing, and it is influencing the teaching and learning processes in higher education. Immediate support is provided to students through the use of chatbots and AI-powered virtual assistants. Any queries related to assignments or other course contents can be addressed with 24/7 accessibility (Ocaña-Fernández, et al., 2019, p. 561). There are various learning analytics tools that help in tracking the progress of students and predicting their performances in the future. Such tools can also prove to be helpful for refining teaching strategies and optimizing curriculum designs. Thus, the information that has been discussed in this section lays emphasis on the benefits, challenges, potential applications, and ethical considerations with regard to the use of AI in the field of education. If AI is used effectively in the educational field, it would bring an immense improvement to the teaching and learning methods. But this also requires proper management so that the related risks can be avoided. However, artificial intelligence can make the learning environment better and also make the learning process student-centered and more inclusive.

Theoretical framework

A widely recognized framework used to explain learners' adoption of new technologies or software applications is the Technology Acceptance Model (TAM) (Davis et al., 1989; Venkatesh & Davis, 1996). TAM was designed to predict and clarify the factors influencing users' acceptance and utilization of emerging technological systems. Over time, it has been extensively applied, refined, and expanded (Chuttur, 2009; Yousafzai et al., 2007a). The model emphasizes four primary constructs: perceived ease of use, perceived usefulness, intention to use, and actual system use.

Perceived ease of use reflects the degree to which individuals find a technology straightforward and effortless to operate; technologies that are simpler to handle are typically adopted more readily, as they minimize the effort required for learning and interaction (Venkatesh & Davis, 2000). Perceived usefulness, on the other hand, relates to the belief that using a technology enhances one's effectiveness or performance (Opoku & Enu-Kwesi, 2019). Intention to use concerns an individual's motivation or willingness to employ the technology, while actual system use refers to the observable frequency and extent of its application.

According to the extended version of TAM (Venkatesh & Davis, 1996), both perceived usefulness and perceived ease of use directly influence an individual's intention to use, which subsequently predicts actual use behavior. Various external factors—such as users' experience with technology, educational background, digital self-efficacy, and age—can shape perceptions of ease of use and usefulness. However, studies have not reached a

consensus on which factors exert the greatest influence, as findings vary across contexts (Chuttur, 2009; Yousafzai et al., 2007a). Davis et al. (1989) further noted that the effect of perceived ease of use on behavioral intention tends to decrease as users become more familiar with a system—a trend supported by subsequent research indicating that this influence is strongest during early adoption and lessens over time (Adams et al., 1992; Chau, 1996; Gefen & Straub, 2000; Igbaria et al., 1996).

In the present study, perceived usefulness refers to students' beliefs that generative AI tools such as ChatGPT, Gemini, and Copilot enhance their learning effectiveness, efficiency, and academic outcomes. Perceived ease of use describes the extent to which students view these tools as user-friendly and requiring minimal effort to operate. When students hold positive perceptions of both usefulness and ease of use, they are more likely to adopt and consistently engage with generative AI tools in their academic activities.

Self-Determination Theory

This study employs Self-Determination Theory (SDT) as the foundational framework to understand student motivation in relation to generative AI usage and academic engagement. SDT is well-supported by extensive theoretical and empirical research (Bureau et al., 2022; Howard et al., 2021) and is widely recognized as a powerful lens for examining motivation across diverse settings, including education (Bureau et al., 2022; Howard et al., 2021), healthcare (Ntoumanis et al., 2021), and business environments (Van den Broeck et al., 2021). SDT distinguishes motivation based on the extent to which it is internalized by the individual. At the highest level of internalization is intrinsic motivation, which drives engagement purely for the inherent interest, enjoyment, or personal satisfaction derived from the activity itself. Meanwhile, extrinsic motivation refers to actions triggered by external factors and is further classified into types based on internalization levels: integrated regulation (fully embracing the value of the behavior), identified regulation (recognition of the behavior's importance), introjected regulation (participation driven by self-esteem maintenance and avoidance of guilt), and external regulation (behavior controlled by external rewards or pressure). Amotivation, in contrast, describes a lack of motivation or intention to engage in an activity (Ryan & Deci, 2000, 2020).

Autonomous motivation, comprising intrinsic motivation, integrated regulation, and identified regulation, is generally associated with more positive and adaptive outcomes compared to controlled motivation, which includes introjected and external regulation (Ryan & Deci, 2000, 2020; Vansteenkiste et al., 2009). Applying this theory in the context of generative AI use, it suggests that students who internalize the value of AI as a learning tool and engage with it for autonomous reasons are likely to experience higher academic engagement and better educational outcomes. Controlled motivation or amotivation toward AI use, on the other hand, may limit these benefits.

METHODOLOGY

Integration

The integration of quantitative and qualitative data greatly enhances mixed methods research, offering several advantages (Bryman, 2006; Creswell & Plano Clark, 2011). For example, qualitative data can validate quantitative results, while quantitative data can help inform qualitative sample selection or clarify qualitative findings. Qualitative inquiry can also guide the development or refinement of quantitative tools or generate hypotheses for testing quantitatively (O'Cathain, Murphy, & Nicholl, 2010). Despite these potential benefits, many mixed methods studies underutilize integration (Bryman, 2006; Lewin, Glenton, & Oxman, 2009). Nevertheless, established approaches exist to integrate qualitative and quantitative methods and data at various stages, including design, data collection, analysis, and reporting (O'Cathain, Murphy, & Nicholl, 2010; Creswell & Plano Clark, 2011).

Integration at the study design Level

The study adopted a mixed-method research approach, which involves gathering and analyzing both quantitative and qualitative data to provide a comprehensive understanding of the relationship between generative AI use and students' academic engagement. A sequential-explanatory design was specifically employed, beginning with

the collection and analysis of quantitative data, followed by qualitative data to build on and explain the initial results. This design was chosen because it allows for richer data collection and deeper insights by encouraging active respondent participation and addressing research gaps more effectively (Creswell, 2018).

Integration at the interpretation and reporting Level

The sequential-explanatory design allowed for data integration where qualitative findings enriched the interpretation of quantitative results. Quantitative analysis yielded a significant positive correlation ($r = 0.785$, $p < 0.00001$) between generative AI use and academic engagement. Qualitative themes such as active learning, motivation, and improved problem-solving helped explain the mechanisms underlying this correlation. The integrated reporting presents a comprehensive narrative combining numerical trends with detailed student perspectives, thereby enhancing the explanatory power and practical relevance of the findings for educators and policymakers.

Population

In research, the term “population” refers to the entire aggregation of individuals, objects, or elements that share common characteristics relevant to a particular study and from which the researcher intends to draw conclusions (Norman, 2000). The population therefore represents the broad group about which the researcher seeks to gain insight or make generalizations.

For the purpose of this study, the population consisted of all students enrolled in a selected College of Education located in the Central Region of Ghana. This group was chosen because the college has integrated various digital learning approaches and has witnessed increasing exposure of students to generative artificial intelligence (AI) tools. The total student population of the institution at the time of the study was approximately 320, covering different academic levels and specializations. This population was deemed appropriate for the investigation because teacher trainees at the College of Education are expected to develop strong digital literacy and innovative learning habits, both of which align closely with the objectives of exploring generative AI usage and academic engagement. By focusing on this specific population, the study sought to understand how future teachers in training are adopting and interacting with generative AI tools and how these interactions may shape their engagement, learning outcomes, and preparedness for teaching in technology-enhanced educational environments.

Sample and sampling techniques

The study involved a sample of ninety-eight (98) Level 300 students from the College of Education. Participants were selected through a convenience non-probability sampling technique, which was considered appropriate due to the accessibility and availability of the students during the data collection period. This approach allowed the researcher to gather responses from students who were readily available and willing to participate in the study.

The selection of Level 300 students was intentional because they were in their final semester, preparing for the mandatory internship program. This group was considered suitable for the study since they had extensive academic exposure and were actively using generative AI tools such as ChatGPT, Gemini, and Copilot to support their coursework and professional preparation. The researcher aimed to explore the extent to which these students utilize generative AI technologies and how such use influences their academic engagement and learning experiences.

Research instrument

The study adopted a mixed-methods approach, employing a survey questionnaire, individual interviews, and focus group discussions to examine the relationship between the use of generative artificial intelligence (AI) and the level of academic engagement among students in a College of Education. The purpose was to gain both quantitative and qualitative insights into how generative AI influences students' learning behaviors, participation, and overall academic involvement. The survey instrument consisted of structured items designed to measure students' perceptions and experiences with generative AI tools. Responses were captured using a

five-point Likert scale, ranging from “Strongly Disagree” to “Strongly Agree.” This scale allowed participants to express varying degrees of agreement with statements related to their use of AI tools and their corresponding engagement levels. Complementing the survey, face-to-face interviews and focus group discussions provided a deeper understanding of students’ perspectives, attitudes, and lived experiences regarding generative AI. These qualitative methods enriched the quantitative findings by revealing nuanced views on how AI tools affect motivation, participation, and learning outcomes within the academic environment.

Validity and Reliability of the Study

The validity of this study was ensured through a rigorous pilot testing process prior to the main data collection. Specifically, the questionnaire and interview schedule were piloted with a smaller sample of students to assess their clarity, relevance, and comprehensiveness. This pilot phase facilitated the identification and correction of ambiguous or misleading items, thereby enhancing content validity—the degree to which the instruments accurately capture the constructs related to generative AI usage and academic engagement. Additionally, expert reviewers with extensive experience in digital technology integration reviewed the instruments to ensure they comprehensively covered all relevant aspects of the research.

Regarding reliability, the study employed a test-retest reliability method to assess the consistency and stability of the responses over time. The same questionnaire was administered to the same group of students on two separate occasions spaced appropriately to minimize recall bias while assuming no significant change in their perceptions. The responses from both administrations were then correlated to quantify the degree of agreement, reflecting temporal stability. The Pearson correlation coefficient obtained was 0.785, indicating acceptable to good reliability. This value suggests that the instrument yields stable and consistent results over time, with minimal measurement error.

Ethical Considerations

This study was conducted in accordance with ethical principles to protect the rights and welfare of participants. Prior to data collection, participants were fully informed about the purpose of the research, the procedures involved, and how their information would be used. Additionally, the researcher protects participant privacy and confidentiality, minimizes the risk of harm, and ensures bias and fairness in the test (Kumar, 2014). Obtaining informed consent is a fundamental principle, where the researcher must fully inform participants about the purpose of the test, procedures, and potential risks and benefits (Creswell, 2017). Anonymity and confidentiality were strictly maintained by excluding names or other personal identifiers from data collection, analysis, and reporting. All information provided was treated with discretion to ensure privacy and security. The research instruments, including tests, Likert-scale questionnaires, and evaluation surveys, were carefully designed to be fair, unbiased, and respectful. Measures were taken to minimize any potential risks, and participants were treated with dignity and fairness throughout the study. Debriefing and feedback were provided as appropriate to foster transparency and trust. Ethical approval for this study was obtained from the University Research Ethics Committee before data collection commenced.

Limitations of the study

This study centers on the specific generative AI tools students employ, how they integrate these technologies into their learning practices, and the overall effects on their academic engagement within a selected college of education in Ghana. While the findings illuminate significant aspects of AI adoption and student engagement in this localized setting, caution is warranted in extending these conclusions to other higher education contexts. Differences in institutional infrastructure, curricular frameworks, cultural attitudes toward technology, and access to digital resources likely impact the deployment and influence of generative AI across various educational environments. Consequently, the results contribute valuable localized insights while highlighting the need for further studies to explore generative AI’s role and impact in other institutional and cultural landscapes.

RESULTS AND DISCUSSION

Data analysis procedure

Data analysis was done using IBM SPSS 24, including cleaning for completeness and consistency. Descriptive statistics was used to analyze the quantitative survey data, whilst thematic analysis was used to analyse the qualitative data. The reliability of the survey instrument was confirmed using Cronbach's alpha (Cronbach, 1951) to ensure internal consistency of the items. We obtained a Cronbach's alpha value of 0.785, which indicates a high level of reliability, suggesting that the survey items are consistently measuring the same underlying concept. Construct validity, which assesses the accuracy with which a survey measures the theoretical construct it intends to measure, was confirmed through factor analysis, following the method outlined in Hair et.al., (2009). This verifies that the questionnaire items are appropriately grouped under their respective constructs, further affirming the validity of the survey instrument used in this study.

Table 1: The Effect of AI on Student's Academic Engagement

Dimension of Engagement	Generative AI Effect on Academic Engagement	M	Interpretation
Cognitive Engagement	Generative AI supports me in developing critical thinking and problem-solving skills.	3.59	High
	Using generative AI encourages me to reflect on and improve my learning strategies.	3.98	High
Cognitive mean		3.785	High
Participatory Engagement	Using generative AI in group work helps me collaborate more effectively with peers.	3.56	High
	Generative AI enhances my capacity to engage thoughtfully in academic conversations.	3.49	Moderate
Participatory mean		3.525	High
Behavioral Engagement	Generative AI motivates me to dedicate more time to studying.	3.57	High
	The assistance I get from generative AI leads me to engage more actively in class discussions.	2.67	Moderate
Behavioral mean		3.120	Moderate
Emotional Engagement	Generative AI helps reduce my anxiety when faced with difficult assignments.	3.93	High
	Using generative AI boosts my confidence in my academic work.	3.18	Moderate
Emotional mean		3.555	High
Total Weighted Mean		3.496	High

NB: 1-1.49=very low/strongly disagree; 1.50-2.49=low/disagree; 2.50-3.49=moderate/neutral; 3.50-4.49=high/agree; 4.50-5.49=very high/strongly agree

Table 1 shows the effect of using generative AI on students' academic engagement. Based on the overall result of Table 1, it is evident that generative AI has highly affected students' academic engagement.

The dimension of engagement among the four dimensions with the highest mean value is the cognitive domain, with a mean value of 3.785. Under the cognitive engagement, the statement "Using generative AI encourages

me to reflect on and improve my learning strategies” and the statement “Generative AI supports me in developing critical thinking and problem-solving skills” have mean values of 3.98 and 3.59, respectively, both interpreted as strong agreement.

Emotional engagement is the second dimension of engagement, with a mean value of **3.555**. The statements “Using generative AI boosts my confidence in my academic work” and “Generative AI helps reduce my anxiety when faced with difficult assignments” have mean values of 3.18 and 3.93, respectively, also indicating strong agreement.

The next dimension of engagement responded to by the students was participatory engagement, with a mean value of **3.525**. The statement “Using generative AI in group work helps me collaborate more effectively with peers” had a mean value of 3.56, whilst the statement “Generative AI enhances my capacity to engage thoughtfully in academic conversations” had a mean value of 3.49

The least dimension of engagement with a moderate verbal interpretation of the mean value of **3.120** was behavioral engagement. The statements “The assistance I get from generative AI leads me to engage more actively in class discussions” and “Generative AI motivates me to dedicate more time to studying” had mean values of 2.67 and 3.57, respectively, also indicating moderate agreement

To gather qualitative data, focus group discussions and follow-up interviews with students were conducted. The first theme that emerged was active engagement.

Excerpts from face-to-face interview and focus group discussion

Respondent 2: “GenAI has inspired me to dedicate more time to academic tasks. With motivation from GenAI, I’m able to complete any assigned task given to me.”

Respondent 8: “I personally feel motivated using GenAI in all my searches.”

Respondent 13: “Generative AI has definitely helped me to become more active in class, especially in class contribution.”

Respondent 4: “GenAI has changed my passive mood in class. I’m now active when it comes to classroom interaction.”

The last theme that emerged was problem-solving.

Respondent 1 explained that GenAI has made solving complex questions much easier, noting that while some responses are difficult to grasp, others provide clear understanding. Similarly, Respondent 5 affirmed that entering challenging questions into GenAI enables effective problem-solving through critical thinking.

The study revealed that generative AI improved students’ problem-solving, critical thinking, and comprehension skills, aligning with modern educational goals of developing twenty-first-century competencies. This finding supports Buchanan et al. (2022), who noted that GenAI use promotes active participation in collaborative problem-solving tasks.

Table 2: Significant Relationship between the Use of Generative AI and Students’ Academic Engagement

Indicators	Pearson r value	P value	Remarks	Decision
The effect of Generative AI usage on students’ academic engagement	0.785	0.00001	Correlation Highly Positive	Null hypothesis rejected
Significant at 0.05				

As shown in Table 2 above, for the relationship between the use of generative AI and students' academic engagement in the selected college of education, a p-value of 0.00001 was obtained, which was lower than the significance level of 0.05. This indicates a significant relationship between the use of generative AI and students' academic engagement in the selected college of education. This means that both of the variables have a high positive correlation. In the qualitative stage of the study, the researchers got the chance to assess how the utilization of generative AI has affected the respondents' academic engagement. Eager Learners. The first theme that appeared based on the experiences of most of the respondents is Eager Learner. The majority of them have stated that their use of generative AI has affected their academic engagement in school. They have been able to recite, participate in class discussions, ask and answer questions, and more by using AI. The respondents shared the following:

Focus Group Discussion Excerpt:

One participant shared that AI has boosted their academic engagement by offering support when they encounter difficult lessons, which helps them respond confidently and participate actively in class activities. Another commented that AI tools like ChatGPT have significantly aided their preparation for class presentations, making them more interactive and engaged during discussions. Students' engagement in generative AI positively affects their academic involvement by making challenging lessons easier to understand, boosting their willingness to participate, and answering questions confidently. This aligns with the study by Kurniati and Fithriani (2022), which found favorable student attitudes toward generative AI use in learning.

Conclusions drawn from the findings are as follows:

Usage of GenAI helps reduce students' anxiety when faced with challenging questions.

Students also utilized generative AI to improve their understanding of grammar and challenging vocabulary encountered online. The suggestions, corrections, and feedback from AI tools helped them refine their grammar skills and grasp unfamiliar words.

Generative AI tools have fostered greater creativity and academic engagement among students by helping generate ideas despite the fact some students might rely too heavily on AI, leading to decreased engagement.

The use of generative AI among college of education students shows a strong positive correlation with their academic engagement. These tools supported students in participating and interacting more effectively in class, making it easier for them to learn and encouraging active involvement.

Study Implications

Generative AI holds considerable promise to revolutionize higher education by making learning experiences more tailored, engaging, and interactive, particularly in settings with limited resources.

The strong positive link between generative AI use and academic engagement indicates that these technologies can increase student motivation, participation, and confidence.

Nonetheless, the dual effects of generative AI require vigilant oversight to avoid dependency and to uphold academic standards and integrity.

Educational institutions must revise curricula and teaching approaches to effectively incorporate AI tools while also fostering students' digital literacy and responsible AI use skills.

Policymakers and curriculum developers should promote responsible AI adoption that benefits learners and addresses the distinct challenges present in various educational contexts.

RECOMMENDATIONS

Educators and institutions should adopt generative AI tools responsibly to promote students' cognitive, emotional, behavioral, and participatory engagement

Generative AI should be used as a supportive aid to ease anxiety over complex tasks, improve problem-solving, and stimulate creativity.

Future research should explore the long-term effects of generative AI on students' academic skills and engagement through longitudinal or experimental designs to establish clearer causal relationships.

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