Journal of Information and Organizational Sciences
Volume 49, Number 2 (2025)
Journal homepage: jios.foi.hr

JIOS

DOI: 10.31341/jios.49.2.10
Open Access

UDC 004.8:378:159.9-047.37
Original Scientific Paper

The Impact of Generative AI on University Students' Learning Experience: A Study on Cognitive and Affective Outcomes

Sajeda Ben Otman[1], Sourur Ben Otman[1] and Gökçe Karahan Adalı[2*]

[1]Department of Management Information Systems, Halic University
[2]Department of Software Engineering, İstanbul Sabahattin Zaim University
[*]Correspondence: gokce.karahanadali@izu.edu.tr

PAPER INFO

Paper history:
Received 29 August 2025
Accepted 29 November 2025

Citation:
Otman, S. B., Otman, S. B & Adali, G. K. (2025). The impact of Generative AI on University Students' Learning Experience: A Study on Cognitive and Affective Outcomes. In Journal of Information and Organizational Sciences, vol. 49, no. 2, pp. 329-344

ABSTRACT

Generative Artificial Intelligence (GenAI) is rapidly transforming higher education, yet its impact on learning experiences remains contested. Existing research often isolates either cognitive outcomes (e.g., comprehension, creativity) or affective outcomes (e.g., motivation, engagement), leaving a gap in integrated analyses that also account for heterogeneity across student groups. This study investigates both dimensions simultaneously by examining university students' perceptions of GenAI, focusing on learning, creativity, motivation, and engagement, alongside perceived risks such as overreliance, ethical concerns, and difficulties in verifying accuracy. Data were collected from 93 students and analyzed through Spearman's correlations and unsupervised clustering (k-means) with PCA visualization. Findings indicate low to moderate positive correlations between GenAI usage and learning outcomes, particularly problem-solving and motivation. Cluster analysis reveals diverse usage–perception profiles, including paradoxical cases where frequent users report limited cognitive benefit. These results align with Technology Acceptance Model (TAM) and UTAUT assumptions of perceived usefulness and performance expectancy, while also showing that digital literacy moderates these relationships, especially in critical thinking and responsible use. The study contributes by integrating cognitive and affective outcomes, revealing latent profiles beyond averages, and bridging adoption models with responsible AI frameworks. Practical implications highlight the need for AI literacy training, ethical policies, and instructional design to foster effective and responsible GenAI integration in higher education.

Keywords: Generative Artificial Intelligence, Higher Education, Learning Experience, Technology Acceptance Model, Responsible AI

1. Introduction

In recent years, higher education witnessed huge transformations powered by technological advancements. GenAI comes to the fore with smart tools capable of producing new content such as text, descriptions, and codes, based on the prompts it receives. ChatGPT, Bard, Copilot, and other tools are now an educational reality as university students increasingly adopt such tools to support their self-learning, which includes aiding in academic tasks, concept understanding, idea creation, and much more. However, while these tools seem to promise endless opportunities, the actual impact on the learning experience remains debated. Our study aims to analyze the impact of GenAI tools on the university learning experience in two dimensions, which are the cognitive outcomes, including learning and creativity, and the affective aspects, like motivation and engagement. Moreover, we aim to learn about the students' perceptions of the potential benefits and risks aligning with GenAI. All of this study aims to provide a comprehensive view that could contribute to guiding the responsible use of this technology.

2. Literature review

GenAI is a unique type of artificial intelligence focused on producing new content. It does this by leveraging existing patterns of data to create a statistical model predicting what response it would give based on the prompts it receives. GenAI has gone through the developments that have taken place over the decades, beginning in the mid-20th century when GenAI was very basic, depending on the rules to produce language, and continuing through the late 20th century when we witnessed a massive leap forward with the emergence of neural networks that have made voice recognition and imaging tech as we know it today possible, and finally, what opened up the door for the generation of high-quality text, images, and other content we see today was down to deep learning techniques like Generative adversarial networks (GANs) and variational Autoencoders (VAEs). (Yu and Guo, 2023).

According to Albadarin et al. (2024), ChatGPT serves as a virtual intelligent assistant in its ability to offer rapid responses, immediate feedback, and easy-to-understand explanations.

AI tools have also been utilized in writing and language tasks, assisting in essay writing, paraphrasing, translating text, and grammar checking. In addition, ChatGPT enhances self-directed and personalized learning by helping students understand concepts, clarify assignments, and organize learning plans based on individual needs. (Albadarin et al., 2024).

While this can be seen as an educational opportunity, there are significant risks in using AI-based tools for academic work. The reliability and accuracy of these tools are significant issues, for instance. Students need the requisite skills and competencies to be able to use them effectively and to judge the quality of the generated responses (Albadarin et al., 2024). Albadarin et al. (2024) emphasize that setting clear guidelines regarding the potential risks of AI, such as misinformation, plagiarism, and unequal access to AI tools, is crucial.

2.1. Cognitive Impact of Generative AI

Generative AI tools such as ChatGPT, Google Bard, and Bing AI promote new approaches in educational environments to a better student learning experience (Schei et al., 2024).

One of the cognitive advantages of these tools is that they can be really useful for students in understanding complex concepts. According to Albadarin et al. (2024), ChatGPT is used in idea generation, text translation, and alternative explanations that reinforce students' academic understanding across various disciplines. Bahroun et al.'s (2023) review also supports that AI chatbots assist in breaking down complex topics. Moreover, AI-based tools have also demonstrated improvement in learning efficiency by providing well-organized and structured responses (Albadarin et al., 2024). In the study examining papers on students' perceptions of AI tools, it was identified that AI tools decrease the cognitive load on learners, making the learning process less time-intensive (Schei et al., 2024). Additionally, AI tools can be significant in shaping students' critical thinking skills. A few studies claim that they enhance critical thinking and reasoning abilities by informing students in an interactive process to analyze and interpret responses (Albadarin et al., 2024). In the study investigating papers about students' perceptions and usage of AI chatbots, it was determined that ChatGPT encourages students to consider alternative perspectives and critically evaluate arguments. The study indicates that AI tools such as ChatGPT can improve creative problem-solving, as well (Schei et al., 2024). One study, for instance, found that students who used ChatGPT wrote more elaborate works than students who didn't. Others argue that AI poses a significant risk to reducing deep thinking and independent creativity (Schei et al., 2024). One study found that students worried that ChatGPT gives concise answers and that there is no opportunity to think independently (Schei et al., 2024). Despite this concern, research has shown AI could be a "collaborative creative agent" rather than a substitute for human creativity (Vinchon et al, as cited in Habib et al., 2024). They call this the era of "assisted creativity," in which AI helps and enhances the human creative processes. In the study examining how GenAI affects creativity, undergraduate students performed a creative task with and without the assistance of ChatGPT-3. The results showed that AI enhanced fluency, flexibility, elaboration, and originality in idea generation. But some students suggested that AI made them feel like they were becoming dependent and less confident in their ability to come up with original ideas (Habib et al., 2024). Similarly, Schei et al. (2024) highlighted the potential risk of declining cognitive development and academic depth as students may prefer being given quick answers instead of a deep search.

2.2. Affective Impact of Generative AI

Motivation and engagement are key elements in the learning process as they help learners achieve their learning goals. In an experimental study on computer engineering students, it was revealed that students using AI-supported chatbots in their courses were more motivated than those who did not use chatbots (Neji et al., 2023). In fact, ChatGPT has been shown to dramatically increase student engagement and participation. A review by Schei et al. (2024) found that in general, students find such tools helpful and motivating. A study showed that ChatGPT makes students more motivated to complete reading and writing tasks. Another study showed that ChatGPT increases self-efficacy in academic task completion (Schei et al., 2024). Furthermore, Muñoz et al. (2023) observe that "ChatGPT gave a sense of empowerment and increased engagement" in language learning. They discovered that direct interaction with ChatGPT while exploring a specific concept leads to commendable feedback and aid, which further stimulates a learner's enthusiasm for studying. Similarly, Sandu et al. (2024) found that ChatGPT facilitates student engagement, where they reported it with an engagement score of 3.18 out of 5 through their Australian case study. While some students noted difficulties like a "lack of human interaction", the authors characterize ChatGPT as providing an "interactive and dynamic learning environment for students". However, not every study shows a positive influence. Zhu et al. (2024) discussed that non-STEM students were better engaged in scenarios without ChatGPT; therefore, ChatGPT may not facilitate engagement for all students. The study noted that engagement might depend on the instructional design since the students who participated in tasks with a debate style had higher levels of engagement than those in tasks with a fact style. It is noteworthy that AI tools can promote procrastination and surface learning (Schei et al. 2024), which thus can lead to a loss of motivation when, in some cases, students turn into passive learners.

2.3. GenAI challenges and limitations in higher education

The literature also points out to limitations and ethical issues that should be addressed to ensure that AI tools effectively facilitate the learning process while minimizing the risks involved.

- **Academic Integrity and Ethical Concerns:** Research by Schei et al. (2024) argues that plagiarism has become easier and more accessible because chatbots generate output that is both novel and humanlike, which traditional plagiarism detection systems struggle to identify. The employment of these tools could lead to work that is not a student's own. This raises ethical questions around credit and authorship. If these issues are ignored, they may diminish academic standards, intellectual growth, and disrupt educational process.
- **Accuracy and Reliability of AI Responses:** A study by Zhu et al. (2023) discovered that students usually met with inaccurate responses from AI and had to fact-check that information. Another study mentioned by Mittal et al. 2024 review reported that even advanced models like GPT-4 struggle with accuracy, and that they often approve incorrect code. Thus, AI chatbots are not yet perfect and may misinterpret questions or provide incorrect answers.
- **Limited Contextual Understanding:** AI chatbots can be of benefit, but they still might have issues understanding contexts as we humans do. For instance, Neji et al. (2023) demonstrate that these tools actually rely on patterns and keywords, leading to misinterpretations of questions and superficial answers. Zhu et al. (2023) found that students were dissatisfied with the generic responses provided by ChatGPT, which contained no specific details or insights.
- **Bias in AI-generated Content:** AI models learn from large data sets, and they may retain some biases. A study by Zhu et al. (2023) found that students were worried that ChatGPT might not be accurate. They reported that chat responses might mirror biases in the system and tend to preserve the user's perception. Given the potential for the creation of misleading content, it is important to be wary of misinformation and to refine AI-generated content through critical thinking.
- **Student Dependency and the Impact on Critical Thinking:** Relying too heavily on AI-written responses can promote surface learning rather than conceptual learning. (Schei et al. 2024). In this experimental study by Zhu et al. (2023), students reported that they allowed the AI to think for them. One student said, "It stops me from thinking." Thus, excessive dependency on AI tools might result in diminished original thinking.

2.3.1. Research Gap and Contribution

Although prior studies document numerous applications of Generative AI in higher education, the literature often remains fragmented. Most investigations focus either on **cognitive outcomes** (e.g., comprehension, problem-solving, creativity) or on **affective outcomes** (e.g., motivation, engagement), but rarely address both perspectives simultaneously. Furthermore, existing work tends to report descriptive findings without exploring **heterogeneity across student groups**. Thus, we still lack an integrated, data-driven perspective on how GenAI shapes both cognitive and affective dimensions of learning and how these dimensions interact across different usage profiles.

Our study addresses this gap by combining correlational analysis with **unsupervised clustering (k-means) and PCA visualization** in a university sample. This approach not only examines direct relationships between GenAI use and learning outcomes, but also reveals distinct clusters of student experiences, including paradoxical profiles such as **high-usage but low cognitive belief**. By capturing such nuances, we offer a comprehensive contribution that extends the existing literature.

2.3.2. Theoretical Framework

To strengthen the interpretation of our findings, we ground the study in established theories of technology adoption and digital literacy.

- **Technology Acceptance Model (TAM).** Davis (1989) proposed that technology acceptance is shaped by **perceived usefulness (PU)** and **perceived ease of use (PEOU).** In our study, students' beliefs that GenAI helps in problem-solving and understanding complex concepts correspond to PU, while their confidence in using GenAI aligns with PEOU. The positive correlations we observe between usage frequency and perceived learning benefits are consistent with TAM's assumptions.

- **Unified Theory of Acceptance and Use of Technology (UTAUT).** According to Venkatesh et al. (2003), adoption is influenced by **performance expectancy, effort expectancy, social influence, and facilitating conditions**. Our results particularly reflect performance and effort expectancy, as students who perceive GenAI as effective tend to show higher motivation and engagement. These insights allow us to situate affective outcomes such as motivation within a well-established theoretical lens.

- **Digital Literacy and Responsible AI Use.** Beyond adoption models, digital literacy frameworks emphasize critical evaluation and responsible use of technology (van Deursen & van Dijk, 2014). In our context, concerns about misinformation, plagiarism, and dependency mirror this perspective. For example, students reporting difficulty in verifying GenAI's outputs illustrate how insufficient digital literacy can weaken the link between technology use and learning gains. Thus, our framework integrates **TAM/UTAUT mechanisms** with digital literacy as a **moderating condition** that explains paradoxical patterns (e.g., frequent use coupled with low cognitive belief).

This theoretical grounding allows our study to contribute not only empirical evidence but also conceptual insights into how GenAI reshapes learning in higher education.

3. Methodology

In this study, the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework is adopted for data analysis. This framework consists of six steps, which are business understanding, data understanding, data preparation, modeling (data analysis), evaluation, and deployment, that aim to guide and facilitate data mining and analysis projects (Shearer, 2000). Based on the study aims, the first four steps are followed to understand the research problem, analyze the data, prepare the collected data for analysis, and perform the statistical analysis.

3.1. Business Understanding

This study aims to evaluate the impact of GenAI tools use on university students' learning experiences, with a focus on variables like comprehension, learning efficiency, critical thinking, creativity, motivation, and engagement. Therefore, a key focus of this study is a comprehensive analysis about GenAI use and its effect on these variables based on demographic characteristics such as gender, age, and department, as well as frequency of use, confidence in using GenAI, and purposes of GenAI use. By determining the impact of GenAI use on both aspects of learning, cognitive and emotional, better-informed decisions can be made about the use of GenAI tools by educators and policymakers.

3.2. Data Understanding

This study is based on survey data obtained from online questionnaires. The questionnaires were shared between 12 March and 12 April 2025, and distributed through online links in WhatsApp, LinkedIn, and face-to-face conversations with students, using a convenience sampling strategy based on participants' availability and willingness to take part in the study. The survey covered a total of 93 participants, including undergraduate and postgraduate students from various disciplines. This survey consists of 21 closed-ended questions, including multiple choices and a 5-point Likert scale to measure agreement from "Strongly Disagree" to "Strongly Agree" as well as frequency scales. Survey topics encompassed of demographics (such as gender, age, department and academic year), GenAI usage, frequency of use, confidence in GenAI, purposes of use, willingness to recommend GenAI for others, perceptions of how GenAI affects problem-solving, learning efficiency, critical thinking, creativity, engagement and motivation as well as challenges associated with GenAI use.

The first variable group is about demographics, the sample has a female proportion of 64.5% whereas male is 35.5%. Distribution based on age is given in a bar chart in four age groups (18-20, 21-23, 24-26, and 27 and above) in **Error! Reference source not found.**. The highest population comes from age group two, which is 21-23 years, and represents 59.1% of the participants.

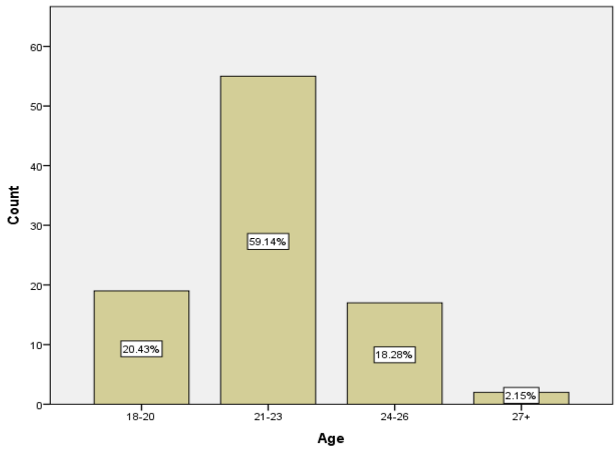

Figure 1. Age distribution

Considering departments, five choices were made (STEM, Social Science and Humanities, Business and Economics, and Arts and Design) along with an "Other" option to specify other majors; however, 20.43% specified their majors in "Other" regardless of that major being listed or not. The highest population is from STEM with 39.78% then Business and Economics with 29.03%.

As for academic year, 15.05% of the respondents are postgraduate students, the biggest population are "fourth year or above" students, and they represent 44.09%, after them, "second year" students represent 20.43% of the total sample.

Other variables were analyzed about GenAI usage, frequency of use, purposes of use, and GenAI associated challenges to measure different aspects to better understand who is affected by GenAI tools in what sense. For "GenAI usage" 95.7% of the participants answered *"Yes"* that they have used GenAI tools for academic purposes, which indicates the popularity of these tools in academia, while 4.3% answered *"No"* they never used them.

Considering "Frequency of use", it is clear that most of the students use them regularly as 22.58% stated that they use them "*Daily*" and 44.09% selected "*A few times a week*" whereas the less frequent usage was those 16.13% who use it *"A few times a month*" along with the 12.9% and 4.3% who chose *"Rarely*" and "*Never*" respectively. (**Error! Reference source not found.**).

Next, in order to analyze how students are impacted by GenAI tools, it was vital to observe what tasks they use them for. Participants were asked to rate the frequency of use for various academic tasks on a 5-point Likert scale from "*Never*" to "*Always*". According to the frequency average (based on the Likert scale), "*Research and Study*" is the most common use of these tools as more than half of the sample (n = 51) selected the level 4 or 5, followed by "*Writing essays/reports", "Generating ideas*", and *"Solving problems"* respectively. The average usage frequency for each purpose is presented in.

When participants were asked about how confident they are to use GenAI for their academic work, generally they showed varied confidence levels as 10.8% noted they were "extremely confident", 37.6% were "very confident", 41% were "slightly confident", and 9.7% were "not confident at all".

These results show that most respondents are confident, although the degree to which they trust it varies.

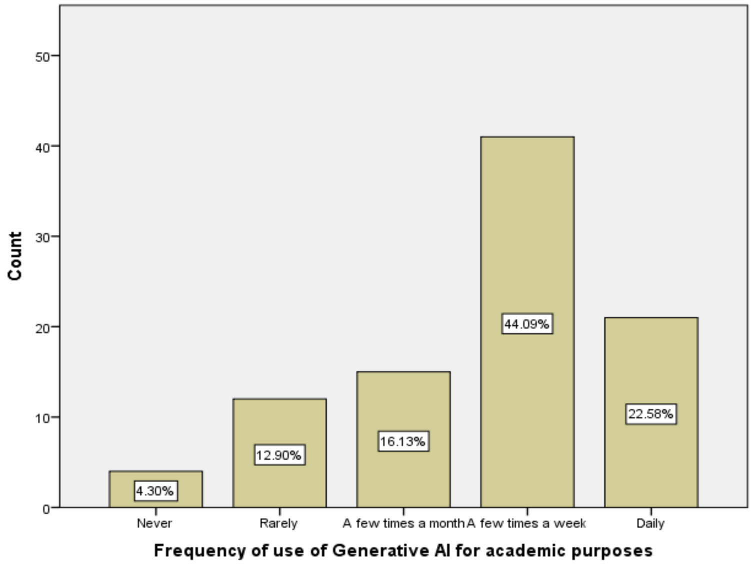

Figure 2. Frequency of use GAI for academic purposes

The second part of the survey questions was regarding the main variables of our research (learning, creativity, motivation, engagement).

We asked participants various questions, such as a Likert-type agreement scale, and some nominal questions (Table 1).

Variable	Question	Values
V1	Generative AI supports my ability to analyze and solve complex problems.	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V2	Compared to traditional learning methods (e.g., textbooks, lectures), how effective do you find Generative AI in understanding complex topics?	"Much less effective than traditional methods", "Slightly less effective", "About the same", "Slightly more effective", "Much more effective"
V3	Do you believe that Generative AI reduces your ability to think critically and independently?	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V4	I feel that Generative AI expands my creative thinking beyond what I would normally generate myself.	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V5	How does generative AI influence your approach to problem-solving?	"Encourages me to explore innovative solutions", "Helps structure my thoughts but does not increase creativity", "Has no impact

Variable	Question	Values
		on my problem-solving process", "Reduces my originality by making me rely on pre-existing ideas", "Other"
V6	How do you think Generative AI affects your creative thinking process?	"Encourages me to develop unique solutions", "Provides structured ideas but does not enhance my creativity"," Limits my creativity by making me depend on existing ideas", "No effect"
V7	Using generative AI increases my motivation to engage with academic content.	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V8	Generative AI encourages me to explore new academic topics beyond what is required.	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V9	Generative AI makes learning more interactive and engaging for me.	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V10	Using generative AI increases my participation in class or group discussions.	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V11	Does the availability of Generative AI reduce your motivation to study independently?	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"
V12	Would you recommend using Generative AI for studying to other students?	"Strongly Disagree", "Disagree", "Neutral", "Agree", "Strongly Agree"

Table 1. Survey Variables

Our analysis indicates that students' perceptions generally tended to be positive, but with interesting contrasts. For instance, 54.9% of total participants (agree and strongly agree) agreed that GenAI supports their ability to solve complex problems, whereas only 17.2% disagreed with that. Furthermore, 73.1% reported that GenAI was more effective than traditional learning methods in terms of understanding complex problems, indicating a general positive trend among students to view these tools as effective.

Despite this positive attitude, a decent percentage of students reported concerns about the potential negative influence on critical thinking and independent studying. 40.9% noted that GenAI reduced their ability to think critically and independently, which is not a small proportion, indicating the participants' awareness of the potential drawbacks.

Considering creativity, 40.9% agreed on the fact that GenAI expands creative thinking; however, 24.7% expressed their disagreement with that. Notably, when participants were asked how generative AI affects their creative thinking process, 18.3% reported that generative AI limits their creativity by making them depend on existing ideas.

As for motivation and engagement, our data showed that 42% agreed that GenAI increases their motivation, with a decent percentage undecided, 38.7%.

Interestingly, when participants were asked about studying independently, more than one-third (38.7%) of the students expressed that the availability of GenAI tools reduces their motivation to study on their own; however, a similar percentage (34.4%) disagreed with that view. This suggests that students' views of GenAI are diverging.

55.9% of total students revealed that GenAI makes learning more interactive, whereas 17.2% disagreed with that view. It is noteworthy that the impact on class participation was the least, as only 36.5% expressed that it encourages them to participate actively in class.

Notably, 67.7% of total students stated that they are willing to recommend GenAI tools to their peers, reflecting that students generally recognize its benefits and usefulness.

3.2.1. Challenges with Using and Trusting GenAI for Academic Work

When all participants were asked to select which challenges they might face from multiple choices about using GenAI for their academic work, it was found that most students face challenges related to "*Difficulty in verifying the accuracy of informatio*n", with 61.3% (n = 57) of total students opting for it. The second highest frequency was then for "*Ethical concerns*" (n = 34, 36.6%), followed by "*Technical issues*" (n = 28, 30.1%). Other challenges are as follows: "*Over-reliance on AI-generated content*" (n = 25, 26.9%), *"Lack of creativity in AI-generated outputs"* (n = 25, 26.9%), "*Limited understanding of how to use the tools effectively"* (n = 24, 25.8%) (Figure 3).

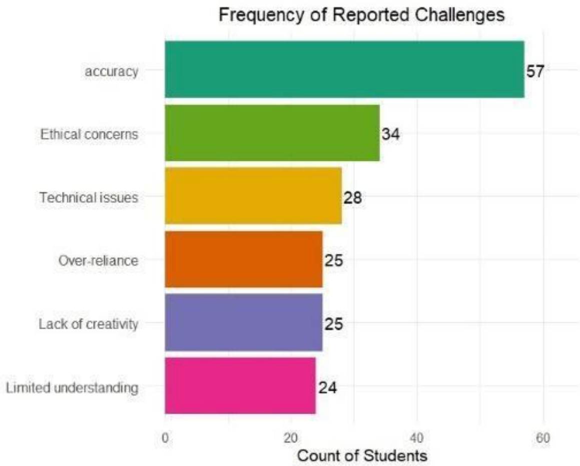

Figure 3. Frequency of Reported Challenges

Thus, our findings show that the major challenges are not merely related to content itself but extend to issues related to ethical and technical aspects. The high percentage of those who have difficulty verifying information points to a serious concern about the accuracy of the generated content, suggesting the importance of developing students' capabilities related to critical evaluation. Also, the high proportion of students mentioning ethical concerns might reflect a growing understanding of the responsible use of these tools. Other challenges that over 25% opted for, like technical issues and the limited understanding of how to use it, might indicate a gap in digital literacy. Overall, Findings reveal that despite the benefits GenAI provides in supporting the learning experience, some actual concerns and challenges that students noted should be addressed to ensure effective and responsible use.

3.3. Data preparation

For the open-ended option "other" in the field of study question, we cleaned the typos and categorized them into the predefined categories. Also, for "other" in the "What challenges have you faced while using generative AI for academic purposes?", there was one "other" specified; we removed it due to its irrelevance. All the responses were coded accordingly, and Statistical Package for the Social Sciences (SPSS) was used to prepare and analyze the dataset.

3.4. Data Analysis

In this study, Spearman's rank correlation coefficient is employed to test the strength and direction of the relationship between GenAI usage and perceived impact on the four determined learning outcomes (learning, creativity, motivation, engagement). Data Analysis was performed using SPSS.

The Spearman's coefficient ranges from -1 to +1; positive signs indicate a positive relationship, whereas a negative sign means an inverse relationship, and zero indicates no correlation (Zar, 2005). The correlation coefficient can be interpreted as follows: "If $0 < r \leq 0.4$, low correlation, If $0.4 \leq r < 0.7$, moderate correlation, and If $0.7 \leq r < 1$, high correlation." (Kafle, 2019).

Additionally, for a better understanding of how GenAI usage shapes their perceptions, k-means clustering was employed to classify students based on their GenAI usage. Before performing K-means clustering, the dataset was standardized using the Z-score standardization method.

The Silhouette method was used to choose the optimal number of clusters (k). "Silhouette is the score of comparing within-cluster distances with between-cluster distances." (Kim, 2023) The silhouette score ranges from -1 to +1, and the higher score indicates better clustering quality.

After performing k-means, Principal Component Analysis (PCA) was used to reduce the dimensionality to visualize the clusters (Ding and He, 2004). RStudio software was used to conduct the analysis, and R's functions such as scale(), silhouette(), and k-means() were utilized.

Lastly, in order to draw conclusions about the characteristics of the clusters and for descriptive profiling purposes, we applied T-tests and one-way ANOVA to determine if there are statistically significant differences in the mean value. T-tests and One-way ANOVA were performed using R's t.test() and aov() functions. For the ANOVA tests that turned out to be significant, we used Scheffe post-hoc tests from RStudio's DescTools library to determine which pairs of means are statistically significant.

4. Findings

4.1. Correlation method

Throughout Spearman's correlation analysis, findings reveal the following:

- Variable v1 "*Generative AI supports my ability to analyze and solve complex problems*".

A statistically significant relationship between the frequent use of GenAI for academic purposes and the ability to analyze and solve problems. ($r = 0.276$, $p = 0.007$) Results show that the relationship was stronger when using GenAI for the purpose of" research *and studying",* as the correlation coefficient reached 0.487. A moderate correlation ($r = 0.439$, $p = 0.000$) was found when students it particularly for *"Solving problems",* indicating that the direct use for problem-solving itself enhances the students' feeling of their analytical competence. Results also show that there is a weaker correlation with the purpose of *"Generating ideas"* ($r = 0.300$, $p = 0.003$) (**Error! Reference source not found.**).

- Variable v2 *"Compared to traditional learning methods, how effective do you find Generative AI in understanding complex topics?"*

It is apparent from **Error! Reference source not found.** that the strongest correlation is with the more frequent use of GenAI tools (correlation = 0.336, p-value = 0.001), revealing that when students adopt these tools more frequently, they have a higher perception of their ability to understand complex topics, and that GenAI tools are more effective as compared to traditional methods. A statistically significant weak correlations were found when students frequently utilize these tools for "*Research and studying*" (correlation = 0.283, $p = 0.006$) and "*Solving problems*" (correlation = 0.216, $p = 0.038$). The results also indicate that *"Confidence in GenAI*" has a positive correlation with students' perceived ability of their understanding ($r = 0.239$, $p = 0.021$), suggesting that an increase in the confidence of GenAI tools results in an increase in students' perceptions of how they can understand complex concepts. (**Error! Reference source not found.**)

- Variable v4 "*I feel that Generative AI expands my creative thinking beyond what I would normally generate myself*"

Finding reveal significant low relationships with the frequent use of GenAI for "research and studying ($r = 0.288$, $p = 0.005$) and for "idea generation and brainstorming" ($r = 0.250$, $p < 0.05$). This means that students who use GenAI tools during the initial stages of thinking and brainstorming are more likely to perceive them as helpful in generating new and creative ideas. (**Error! Reference source not found.**)

- Variable v7 "*Using generative AI increases my motivation to engage with academic content.*"

Analysis revealed weak positive correlations with the frequency of GenAI use for the purposes "*Solving problems*", "*Research and studying*", and "*Writing essays/reports*", with the values: $r = 0.336$, $r = 0.333$, $r = 0.205$, respectively. This can be interpreted as the students who utilize GenAI more frequently for "*solving problems*" and "*research*" are likely to sense higher motivation for learning. And with $r = 0.205$ for "writing essays/reports", it is likely that students feel more motivated to engage with learning, but a relatively lower association. (**Error! Reference source not found.**)

- Variable v8 "*Generative AI encourages me to explore new academic topics beyond what is required.*"

It was found that using GenAI tools for academic tasks more frequently is relatively correlated with higher motivation in terms of encouraging students to set goals to explore more topics. ($r = 0.219$, $p = 0.035$). Particularly, the higher frequency of utilizing GenAI tools for the purpose of solving problems was found to have a stronger correlation with making students more motivated for exploring academic materials ($r = 0.243$, p = 0.019). And even a stronger relationship when used for (research and studying), as the correlation reached 0.313. (**Error! Reference source not found.**)

- Variable v9 "*Generative AI makes learning more interactive and engaging for me",*

It was found that the sample of students who are leveraging GenAI tools at a higher rate feel a higher sense of engagement and interactivity (correlation = 0.245, p = 0.018).

The results confirm that GenAI could enhance the overall learning experience for students through providing interactive content, supporting comprehension, and encouraging students to learn and explore. Therefore, it can be inferred that leveraging GenAI in academic work has the potential to support both the cognitive and emotional aspects of learning. (**Error! Reference source not found.**)

Notably, Spearman's correlation analysis did not reveal statistically significant relationships between the variables:

- V3: Do you believe that Generative AI reduces your ability to think critically and independently?
- V10: Using generative AI increases my participation in class or group discussions.
- V11: Does the availability of Generative AI reduce your motivation to study independently?

And the independent variables associated with GenAI tools, including usage frequency, frequency of use for particular academic purposes, and confidence in GenAI. The results indicate that perceptions related to the reduction of critical thinking, reduction of motivation for studying independently, as well as class participation, do not correlate with GenAI usage, the purposes of use, or confidence in these tools.

Variable	Frequency of Use	Frequency (Research &Studying)	Frequency (Solving Problems)	Frequency (Generating Ideas)	Frequency (Writing)	Confidence in GenAI
V1	0.276**	0.487**	0.439**	0.300**	0.189	0.158
V2	0.336**	0.283**	0.216*	0.165	0.086	0.239*
V4	0.103	0.288**	0.147	0.250*	0.145	0.134
V7	0.170	0.333**	0.336 **	0.150	0.205*	0.198
V8	0.219*	0.313**	0.243*	0.172	0.137	0.136
V9	0.245*	0.178	0.168	0.183	0.109	0.121

** p < 0.05, ** p < 0.01 V1: "Generative AI supports my ability to analyze and solve complex problems"., V2: "Compared to traditional learning methods, how effective do you find Generative AI in understanding complex topics?" V4: "I feel that Generative AI expands my creative thinking beyond what I would normally generate myself", V7: "Using generative AI increases my motivation to engage with academic content.", V8 "Generative AI encourages me to explore new academic topics beyond what is required.", V9: "Generative AI makes learning more interactive and engaging for me".*

Table 2. Spearman Correlation results

4.2. Clustering method

In this work, two models were employed to classify participants based on their perceptions of GenAI's impact on their learning experiences. The first model focuses on the cognitive outcomes, using the following key variables: GenAI usage frequency, support for problem-solving (v1), effectiveness compared to traditional learning (v2), concerns about critical thinking loss (v3), and support for creativity (v4).

The second model aims to classify students based on how they perceive GenAI to influence their affective outcomes, and the variables: GenAI usage frequency, motivation (v7), encouragement to explore topics (v8), interactivity (v9), and class participation (v10) were used.

In the clustering based on cognitive outcomes, the dataset was standardized to z-scores, and with the R language function *silhouette()*, average silhouette scores were calculated to choose the right number of clusters. K = 4 was the value that gave the highest score (**Error! Reference source not found.**), and thus four clusters were used when applying the *k-means* function. Our results show that participants were classified into the four clusters as follows: 18, 20, 20, and 35, respectively. Figure 5 shows the PCA clusters. The results show four different patterns in students' interactivity with GenAI tools (Table).

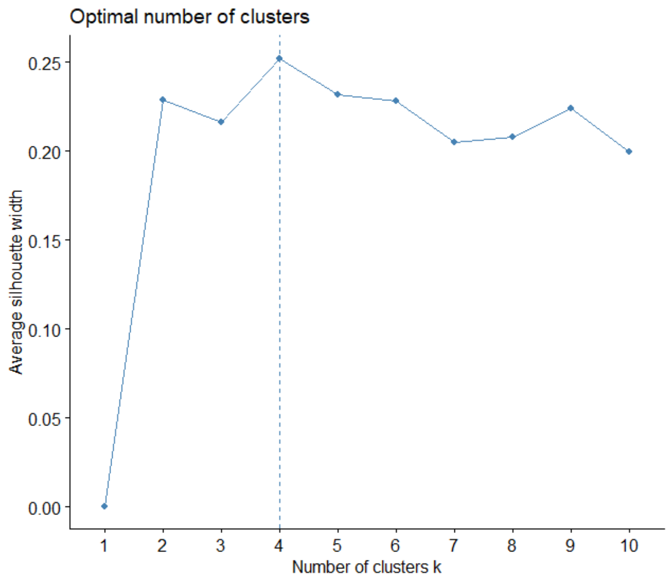

Figure 4. Optimal number of cognitive outcomes clusters

These clusters differ in terms of usage frequency, concerns about negative effects, and cognitive impact perceptions.

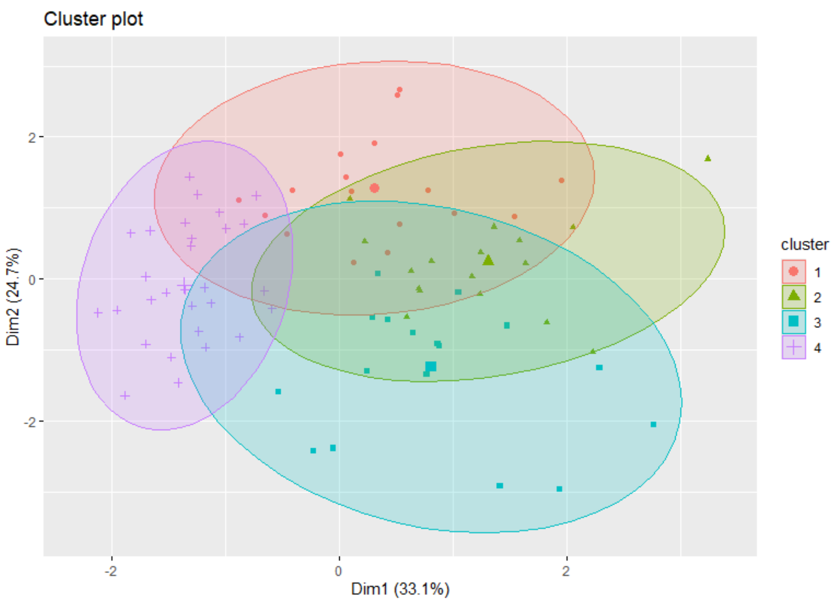

Figure 5. PCA clusters

Variables / Clusters	Cluster 1: Moderate but Cognitively Concerned	Cluster 2: Neutral and Low Engagement	Cluster 3: High Usage, Low Cognitive Belief	Cluster 4: Active and Cognitively Positive
GenAI Usage Frequency	3.88	2.10	4.05	4.26
Support Problem-Solving	3.44	3.05	2.45	4.43
Effectiveness Compared to Traditional Learning	2.55	3.60	4.35	4.80
Concern about Loss of Critical Thinking	4.00	3.15	2.50	3.46
Support for Creativity	3.56	2.85	2.05	3.80

Table 3. means of the clusters

GenAI usage frequency: ANOVA analysis revealed a significant difference in the usage level of GenAI tools among the four clusters. ($F(3, 89) = 42.72$, $p < 0.001$) Post-hoc Scheffe tests indicated that cluster 2 has a significantly lower usage level than cluster 1. Both clusters 3 and 4 have significantly higher GenAI usage than cluster 2, indicating various usage patterns among the students.

Support for problem solving: Findings of ANOVA revealed significant differences among the clusters in terms of their agreement that GenAI supports in their problem-solving ($F(3, 89) = 30.42$, $p < 0.001$). Scheffe tests indicated that cluster 3 has a significantly lower level of agreement than cluster 1. Cluster 4 significantly demonstrated stronger agreement that GenAI aids in solving problems compared to clusters 2 and 3.

Effectiveness compared to traditional learning: The analysis shows significant differences in the perceptions of the four clusters in terms of how effective GenAI is compared to traditional learning ($F(3, 89) = 58.27$, $p < 0.001$). It is apparent that cluster 4 has the highest perceived effectiveness of GenAI tools, significantly more than clusters 1 and 2, followed by cluster 3 and then cluster 2. The differences between cluster 1 and the other clusters were also significant, suggesting that cluster 1 has the lowest level of agreement among all.

Concerns about the loss of critical thinking: ANOVA analysis for the concerns about the loss of critical thinking due to relying on GenAI tools revealed significant differences between the clusters ($F(3, 89) = 6.65$, $p < 0.001$). Cluster 1 showed the highest level of concerns about GenAI reducing the ability of critical thinking. Notably, cluster 3 has the lowest level of concern and was significantly different from clusters 1 and 4. Cluster 4 has the second highest level of concern, just after Cluster 1.

Support for creativity: The ANOVA analysis revealed significance in the mean value between the clusters for their perceptions on how it supports their creativity. Scheffe post hoc tests show that cluster 4 has the strongest agreement that GenAI tools support creativity, whereas cluster 3 reported the least agreement. It is noteworthy that there are many significant pairs of means, particularly between clusters 1 and 3, clusters 3 and 4, and clusters 2 and 4.

Based on the significant differences observed in the data, cluster 1 can be labeled as “moderate but cognitively concerned” as they represent the moderate usage group but the most cognitively concerned. Cluster 2 labeled as “neutral and low usage” as they are significantly low frequent users who are in a neutral position about how GenAI impacts cognitive outcomes. As for clusters 3 and 4, they can be labeled as “high usage and low cognitive believe” and “active and cognitively positive”, respectively. This is grounded by how cluster 3 recorded the second highest usage frequency, and at the same time, it showed a limited cognitive impact, and that cluster 4 is the most frequent user and optimistic towards GenAI cognitive impact.

Overall, the findings confirm substantial differences and unexpected patterns in students' attitudes about GenAI, particularly in cluster 3, where they were frequent users (second highest frequency rate) and had the lowest levels of agreement that GenAI supports creativity or problem solving, but also the lowest level of agreement that the reliance on these tools could reduce critical thinking. Notably, cluster 4 demonstrated the highest frequency users and they had the most optimistic perception for effectiveness, support for problem solving and creativity, yet they were the most concerned group about the loss of critical thinking. These various patterns suggest that the more frequent use of GenAI does not always translate to more optimistic perceptions. Our results suggest that students’ attitudes toward GenAI are different, and their perceptions are formed in a complex way between the perceived benefits and potential concerns.

Variable	F	df (between, within)	p-value
GenAI usage frequency	42.72	(3, 89)	< 0.001***
Support for problem-solving	30.42	(3, 89)	< 0.001***
Effectiveness Compared to Traditional Learning	58.27	(3, 89)	< 0.001***
Concerns about critical thinking	6.65	(3, 89)	< 0.001***
Support for creativity	21.77	(3, 89)	< 0.001***

*** p < 0.001.

Table 4. Anova Test

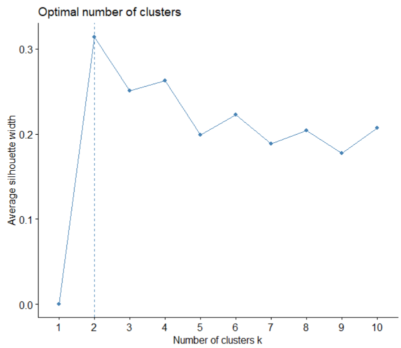

Figure 6. Optimal number of affective outcomes clusters

Considering the clustering based on the affective outcomes, the data was first rescaled into z-scores, and using the R *silhouette()* function, it was determined that k = 2 gives the largest silhouette score (Figure 6). Therefore, two clusters were used in the application of the *k-means* function. The results show that 42 and 51 participants were classified in cluster 1 and cluster 2, respectively.

The means (M) of cluster 2 among all variables (GenAI usage frequency, motivation, encouragement to explore topics, interactivity, class participation) were higher than those in Table 5.

Figure 7 shows the PCA visualization for the clusters. In order to compare the affective perceptions among the two clusters, independent sample t-tests were performed, and their results are shown in Table 5.

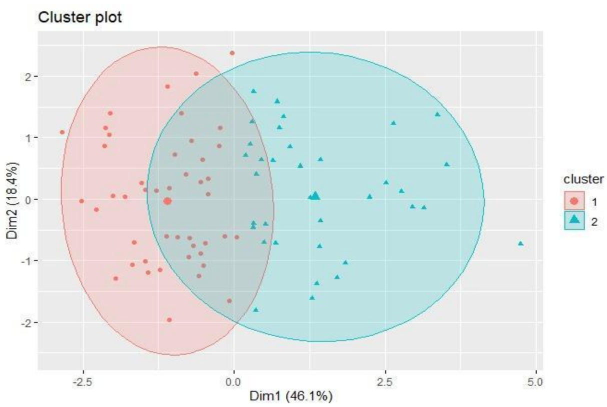

Figure 7. PCA visualization

The results revealed statistically significant differences ($p < 0.05$) in all five variables between the two clusters. Cluster 2 students reported significantly higher levels of motivation, curiosity to explore new topics, interactivity, and class participation, compared to students of cluster 1.

Thus, cluster 1 is labeled as "Low-Motivation and Low-Engagement Users," while cluster 2 as "Highly Motivated and Engaged Users". Findings of this study support that higher frequency usage of GenAI tools is associated with higher levels of motivation and engagement in learning contexts. It is noteworthy that the largest mean difference between the two clusters was in the variable related to encouragement to explore new topics.

Variable	Cluster 1 (n = 42)		Cluster 2 (n = 51)		t	P
	M	***SD***	***M***	***SD***		
GenAI usage frequency	**3.19**	**1.254**	**4.08**	**0.744**	-4.040***	0.000
Motivation	**2.52**	**0.833**	**3.80**	**0.664**	-8.067***	0.000
Encouragement to explore topics	**2.33**	**0.954**	**4.02**	**0.620**	-9.388***	0.000
Interactivity	**2.67**	**1.052**	**4.24**	**0.651**	-8.429***	0.000
Class participation	**2.26**	**1.061**	**3.51**	**0.987**	-5.825***	0.000

*** $p < 0.001$.

Table 5. Independent Samples t-Tests

5. Discussion and conclusion

The analysis shows that students are increasingly adopting GenAI tools in their academic tasks for different purposes, indicating that these tools play an important role in the lives of higher education students. Thus, understanding and adopting these tools is an inevitable reality. In our findings, students view GenAI tools positively in general, and particularly in facilitating comprehension, enhancing efficiency, and increasing enthusiasm towards learning. However, at the same time, a decent number of students reported some concerns and risks related to the adoption of GenAI tools, especially in regard to the difficulty of validating the accuracy of the content generated by these tools which aligns with what Zhu et al. (2023) stated that accuracy was a problem noticed by students, the overreliance on them and the potential drawback of reducing critical thinking, that was similar to Zhu et al. (2023) findings that many students think that AI might affect them badly by thinking on behalf of them. In addition, challenges related to ethical aspects and the necessary skills and competencies to use these tools were posed.

Furthermore, Spearman's correlation analysis revealed that students with higher usage rates feel an increase in problem solving, creativity, motivation, and engagement in their learning processes. However, the clustering analysis findings emphasize a large variety in the evaluation of GenAI's cognitive impact, indicating that a higher usage rate does not necessarily lead to increased positive perception of GenAI's cognitive impact.

As for the affective aspect, the cluster analysis took similar patterns with correlations. The clusters were a group of those who use it more frequently with higher levels of engagement and motivation in their learning process, which aligns with part of Liang et al. (2023)'s findings, as they stated that the students who use it more have higher self-efficacy as well as a group with less frequent usage and lower levels of motivation and engagement.

This study highlights that GenAI use enhances both motivation and learning efficiency, yet overreliance may hinder critical thinking. Future work should explore these paradoxes with larger and more diverse samples. Our findings call for a balance between innovation and responsibility in AI-integrated education.

5.1. Linking Findings to Theory and Contributions

The results reinforce the mechanisms of **Technology Acceptance Models (TAM/UTAUT)** by showing that perceived usefulness and performance expectancy explain why higher use correlates with stronger learning outcomes and motivation. At the same time, the "high-use but low-belief" cluster illustrates that **digital literacy moderates** these pathways, highlighting that critical evaluation skills are essential for GenAI adoption to yield positive cognitive gains. Scientifically, the study contributes by (i) integrating cognitive and affective outcomes in one framework, (ii) moving beyond descriptive analysis through clustering, and (iii) bridging adoption models with responsible-use perspectives.

5.2. Practical and Policy Implications

For universities, these findings suggest that the success of GenAI integration depends not only on access but also on **instructional design and governance**. Institutions should:

- Develop **clear policies** on responsible use, plagiarism, and verification.
- Incorporate **AI literacy modules** into curricula to train students in prompt design, fact-checking, and ethical considerations.
- Support faculty in creating assessments that balance AI-assisted creativity with independent reasoning. Such practices can maximize motivation and engagement while safeguarding critical thinking and academic integrity.

5.3. Limitations and Future Research

This study is limited by its sample size ($n = 93$) and its reliance on self-reported, cross-sectional data, which reduce generalizability and preclude causal inference. Because the participants were recruited from a single institutional context, disciplinary and cultural variations in GenAI use could not be captured, further constraining external validity. Moreover, certain constructs such as creativity and participation were measured with single items. While this approach minimizes survey length, it may restrict construct reliability and fail to capture the multidimensional nature of creativity and engagement. Future studies should adopt validated multi-item scales to strengthen psychometric robustness.

The policy implications discussed in this study are exploratory and may vary across institutional contexts depending on infrastructure, digital literacy, and governance frameworks. Therefore, the recommended actions (e.g., responsible-use policies, AI-literacy modules, faculty training) should be adapted to local needs rather than applied uniformly.

Future research should use larger, more diverse and multi-institutional samples, apply longitudinal designs to capture changes over time, and combine surveys with qualitative methods (e.g., interviews, focus groups) to uncover deeper insights. Testing moderated models (e.g., SEM) could also clarify how digital literacy and institutional conditions shape the adoption and outcomes of GenAI.

References

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. Discover Education, 3(1), 60. https://doi.org/10.1007/s44217-024-00060-0

Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. Sustainability, 15(17), 12983. https://doi.org/10.3390/su151712983

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Ding, C., & He, X. (2004, July). K-means clustering via principal component analysis. In Proceedings of the 21st International Conference on Machine Learning (pp. 29–36). ACM. https://doi.org/10.1145/1015330.1015408

Habib, S., Vogel, T., Anli, X., & Thorne, E. (2024). How does generative artificial intelligence impact student creativity? Journal of Creativity, 34(1), 100072. https://doi.org/10.1016/j.yjoc.2024.100072

Kafle, S. C. (2019). Correlation and regression analysis using SPSS. The OCEM Journal of Management, Technology, and Social Sciences, 1(1), 125–132. https://doi.org/10.3126/ojmts.v1i1.29287

Kim, S., Cho, S., Kim, J. Y., & Kim, D. J. (2023). Statistical assessment on student engagement in asynchronous online learning using the k-means clustering algorithm. Sustainability, 15(3), 2049. https://doi.org/10.3390/su15032049

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. Frontiers in Psychology, 14, 1285392. https://doi.org/10.3389/fpsyg.2023.1285392

Mittal, U., Sai, S., & Chamola, V. (2024). A comprehensive review on generative AI for education. IEEE Access, 12, 10345–10360. https://doi.org/10.1109/ACCESS.2024.3355555

Muñoz, S. A. S., Gayoso, G. G., Huambo, A. C., Tapia, R. D. C., Incaluque, J. L., Aguila, O. E. P., & Arias-Gonzáles, J. L. (2023). Examining the impacts of ChatGPT on student motivation and engagement. Social Space, 23(1), 1–27.

Neji, W., Boughattas, N., & Ziadi, F. (2023). Exploring new AI-based technologies to enhance students' motivation. Issues in Informing Science & Information Technology, 20, 123–136. https://doi.org/10.28945/5135

Sandu, R., Gide, E., & Elkhodr, M. (2024). The role and impact of ChatGPT in educational practices: Insights from an Australian higher education case study. Discover Education, 3(1), 71. https://doi.org/10.1007/s44217-024-00071-x

Schei, O. M., Møgelvang, A., & Ludvigsen, K. (2024). Perceptions and use of AI chatbots among students in higher education: A scoping review of empirical studies. Education Sciences, 14(8), 922. https://doi.org/10.3390/educsci14080922

Shearer, C. (2000). The CRISP-DM model: The new blueprint for data mining. Journal of Data Warehousing, 5(4), 13–22.

Van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in digital skills: A model and critical review. *New Media & Society, 16*(3), 507–526. https://doi.org/10.1177/1461444813487959

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Yu, H., & Guo, Y. (2023, June). Generative artificial intelligence empowers educational reform: Current status, issues, and prospects. Frontiers in Education, 8, 1183162. https://doi.org/10.3389/feduc.2023.1183162

Zar, J. H. (2005). Spearman rank correlation. In B. Everitt & D. Howell (Eds.), Encyclopedia of statistics in behavioral science (pp. 4973–4975). Wiley. https://doi.org/10.1002/0470013192.bsa598

Zhu, G., Fan, X., Hou, C., Zhong, T., Seow, P., Shen-Hsing, A. C., & Poh, T. L. (2023). Embrace opportunities and face challenges: Using ChatGPT in undergraduate students' collaborative interdisciplinary learning. arXiv preprint arXiv:2305.18616. https://doi.org/10.48550/arXiv.2305.18616