

Mapping University Students Risk of Dependence on Generative Artificial Intelligence Using K-Means Clustering

Hafiz Fadhillah^{1*}, Taufiq²

¹²Department of Informatics Engineering, Faculty of Engineering, Universitas Malikussaleh, Aceh, Indonesia

¹hafiz.240170162@mhs.unimal.ac.id, ²taufiq.te@unimal.ac.id



*Corresponding Author

Article History:

Submitted: 02 October 2026

Accepted: 10 October 2026

Published: 17 October 2026

Keywords:

Academic Independence;
Dependence Risk; Generative
Artificial Intelligence; K-Means
Clustering; Student Behavior;
University Students.

**GASET: Global Advances in
Science, Engineering &
Technology** is licensed under a
Creative Commons Attribution-
NonCommercial 4.0 International
(CC BY-NC 4.0).

ABSTRACT

The growing use of generative artificial intelligence (GenAI) in higher education has changed how university students approach academic tasks. Although these tools can support learning and improve efficiency, frequent reliance on them raises concerns about students' ability to study and solve problems independently. This study aims to identify patterns of GenAI use among university students and explore potential indicators of dependence through K-Means clustering. An exploratory quantitative approach was adopted, using questionnaire responses collected through 15 items measured on a five-point Likert scale. Of the 106 responses received, 104 met the inclusion criteria and were retained for analysis. The data underwent screening, numerical encoding, and reverse scoring before being grouped using the K-Means algorithm. The appropriate number of clusters was selected by comparing Silhouette Scores across solutions containing two to seven clusters. The analysis identified three student groups, with a Silhouette Score of 0.2443. The first group comprised 30 students (28.85%) who showed relatively higher GenAI use and stronger indications of behavioral dependence. The second group included 11 students (10.58%) who reported lower GenAI use but demonstrated limitations in academic independence and understanding. The remaining 63 students (60.58%) formed a group characterized by moderate GenAI use. These findings suggest that frequency of use alone does not adequately reflect the risk of dependence. However, the relatively low Silhouette Score indicates limited separation between groups, meaning that the resulting profiles should be interpreted as exploratory rather than definitive.

INTRODUCTION

Generative Artificial Intelligence (GenAI) has become increasingly relevant in higher education, influencing how academic activities are carried out and how students engage with learning resources. Through natural language interaction, these technologies allow users to generate written content, clarify complex concepts, summarize information, and obtain assistance with various learning tasks (Baig & Yadegaridehkordi, 2024). The growing adoption of GenAI has also extended beyond students, with educators and researchers exploring its potential to support teaching, academic writing, and research activities. Recent studies have highlighted its value in improving learning experiences, supporting productivity, and facilitating skill development. Nevertheless, the integration of GenAI into academic environments also presents challenges that require careful consideration, particularly regarding its appropriate and responsible use (Yusuf, Pervin, Román-González, & Noor, 2024).

University students now use generative artificial intelligence for purposes that extend beyond simply searching for information. These tools have become useful for understanding course materials, developing ideas, preparing written assignments, and completing various academic tasks (Kasneji et al., 2023). Their accessibility also offers opportunities to improve learning efficiency, encourage student engagement, and provide additional academic support (Lo, 2023). Despite these benefits, the increasing integration of GenAI into everyday learning activities has raised concerns about students' critical thinking, academic independence, and academic integrity. Excessive reliance on AI-generated assistance may also affect how students approach academic challenges, particularly when they begin to depend on technological support rather than developing solutions through their own reasoning.

Despite these benefits, the increasing use of generative artificial intelligence has raised concerns about students becoming overly dependent on AI tools when completing academic tasks. Such dependence is not necessarily determined by how frequently students use these technologies, but also by how they evaluate and incorporate AI-generated information into their learning processes. Students may approach AI-assisted problem-solving differently, with some critically examining the responses they receive while others accept them without adequate evaluation. These patterns suggest that reliance on GenAI involves different levels of judgment and engagement rather than simply reflecting usage frequency (Lee et al., 2025). Furthermore, students' intentions to use generative AI may influence their reliance on these



tools, highlighting the importance of critical evaluation and responsible AI use in academic settings.

The risk of dependence on generative artificial intelligence becomes particularly concerning when students begin to rely on AI-generated responses instead of engaging in independent reasoning and problem-solving. Although these technologies can support academic activities, excessive dependence may be associated with reduced engagement in critical thinking and analytical reasoning. (Tian & Zhang, 2025) found that higher levels of AI dependence among university students were associated with lower critical thinking, with cognitive fatigue partly explaining this relationship. However, students' ability to evaluate information critically remains important in determining whether AI-generated responses should be trusted or questioned. (Hou, Zhu, & Sudarshan, 2025) further emphasized the role of critical thinking in shaping how undergraduate students rely on generative AI during problem-solving activities. Therefore, responsible use of GenAI requires students to examine, verify, and reflect on AI-generated information, ensuring that technological assistance supports their learning rather than replaces independent intellectual engagement.

Previous research suggests that university students differ considerably in how they understand, perceive, and engage with artificial intelligence in their academic activities. These differences indicate that students cannot be viewed as a uniform group, making clustering approaches useful for identifying distinct profiles based on shared characteristics. (Medina-Gual & Parejo, 2025) demonstrated that cluster analysis can distinguish university students according to their AI literacy, learning experiences, and patterns of engagement with AI technologies. Similarly, (Polat, 2025) identified different student profiles based on AI literacy, lifelong learning tendencies, and attitudes toward technological innovation. Although these studies provide valuable insights into variations in students' interactions with AI, further investigation is needed to understand how behavioral dependence can be characterized through clustering. Accordingly, the present study focuses on students' patterns of GenAI use, academic independence, understanding of AI-generated responses, information verification practices, and their tendency to prioritize AI assistance when completing academic tasks.

Clustering methods have been applied to examine variations in students' dependence on generative artificial intelligence and their ability to solve complex problems. By identifying groups with similar characteristics, these data-driven techniques can reveal differences in how students rely on AI during academic activities. (Benites-Rodriguez et al., 2026) demonstrated that K-Means clustering can distinguish student profiles based on their levels of GenAI dependence and problem-solving abilities. Building on this approach, the present study investigates patterns of potential GenAI dependence among university students by examining several behavioral indicators, including AI usage patterns, independence in completing academic tasks, understanding of AI-generated responses, information verification practices, and the tendency to seek AI assistance as a primary option. The K-Means algorithm is employed to group students according to similarities across these indicators, allowing distinct behavioral profiles to be identified. These profiles are subsequently interpreted to provide a clearer understanding of how students interact with GenAI and how their learning behaviors may reflect different tendencies toward academic dependence.

LITERATURE REVIEW

Generative artificial intelligence has become an important part of academic learning, offering students new ways to access information, develop ideas, and complete educational tasks. However, its influence on learning outcomes depends not only on the availability of these technologies but also on how students integrate them into their learning activities. (K. Chen, Tallant, & Selig, 2025) examined university students' generative AI literacy and found that students commonly used AI to develop ideas and support academic assignments while maintaining varying levels of critical evaluation. These findings suggest that understanding students' interactions with GenAI requires attention to their learning behaviors, rather than focusing exclusively on how frequently they use these tools.

Academic independence is another important consideration in understanding students' relationships with generative AI. Although AI-supported learning can provide personalized assistance and help students manage academic activities, its contribution to independent learning depends on students' ability to regulate their own learning processes. (Lan & Zhou, 2025) reviewed the role of AI in self-regulated learning and highlighted its potential to support student autonomy through different forms of educational assistance. Nevertheless, the availability of AI-generated support does not necessarily indicate that students are developing independent learning skills. This distinction is particularly relevant when examining whether students use GenAI to strengthen their understanding or increasingly depend on it to complete academic responsibilities.

The relationship between generative AI and students' cognitive abilities has also received considerable research attention. (Sardi et al., 2025) conducted a systematic review examining the influence of GenAI on self-regulated learning and critical thinking. Their findings indicated that AI-supported learning can contribute positively to both areas, particularly when students actively engage in evaluating information and reflecting on their learning processes. However, excessive reliance on technological assistance remains a concern because it may reduce opportunities for independent reasoning. These findings emphasize the importance of examining students' ability to understand, question, and verify AI-generated information when assessing potential dependence.

Beyond learning independence, students' reliance on generative AI is influenced by their trust in the technology and their perceptions of its usefulness. (Wang, Li, Cheung, & Wong, 2025) investigated university students' reliance on and resistance to GenAI in language learning, identifying trust as an important factor associated with their intention to use these technologies. Their findings suggest that reliance involves more than repeated use, as students may differ in how much they trust AI-generated responses and how willing they are to depend on them. This perspective supports the need to examine behavioral indicators, including students' tendency to prioritize AI assistance and their willingness to evaluate information before incorporating it into academic work.

Recent research has also emphasized the importance of distinguishing productive AI assistance from patterns of use that may limit students' intellectual engagement. (Daniel, Msambwa, & Wen, 2025) reviewed the contribution of generative AI to academic skills development in higher education and identified potential benefits for cognitive, technical, and interpersonal competencies. However, the authors also highlighted the importance of responsible implementation and continued evaluation of its educational implications. These findings indicate that the effects of GenAI cannot be understood through usage intensity alone. Instead, students' learning practices, critical judgment, and ability to complete tasks independently should also be considered when examining potential dependence.

Differences in how students use GenAI further suggest that its educational implications cannot be represented by a single behavioral pattern. (an, Koh, & Liu, 2026) systematically reviewed empirical studies of GenAI use in higher education and identified several ways students incorporate these technologies into learning tasks, alongside variations in reported learning outcomes. Their findings provide additional support for examining students' interactions with GenAI from multiple behavioral perspectives. Building on this literature, the present study applies K-Means clustering to identify student profiles based on AI usage patterns, academic independence, comprehension of AI-generated responses, information verification practices, and the tendency to prioritize AI assistance. Rather than treating dependence as a direct consequence of frequent use, this approach seeks to identify differences in students' learning behaviors that may indicate varying levels of reliance on generative artificial intelligence.

METHOD

This study follows a systematic, data-driven procedure to identify patterns of potential dependence on generative artificial intelligence (GenAI) among university students in academic settings. The research process consists of several interconnected stages, beginning with the development of a questionnaire and the collection of student responses. The collected data are subsequently screened, preprocessed, and transformed to prepare them for clustering analysis. After determining an appropriate number of clusters, the K-Means algorithm is applied to group students according to similarities in their GenAI-related behaviors. The resulting clusters are then evaluated and interpreted to identify the distinguishing characteristics of each student group. This sequential procedure provides a structured basis for examining variations in students' academic use of GenAI and developing behavioral profiles that reflect different tendencies toward reliance on AI-assisted learning.

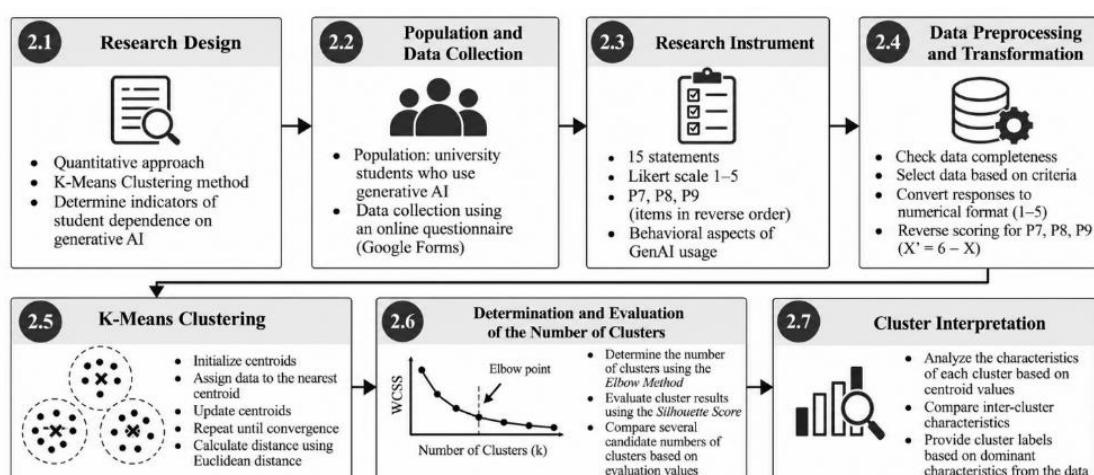


Figure 1. Research Workflow

Research Design



This study adopts a quantitative research approach supported by clustering analysis to examine patterns of potential dependence on generative artificial intelligence (GenAI) among university students in academic settings. A quantitative design was selected because the research relies on questionnaire responses that are converted into numerical data, enabling systematic analysis of individual behavioral characteristics. The K-Means clustering algorithm is employed to categorize respondents into groups based on similarities in their GenAI usage patterns. Rather than assigning participants to predetermined categories, the algorithm identifies clusters according to the characteristics represented in the collected data. Each resulting cluster is subsequently examined to determine its distinguishing behavioral features, providing a basis for understanding variations in students' reliance on GenAI when performing academic activities.

Population and Data Collection

The target population of this study consisted of university students who had used generative artificial intelligence (GenAI) to support their academic activities. Data were collected through an online questionnaire distributed using Google Forms. Before proceeding with the survey, participants were asked to provide their consent to participate in the study. They were then required to provide basic academic information, including their study program and current semester, and indicate whether they had previously used GenAI for academic purposes. Respondents who reported prior experience with these technologies were directed to additional questions addressing their usage patterns and behavioral tendencies associated with potential GenAI dependence. The data collection process was conducted from October 6 to October 12, 2026. The final number of eligible responses was determined after the data collection and screening procedures had been completed.

Research Instrument

The research instrument consisted of a structured questionnaire designed to collect information on students' academic backgrounds, their patterns of generative artificial intelligence (GenAI) use, and behavioral tendencies associated with potential dependence on these technologies. The main section contained 15 statements assessed using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with 2 representing Disagree, 3 representing Neutral, and 4 representing Agree. This response format enabled participants to indicate their level of agreement with each statement in an ordered manner, providing numerical data for subsequent analysis (Aybek & Toraman, 2022).

The questionnaire addressed several dimensions of students' interactions with GenAI, including usage frequency and patterns, reliance on AI when completing assignments, academic independence, comprehension of AI-generated responses, information verification practices, and the tendency to prioritize AI assistance. Three statements, identified as P7, P8, and P9, were formulated in the opposite direction to the construct of dependence. These items were therefore designated for reverse scoring during data preparation to ensure that their numerical values could be interpreted consistently with the remaining indicators. Careful handling of reverse-worded statements is essential because differences in item direction can introduce measurement effects that influence the interpretation of questionnaire responses (Zeng, Jeon, & Wen, 2024).

Data Preprocessing and Transformation

Before proceeding with the clustering analysis, the questionnaire responses underwent a series of preprocessing procedures to ensure that the dataset was suitable for further examination. This process involved checking the completeness of submitted responses, selecting participants who satisfied the research criteria, and converting the five-point Likert responses into numerical values ranging from 1 to 5. The scoring direction of each statement was subsequently reviewed and standardized so that higher scores consistently indicated stronger tendencies toward dependence on generative artificial intelligence (GenAI).

Statements P7, P8, and P9 were formulated in the opposite direction to the construct of GenAI dependence and therefore required reverse scoring before being included in the clustering analysis. For the five-point Likert scale, this transformation converted an original score of 1 into 5, 2 into 4, 4 into 2, and 5 into 1, while the midpoint score of 3 remained unchanged. Because reverse-worded items can affect respondents' scores and measurement characteristics, their scoring direction must be carefully considered during data preparation (İlhan, Güler, Teker, & Ergenekon, 2024). The reverse-scoring procedure was applied using Equation (1):

$$X' = 6 - X \quad (1)$$

Where X represents the original response score and X' denotes the score obtained after reverse coding. This adjustment aligned the scoring direction of the three items with the remaining indicators, ensuring that higher values consistently represented stronger tendencies toward GenAI dependence.

K-Means Clustering



K-Means is an unsupervised learning algorithm designed to partition a dataset into distinct groups according to the similarity of their characteristics. Each group is represented by a central point, known as a centroid, which serves as the reference for assigning observations to the nearest cluster. The algorithm operates through an iterative procedure that begins with centroid initialization, followed by the assignment of observations to their closest centroids. Subsequently, the centroid positions are recalculated using the mean values of the observations within each cluster. These steps are repeated until the cluster assignments stabilize or the algorithm reaches convergence (Ikotun, Ezugwu, Abualigah, Abuhaija, & Heming, 2023).

In this study, each respondent was represented by a set of numerical features obtained from the transformed questionnaire responses. The similarity between individual observations and cluster centroids was assessed using Euclidean distance. Each respondent was assigned to the cluster associated with the nearest centroid. Once all observations had been assigned, the centroid of each cluster was updated by calculating the mean of its constituent observations. This iterative process continued until no substantial changes occurred in the resulting cluster configuration.

The Euclidean distance between each respondent and the corresponding cluster centroid was calculated using Equation (2):

$$d(x_i, c_j) = \sqrt{\sum_{k=1}^m (x_{ik} - c_{jk})^2} \quad (2)$$

Where $d(x_i, c_j)$ denotes the distance between the i -th respondent and the centroid of the j -th cluster, x_{ik} represents the value of the k -th feature for the i -th respondent, c_{jk} indicates the value of the k -th feature at the centroid of the j -th cluster, and m represents the total number of features used in the analysis.

Cluster Determination and Evaluation

Determining an appropriate number of clusters is an essential consideration in K-Means clustering, as the value of k must be established before the algorithm is executed. In this study, several potential cluster configurations were investigated using the Elbow Method by examining variations in the within-cluster sum of squares (WCSS) across different values of k . The point at which the reduction in WCSS begins to diminish may provide an initial indication of a suitable cluster number. However, because identifying the elbow point relies on heuristic interpretation and the resulting curve may not always reveal a distinct turning point, this method was not treated as the sole criterion for selecting the number of clusters (Schubert, 2023).

The clustering configurations were further assessed using the Silhouette Score, which evaluates the compactness of observations within their assigned clusters and the degree of separation between different clusters. Silhouette coefficients range from -1 to 1 , with higher values generally reflecting stronger within-cluster similarity and clearer distinctions between clusters. In this study, the mean silhouette coefficient was used to compare the quality of alternative cluster configurations (Juanita & Cahyono, 2024). The silhouette coefficient for each observation was calculated using Equation (3):

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (3)$$

Where $a(i)$ denotes the average distance between observation i and other observations assigned to the same cluster, whereas $b(i)$ represents the minimum average distance between observation i and observations belonging to another cluster. The average silhouette coefficient across all respondents was subsequently considered as one of the criteria for evaluating the quality of the resulting cluster configuration.

Cluster Interpretation

Following the completion and evaluation of the clustering procedure, the resulting groups were examined to identify their distinguishing characteristics. The interpretation was conducted by analyzing the centroid values and respondents' response patterns across the questionnaire indicators. Comparisons among clusters were subsequently performed to determine differences in students' tendencies toward generative artificial intelligence (GenAI) usage and dependence. Each cluster was assigned a descriptive label based on its most prominent characteristics after the clustering results had been obtained, rather than defining the categories before the analysis. This data-driven approach ensured that the interpretation and labeling of clusters reflected the patterns emerging from the observed responses.

RESULT

This study identified patterns of generative artificial intelligence (GenAI) use among university students by

examining 15 behavioral indicators through K-Means clustering. The findings are presented sequentially, beginning with respondent characteristics and data preprocessing, followed by the determination of an appropriate number of clusters and the resulting cluster configurations. The characteristics of each cluster are subsequently examined to identify differences in students' tendencies toward GenAI dependence in academic activities.

Respondent Characteristics

A total of 106 questionnaire responses were collected through an online survey. Following the eligibility screening process, two responses were excluded because the participants reported that they did not use generative artificial intelligence (GenAI) to support their academic activities. Consequently, 104 valid responses, each containing complete answers to all 15 questionnaire indicators, were retained for the subsequent analysis.

Respondents were characterized according to their academic programs, current semesters, most frequently used GenAI services, and frequency of GenAI use for academic purposes. These characteristics provide an overview of the participants' educational backgrounds and their engagement with GenAI technologies. Differences in academic disciplines and stages of study were considered to describe the diversity of the sample, while the distribution of GenAI services and usage frequencies provided additional context regarding students' academic technology-use patterns. A comprehensive summary of respondent characteristics is presented in Table 1.

Table 1. Respondent Characteristics

(N = 104)

Characteristic	Category	Respondents (n)	Percentage (%)
Academic Program	Informatics Engineering	32	30.77
	Public Administration Science	9	8.65
	Law	6	5.77
	Information Systems	5	4.81
	Management	5	4.81
	Chemistry	5	4.81
	Public Administration	4	3.85
	Electrical Engineering	4	3.85
	Pharmacy	4	3.85
	Civil Engineering	3	2.88
	Psychology	3	2.88
	Agroecotechnology	2	1.92
	Agribusiness	2	1.92
	Da'wah Management	2	1.92
	Computer Systems	2	1.92
	Chemistry Education	1	0.96
	Geography	1	0.96
	Islamic Education Management	1	0.96
	Physics Education	1	0.96
	Qur'anic Studies and Interpretation	1	0.96
	Machine Maintenance Engineering	1	0.96
	Economics Education	1	0.96
	Islamic Elementary Teacher Education	1	0.96
	Communication Science	1	0.96
	Sociology	1	0.96
	Indonesian Language	1	0.96
	Entrepreneurship	1	0.96
	Accounting	1	0.96
	Business Administration	1	0.96
	Nutrition	1	0.96
	Unidentified	1	0.96

Characteristic	Category	Respondents (n)	Percentage (%)
Semester	Semesters 1–2	9	8.65
	Semesters 3–4	14	13.46
	Semesters 5–6	45	43.27
	Semesters 7–8	28	26.92
	Above Semester 8	8	7.69
Characteristic	Category	Respondents (n)	Percentage (%)
Most Frequently Used GenAI Service	ChatGPT	65	62.50
	Google Gemini	16	15.38
	Claude	16	15.38
	Perplexity	3	2.88
	Others	4	3.85
Characteristic	Category	Respondents (n)	Percentage (%)
Frequency of GenAI Use	Less than once per week	7	6.73
	1–2 times per week	21	20.19
	3–5 times per week	39	37.50
	6–10 times per week	17	16.35
	More than 10 times per week	20	19.23

Source: Research data processing results.

Note: The Unidentified category refers to one respondent who entered “undergraduate” as their academic program. Percentages were calculated based on a total of 104 respondents and rounded to two decimal places.

As presented in Table 1, the participants represented a diverse range of academic disciplines, with Informatics Engineering accounting for the largest proportion of respondents at 32 students (30.77%). This was followed by Public Administration Science, comprising 9 students (8.65%), and Law, with 6 students (5.77%). The distribution across different academic programs indicates that GenAI adoption within the study sample was not confined to students specializing in information technology.

Regarding academic progression, students in semesters 5–6 constituted the largest group, totaling 45 respondents (43.27%), followed by those in semesters 7–8, with 28 respondents (26.92%). In terms of preferred GenAI platforms, ChatGPT was the most frequently used service, reported by 65 participants (62.50%). Furthermore, the most common usage frequency was 3–5 times per week, representing 39 respondents (37.50%).

These respondent characteristics illustrate the diversity of GenAI utilization in academic activities. Nevertheless, frequent use of GenAI should not automatically be interpreted as evidence of dependence. Accordingly, a more detailed examination of behavioral indicators is necessary to identify distinct patterns of GenAI dependence among different student groups.

Data Preprocessing Results

The questionnaire data were subjected to a preprocessing procedure to ensure their readiness for K-Means clustering analysis. This process included verifying respondents' eligibility, examining the completeness of submitted questionnaires, converting response values into numerical form, and adjusting the scoring orientation of selected indicators. These procedures were carried out to produce a consistent dataset suitable for identifying similarities in students' generative artificial intelligence (GenAI) usage behaviors.

Of the 106 questionnaire responses initially collected, two were excluded because the participants reported that they did not use GenAI to support their academic activities. The remaining 104 responses met the study's inclusion criteria and contained complete answers to all 15 questionnaire indicators. No missing values were identified in the variables included in the clustering analysis. Therefore, 104 valid responses were retained for subsequent data analysis.

The questionnaire responses were transformed into numerical values using a five-point Likert scale, consisting of 1 (Strongly Disagree), 2 (Disagree), 3 (Neutral), 4 (Agree), and 5 (Strongly Agree). Reverse scoring was applied to indicators P7, P8, and P9 because these items assessed students' ability to complete academic tasks independently, their efforts to explore solutions before relying on AI, and their capacity to understand information obtained through AI assistance. Since these indicators were formulated in the opposite direction to the remaining dependence-related statements, their scores were adjusted using the reverse-scoring procedure presented in Equation (1).

In Equation (1), X represents the original response score, whereas X' denotes the transformed score after reverse coding. Following this adjustment, higher values for P7, P8, and P9 indicated lower levels of independent task completion, problem-solving initiative, or comprehension of AI-generated information. Furthermore, one respondent entered “undergraduate” instead of identifying a specific academic program. This response was categorized as Unidentified but remained in the dataset because the participant fulfilled the research criteria and provided complete responses to all clustering indicators.

Upon completion of the preprocessing procedures, the final dataset comprised a 104×15 numerical matrix, representing 104 respondents and 15 behavioral indicators related to GenAI utilization. All indicators were measured on a uniform scale ranging from 1 to 5 and were incorporated into the K-Means clustering analysis without additional standardization. The processed dataset was subsequently used to evaluate potential cluster configurations and classify respondents according to similarities in their GenAI usage patterns.

Determination of the Number of Clusters

The appropriate number of clusters was determined by evaluating alternative grouping configurations against the characteristics of the research dataset. This evaluation combined the Elbow Method and Silhouette Score across cluster configurations ranging from $k = 2$ to $k = 7$. The K-Means algorithm was implemented using Euclidean distance, a random state of 42, and 30 initializations ($n_init = 30$). Both evaluation methods were considered to establish a more systematic basis for selecting the cluster configuration used in the subsequent analysis.

The Elbow Method was employed to examine changes in the Within-Cluster Sum of Squares (WCSS) across different cluster configurations. WCSS represents the sum of squared distances between individual observations and their corresponding cluster centroids. The evaluation results indicated that WCSS decreased from 1,151.60 at $k = 2$ to 899.50 at $k = 3$, reflecting an improvement in within-cluster compactness as the number of clusters increased. The results of the Elbow Method evaluation are illustrated in Figure 2.

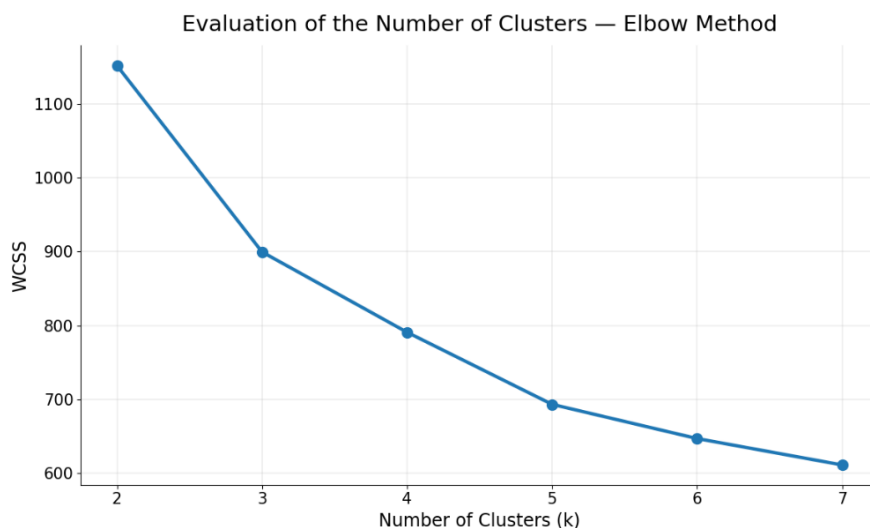


Figure 2. Evaluation of the Number of Clusters Using the Elbow Method

As illustrated in Figure 2, WCSS values declined consistently as additional clusters were introduced. A comparatively substantial reduction was observed up to $k = 3$, whereas subsequent decreases became more gradual. This pattern suggested that a three-cluster configuration could represent a suitable candidate for grouping the respondents. Nevertheless, because identifying an elbow point involves heuristic judgment, an additional assessment using the Silhouette Score was conducted. This complementary evaluation allowed the selection process to consider not only within-cluster compactness but also the relative separation between clusters.

The Silhouette Score was calculated to assess how closely each observation corresponded to its assigned cluster relative to neighboring clusters. Higher silhouette values generally indicate better-defined group separation. This measure also enabled a comparative assessment of clustering quality across the evaluated values of k . The WCSS and Silhouette Score results for each configuration are summarized in Table 2.

Table 2. Evaluation Results for Different Numbers of Clusters

Number of Clusters (k)	WCSS	Silhouette Score
2	1,151.60	0.2156
3	899.50	0.2443
4	790.86	0.1947
5	693.33	0.2164
6	647.05	0.1882
7	611.35	0.1877

Source: Research data processing results.

As shown in Table 2, the highest Silhouette Score was obtained at $k = 3$, reaching 0.2443. This value exceeded those recorded for all other cluster configurations within the evaluated range. Accordingly, the three-cluster solution demonstrated the most favorable relative separation among the alternatives examined. A visual comparison of Silhouette Scores across the tested configurations is presented in Figure 3.

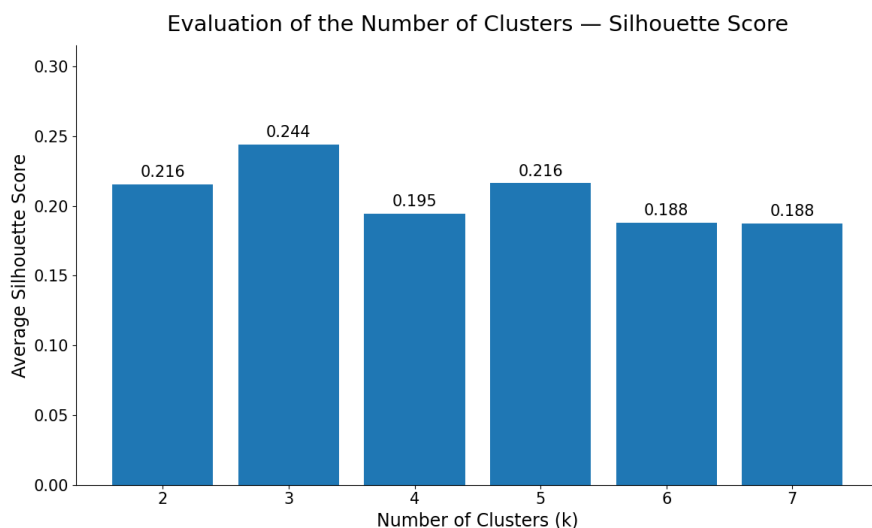


Figure 3. Comparison of Silhouette Scores Across Different Numbers of Clusters

Figure 3 further illustrates that the three-cluster configuration achieved the highest Silhouette Score of 0.2443. Considering the combined evidence from the Elbow Method and Silhouette Score evaluation, three clusters were selected for the subsequent analysis. However, the relatively low silhouette value indicates that the resulting clusters were not strongly separated. Therefore, the clustering outcomes were interpreted as exploratory representations of variations in students' GenAI usage patterns rather than definitive classifications with clearly established boundaries.

K-Means Clustering Results

Following the selection of three clusters as the most appropriate configuration, the K-Means algorithm was applied to classify 104 respondents based on 15 behavioral indicators of generative artificial intelligence (GenAI) use. The clustering procedure assigned respondents to groups according to similarities in their questionnaire response patterns, allowing individuals with relatively comparable characteristics to be represented within the same cluster. The resulting classification revealed differences in the number of respondents assigned to each group, as summarized in Table 3.

Table 3. Distribution of Respondents Based on K-Means Clustering Results

Cluster	Number of Respondents (n)	Percentage (%)
Cluster 0	30	28.85
Cluster 1	11	10.58
Cluster 2	63	60.58
Total	104	100.00

Source: Research data processing results.

Note: The 0.01% difference between the sum of the individual cluster percentages and 100% results from rounding the percentages to two decimal places.

As presented in Table 3, Cluster 2 accounted for the largest proportion of respondents, comprising 63 students (60.58%). This was followed by Cluster 0, which included 30 respondents (28.85%), while Cluster 1 represented the smallest group, consisting of 11 respondents (10.58%). These findings indicate that most participants were assigned to Cluster 2, whereas relatively few respondents exhibited the response patterns associated with Cluster 1. The unequal distribution of cluster membership reflects variations in GenAI usage patterns within the study sample.

Although the clusters differed in membership size, the number of respondents within a group does not independently indicate their level of dependence on GenAI. A more detailed examination of cluster centroids across the 15 behavioral indicators is therefore required to establish the distinguishing characteristics of each group. This analysis provides the basis for identifying differences in GenAI usage tendencies and assessing potential dependence-related risks among the resulting clusters.

Analysis of Cluster Characteristics and Dependence Risks

The characteristics of each cluster were examined using the centroid values generated by the K-Means clustering algorithm. Each centroid represents the average score of a particular behavioral indicator within a cluster. Comparing these values provides a basis for identifying differences in students' generative artificial intelligence (GenAI) usage patterns, their reliance on AI assistance when completing academic assignments, and their ability to engage in independent learning. The centroid values obtained for all 15 research indicators are presented in Table 4.

Table 4. Cluster Centroid Values Across the 15 Research Indicators

Indicator	Cluster 0	Cluster 1	Cluster 2
P1	4.13	1.82	3.33
P2	4.37	1.73	3.73
P3	4.03	1.55	3.38
P4	3.87	2.00	2.57
P5	3.40	1.82	2.51
P6	3.97	2.09	2.98
P7*	2.37	4.36	2.43
P8*	2.37	4.18	2.25
P9*	2.17	4.36	2.14
P10	2.93	1.18	2.08
P11	3.23	1.64	2.16
P12	3.00	1.45	2.16
P13	4.13	1.55	2.79
P14	4.13	1.64	2.94
P15	4.20	1.64	2.62

Source: Research data processing results.

Note: Indicators P7, P8, and P9 were reverse-scored according to the procedure described in Equation (1). Higher values on these indicators correspond to lower original scores for statements concerning students' academic independence and comprehension.

As indicated in Table 4, the three clusters exhibited distinct scoring patterns across several behavioral indicators. Cluster 0 recorded relatively high centroid values for most GenAI usage indicators, particularly P1, P2, P3, P13, P14, and P15. In contrast, Cluster 1 demonstrated lower scores on most indicators associated with GenAI use but substantially

higher values for P7, P8, and P9 following reverse scoring. This pattern suggests that limited GenAI use does not necessarily correspond to greater academic independence or comprehension. Meanwhile, Cluster 2 generally displayed intermediate centroid values across most GenAI usage indicators.

These variations indicate that dependence-related risks cannot be adequately interpreted through a single behavioral indicator or an overall average score alone. A more comprehensive assessment should consider the relationship between GenAI usage intensity, students' reliance on AI-generated assistance, and their ability to understand academic material and complete assignments independently. Accordingly, the characteristics of each cluster were examined in greater detail to develop a more comprehensive understanding of potential GenAI dependence risks among the respondents.

To illustrate the differences between clusters more clearly, the centroid values were visualized using a line graph covering all 15 research indicators. This visualization enables a more detailed comparison of score variations across the respondent groups and highlights indicators that exhibit particularly noticeable differences. By examining these patterns, the distinguishing characteristics of GenAI utilization within each cluster can be interpreted more systematically. The centroid comparison is presented in Figure 4.

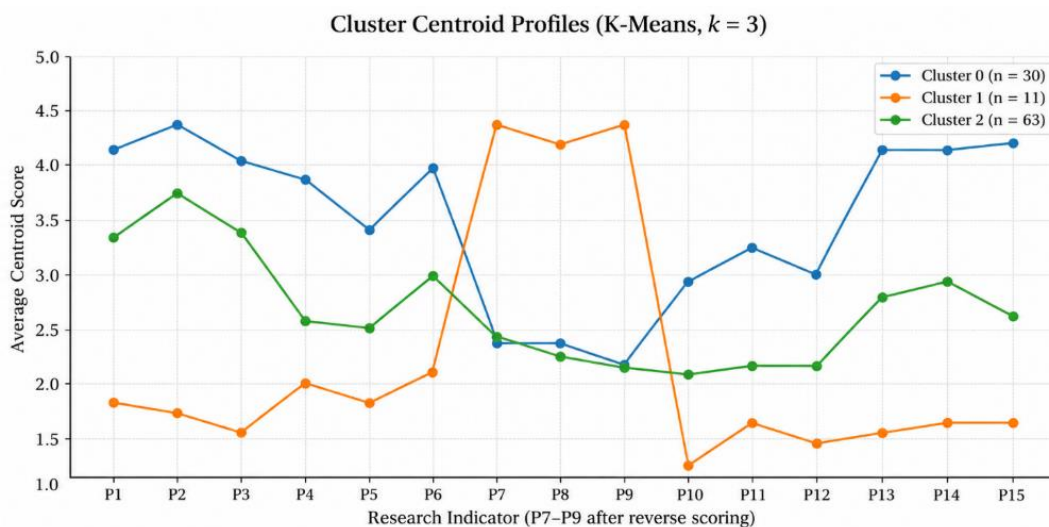


Figure 4. Comparison of Cluster Centroid Values Across the 15 Research Indicators

As illustrated in Figure 4, each cluster displayed a distinct centroid profile across the 15 behavioral indicators. Cluster 0 generally exhibited higher scores on indicators associated with GenAI use, whereas Cluster 2 demonstrated a comparatively moderate usage pattern. Cluster 1, meanwhile, recorded lower scores for most GenAI usage indicators but showed pronounced increases in P7, P8, and P9 after reverse scoring. These differences suggest that the clusters are distinguished not only by their levels of GenAI engagement but also by characteristics related to students' academic independence and comprehension. Consequently, dependence-related risks should be interpreted by considering the complete indicator profile rather than relying on simplified comparisons of usage intensity.

Cluster 0 comprised 30 respondents (28.85%) and demonstrated a relatively high tendency toward GenAI utilization. This pattern was reflected in centroid values of 4.13 for P1, 4.37 for P2, and 4.03 for P3, alongside scores of 4.13, 4.13, and 4.20 for P13, P14, and P15, respectively. The consistently elevated scores across these indicators suggest that GenAI plays a substantial role in the academic activities of this group. Therefore, Cluster 0 may be interpreted as exhibiting relatively stronger indications of behavioral dependence risk. However, this interpretation should not be regarded as a clinical or psychological diagnosis of dependence.

Cluster 1 consisted of 11 respondents (10.58%) and was characterized by relatively low centroid values across most GenAI usage indicators. Nevertheless, this group recorded notably high reverse-scored values for P7 (4.36), P8 (4.18), and P9 (4.36). These findings indicate that lower levels of GenAI utilization do not necessarily imply stronger academic independence or comprehension. Consequently, Cluster 1 is more appropriately characterized as a group with relatively limited GenAI use but potential weaknesses in independent learning and understanding. It would therefore be inappropriate to automatically classify this group as having the lowest dependence-related risk.

Cluster 2 represented the largest group, comprising 63 respondents (60.58%). Its centroid values generally occupied an intermediate position across most GenAI usage indicators, including P1 (3.33), P2 (3.73), and P3 (3.38).

Meanwhile, the reverse-scored values for P7, P8, and P9 were 2.43, 2.25, and 2.14, respectively. This profile indicates that respondents in Cluster 2 incorporated GenAI into their academic activities without demonstrating the same degree of usage intensity observed in Cluster 0. Accordingly, Cluster 2 can be described as exhibiting a relatively moderate GenAI usage pattern, without assuming that all members share an identical level of dependence-related risk.

Overall, the clustering results revealed three distinct patterns of GenAI utilization among the study participants. These differences suggest that potential dependence-related risks are not determined solely by the intensity of AI use but must also be considered alongside students' academic independence and comprehension. The findings therefore highlight the importance of examining multiple behavioral indicators simultaneously when mapping potential dependence risks associated with GenAI use.

DISCUSSION

The findings of this study demonstrate considerable variation in university students' generative artificial intelligence (GenAI) usage patterns, as revealed through K-Means clustering. Differences in centroid values across the three identified clusters reflect variations in students' engagement with AI technologies, their reliance on AI-generated assistance when completing academic assignments, and their capacity for independent learning. These results indicate that the educational implications of GenAI use cannot be adequately assessed through usage frequency alone. Instead, understanding how students incorporate AI assistance into their learning processes is equally important. This interpretation is consistent with (Deng, Jiang, Yu, Lu, & Liu, 2025), who demonstrated that the educational effects of ChatGPT extend across multiple learning dimensions rather than being determined solely by the presence or frequency of technology use.

Cluster 0 exhibited relatively high centroid scores across several GenAI usage indicators, suggesting more intensive engagement with AI technologies than the other groups. This pattern deserves attention because extensive reliance on AI-generated assistance may reduce opportunities for students to develop independent approaches to academic problem-solving. Nevertheless, intensive GenAI use should not automatically be interpreted as evidence of dependence. When incorporated into appropriately structured learning activities, AI technologies may also support academic achievement and higher-order thinking. (S. Chen & Cheung, 2025) similarly found that the effects of GenAI on university students' learning outcomes vary according to instructional conditions, learner characteristics, and the ways in which these technologies are integrated into educational activities.

The characteristics of Cluster 1 indicate that limited GenAI utilization does not necessarily correspond to greater academic independence. Following reverse scoring, indicators P7, P8, and P9 revealed potential difficulties related to independent task completion and comprehension. This finding emphasizes the need to distinguish dependence on GenAI from broader challenges associated with self-directed learning. Students who rarely employ AI tools may nevertheless experience difficulties understanding academic materials or completing assignments without assistance. Consequently, the interpretation of dependence-related risks should account for the specific behavioral dimensions represented by each indicator rather than assuming that lower technology use necessarily reflects stronger learning autonomy.

Cluster 2 demonstrated a comparatively moderate pattern of GenAI utilization, indicating that its members incorporated AI assistance into academic activities without exhibiting the same intensity of use observed in Cluster 0. However, this intermediate profile does not necessarily establish that GenAI was being employed effectively or responsibly. Evaluating its educational implications requires further consideration of students' purposes for using AI, their ability to assess generated information, and their continued participation in independent academic work. Research by (Tzirides et al., 2024) highlights the importance of integrating human judgment with AI-supported learning activities to strengthen students' AI literacy and promote more meaningful engagement with these technologies.

Collectively, the three identified patterns suggest that assessing potential GenAI dependence risks requires a multidimensional understanding of students' academic behaviors. Although the clustering results provide an initial representation of differences among respondents, they should not be interpreted as definitive evidence of particular dependence levels. This consideration is especially important because the obtained Silhouette Score of 0.2443 indicates relatively weak separation between clusters. Accordingly, the identified groups are more appropriately understood as exploratory behavioral profiles rather than clearly differentiated categories of dependence.

The findings provide preliminary insights into variations in students' academic use of GenAI and may inform the development of AI literacy initiatives in higher education institutions. Cluster-based behavioral profiles could assist universities in designing educational programs that emphasize critical engagement with AI technologies and responsible evaluation of AI-generated content. Such initiatives should encourage students to benefit from GenAI assistance while continuing to strengthen their independent reasoning, information evaluation, and understanding of academic material. (Saputra, Asirah, & Syafitri, 2025) similarly reported that university students perceived ChatGPT as potentially beneficial for academic activities and critical thinking, while also expressing concerns about excessive reliance on AI assistance.

From a practical perspective, the clustering outcomes may provide an exploratory foundation for identifying differences in students' academic support needs. Students demonstrating intensive GenAI utilization may benefit from guidance on critically examining AI-generated outputs and maintaining independent approaches to academic assignments. Conversely, students with relatively low GenAI usage but weaker indicators of academic independence or comprehension may require support addressing learning difficulties that are not necessarily associated with technology. Therefore, educational interventions should be adapted to students' broader learning characteristics rather than determined exclusively by their frequency of AI use. This approach is supported by (Song et al., 2025), whose findings emphasize the potential value of guided and supervised GenAI integration for developing students' higher-order thinking skills and AI literacy.

Several limitations should be considered when interpreting these findings. First, the study analyzed 104 university students recruited through a nonprobability sampling approach, which limits the generalizability of the results to the broader student population. Second, the data were obtained through self-reported questionnaires, potentially introducing subjective perceptions and response biases. Furthermore, the research instrument had not undergone comprehensive construct validity testing. Consequently, the resulting clusters should primarily be interpreted as patterns of questionnaire responses rather than validated measurements of psychological or behavioral dependence.

An additional limitation concerns the relatively weak separation between the identified groups, as reflected by the Silhouette Score of 0.2443. This result indicates that respondents assigned to different clusters may still exhibit substantial similarities in their behavioral characteristics. Future investigations should therefore involve larger and more diverse samples, employ thoroughly validated measurement instruments, and compare K-Means clustering with alternative clustering techniques. Further evaluation is also necessary to determine whether the identified behavioral profiles remain consistent across different student populations and research contexts.

CONCLUSION

This study explored patterns of generative artificial intelligence (GenAI) use among university students using the K-Means clustering algorithm. The analysis focused on 15 indicators related to AI utilization, its role in academic activities, and students' ability to learn independently. A total of 106 students participated in the questionnaire, of whom 104 met the criteria for further analysis. To identify the most appropriate clustering configuration, several cluster solutions were evaluated using the Silhouette Score. The results showed that the three-cluster solution achieved the highest score of 0.2443 among the configurations tested, making it the most suitable option for representing the patterns found in the dataset.

The analysis identified three groups with different patterns of GenAI use. Cluster 0 comprised 30 students (28.85%) who showed relatively high levels of GenAI utilization, suggesting a greater potential risk of behavioral dependence than the other groups. Cluster 1 included 11 students (10.58%) who reported lower levels of GenAI use but exhibited scores indicating possible difficulties with academic independence and comprehension. Cluster 2, which accounted for the largest proportion of respondents, consisted of 63 students (60.58%) and demonstrated a moderate pattern of GenAI use. These differences suggest that the intensity of AI utilization alone does not provide a complete picture of students' potential dependence risks. Other aspects of their learning behavior, particularly academic independence and understanding, also need to be considered.

Overall, the findings suggest that K-Means clustering can be a useful exploratory method for identifying variations in how students use GenAI in their academic activities. However, the relatively low Silhouette Score indicates that the differences between the three clusters were not clearly defined. For this reason, the results should be interpreted as an initial overview of students' GenAI usage patterns rather than a definitive assessment of their dependence levels. Future studies are encouraged to include larger and more diverse samples, use validated measurement instruments, and examine alternative clustering methods to obtain more reliable results.

ACKNOWLEDGMENT

The authors sincerely appreciate the students who participated in this study and provided valuable information through the research questionnaire. Their contributions played an important role in supporting the analysis of generative artificial intelligence usage patterns among university students. The authors are grateful for their time and willingness to contribute to this research.

REFERENCES

- an, Q., Koh, J. H. L., & Liu, Q. (2026). Generative artificial intelligence in higher education: A systematic review of student use and learning outcomes. *Australasian Journal of Educational Technology*, 42(3), 62–82. <https://doi.org/10.14742/AJET.10561>
- Aybek, E. C., & Toraman, C. (2022). How many response categories are sufficient for Likert type scales? An empirical study based on the Item Response Theory. *International Journal of Assessment Tools in Education*, 9(2), 534–547.

- <https://doi.org/10.21449/IJATE.1132931>
- Baig, M. I., & Yadegaridehkordi, E. (2024). ChatGPT in the higher education: A systematic literature review and research challenges. *International Journal of Educational Research*, 127, 102411. <https://doi.org/10.1016/J.IJER.2024.102411>
- Benites-Rodriguez, J. ;, Salazar-Sandoval, F. ;, Amaro-Guzman, C. ;, Grados-Espinoza, A. ;, Torres-Quiroz, A. ;, Narciso-Gomez, K. ;, ... -Xiomara². (2026, July 15). *Classification of Student Profiles Based on Generative AI Dependency and Complex Problem-Solving Capacity: A Machine Learning Approach Using K-Means Clustering*. <https://doi.org/10.18687/LACCEI2026.1.1.2413>
- Chen, K., Tallant, A. C., & Selig, I. (2025). Exploring generative AI literacy in higher education: student adoption, interaction, evaluation and ethical perceptions. *Information and Learning Sciences*, 126(1–2), 132–148. <https://doi.org/10.1108/ILS-10-2023-0160>
- Chen, S., & Cheung, A. C. K. (2025). Effect of generative artificial intelligence on university students learning outcomes: A systematic review and meta-analysis. *Educational Research Review*, 49, 100737. <https://doi.org/10.1016/J.EDUREV.2025.100737>
- Daniel, K., Msambwa, M. M., & Wen, Z. (2025). Can Generative AI Revolutionise Academic Skills Development in Higher Education? A Systematic Literature Review. *European Journal of Education*, 60(1), e70036. <https://doi.org/10.1111/EJED.70036>;JOURNAL:JOURNAL:14653435;WGROU:STRING:PUBLICATION
- Deng, R., Jiang, M., Yu, X., Lu, Y., & Liu, S. (2025). Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. *Computers & Education*, 227, 105224. <https://doi.org/10.1016/J.COMPEDU.2024.105224>
- Hou, C., Zhu, G., & Sudarshan, V. (2025). The role of critical thinking on undergraduates' reliance behaviours on generative AI in problem-solving. *British Journal of Educational Technology*, 56(5), 1919–1941. <https://doi.org/10.1111/BJET.13613>;PAGE:STRING:ARTICLE/CHAPTER
- Ikotun, A. M., Ezugwu, A. E., Abualigah, L., Abuhaija, B., & Heming, J. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Information Sciences*, 622, 178–210. <https://doi.org/10.1016/J.INS.2022.11.139>
- İlhan, M., Güler, N., Teker, G. T., & Ergenekon, Ö. (2024). The effects of reverse items on psychometric properties and respondents' scale scores according to different item reversal strategies. *International Journal of Assessment Tools in Education*, 11(1), 20–38. <https://doi.org/10.21449/IJATE.1345549>
- Juanita, S., & Cahyono, R. D. (2024). K-MEANS CLUSTERING WITH COMPARISON OF ELBOW AND SILHOUETTE METHODS FOR MEDICINES CLUSTERING BASED ON USER REVIEWS. *Jurnal Teknik Informatika (Jutif)*, 5(1), 283–289. <https://doi.org/10.52436/1.JUTIF.2024.5.1.1349>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. <https://doi.org/10.1016/J.LINDIF.2023.102274>
- Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *Npj Science of Learning* 2025 10:1, 10(1), 21-. <https://doi.org/10.1038/s41539-025-00319-0>
- Lee, H. P. (Hank), Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025). The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers. *Conference on Human Factors in Computing Systems - Proceedings*. <https://doi.org/10.1145/3706598.3713778>;ISSUE:ISSUE:DOI
- Lo, C. K. (2023). What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature. *Education Sciences* 2023, Vol. 13, Page 410, 13(4), 410. <https://doi.org/10.3390/EDUCSCI13040410>
- Medina-Gual, L., & Parejo, J. L. (2025). University Students' Engagement with Artificial Intelligence: A Cluster Analysis of Learner Profiles in AI Literacy. *Technology, Knowledge and Learning* 2025 31:1, 31(1), 291–309. <https://doi.org/10.1007/S10758-025-09926-7>
- Polat, E. (2025). Artificial intelligence literacy, lifelong learning, and fear of innovation: Identification of profiles and relationships. *Education and Information Technologies* 2025 30:14, 30(14), 20183–20214. <https://doi.org/10.1007/S10639-025-13548-Y>
- Saputra, N., Asirah, A., & Syafitri, S. E. (2025). Integrating ChatGPT in Higher Education: Insights into Student Usage, Critical Thinking, and Independent Learning. *International Journal of Education, Language, and Religion*, 7(1), 91–102. <https://doi.org/10.35308/IJELR.V7I1.11928>
- Sardi, J., Darmansyah, Candra, O., Yuliana, D. F., Habibullah, Yanto, D. T. P., & Eliza, F. (2025). How Generative AI Influences Students' Self-Regulated Learning and Critical Thinking Skills? A Systematic Review. *International Journal of Engineering Pedagogy (IJEP)*, 15(1), 94–108. <https://doi.org/10.3991/IJEP.V15I1.53379>
- Schubert, E. (2023). Stop using the elbow criterion for k-means and how to choose the number of clusters instead. *ACM*

SIGKDD Explorations Newsletter, 25(1), 36–42.
<https://doi.org/10.1145/3606274.3606278>;SUBPAGE:STRING: BASIC

- Song, D., Zhang, P., Zhu, Y., Qi, S., Yang, Y., Gong, L., & Zhou, L. (2025). Effects of generative artificial intelligence on higher-order thinking skills and artificial intelligence literacy in nursing undergraduates: A quasi-experimental study. *Nurse Education in Practice*, 88, 104549. <https://doi.org/10.1016/J.NEPR.2025.104549>
- Tian, J., & Zhang, R. (2025). Learners' AI dependence and critical thinking: The psychological mechanism of fatigue and the social buffering role of AI literacy. *Acta Psychologica*, 260, 105725. <https://doi.org/10.1016/J.ACTPSY.2025.105725>
- Tzirides, A. O. (Olnancy), Zapata, G., Kastania, N. P., Saini, A. K., Castro, V., Ismael, S. A., ... Kalantzis, M. (2024). Combining human and artificial intelligence for enhanced AI literacy in higher education. *Computers and Education Open*, 6, 100184. <https://doi.org/10.1016/J.CAEO.2024.100184>
- Wang, F., Li, N., Cheung, A. C. K., & Wong, G. K. W. (2025). In GenAI we trust: An investigation of university students' reliance on and resistance to generative AI in language learning. *International Journal of Educational Technology in Higher Education* 2025 22:1, 22(1), 59-. <https://doi.org/10.1186/S41239-025-00547-9>
- Yusuf, A., Pervin, N., Román-González, M., & Noor, N. M. (2024). Generative AI in education and research: A systematic mapping review. *Review of Education*, 12(2), e3489. <https://doi.org/10.1002/REV3.3489>;REQUESTEDJOURNAL:JOURNAL:20496613;WEBSITE:WEBSITE:BER A-JOURNALS;WGROU:STRING:PUBLICATION
- Zeng, B., Jeon, M., & Wen, H. (2024). How does item wording affect participants' responses in Likert scale? Evidence from IRT analysis. *Frontiers in Psychology*, 15, 1304870. <https://doi.org/10.3389/FPSYG.2024.1304870>/TEXT