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Clustering generative AI usage among university students based on productivity, verification, and integrity

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ABSTRACT

Purpose: to identify and classify university students' generative AI usage patterns based on three dimensions: academic productivity, information verification, and academic integrity.
Method: this study employed a quantitative cross-sectional survey involving 200 university students. Data were collected using a Likert-scale questionnaire measuring academic productivity, information verification, and academic integrity, and analyzed using K-Means clustering with the Elbow Method, Silhouette Score, and Davies–Bouldin Index.
Findings: identified three distinct generative AI usage profiles among university students: limited-ethical users (15.0%), high-risk pragmatic users (40.0%), and productive-critical-ethical users (45.0%). The findings indicate that the largest group successfully combined high academic productivity, strong information verification, and high academic integrity, while a substantial proportion of students demonstrated high AI utilization with insufficient verification and ethical awareness.
Implications: for higher education institutions to develop targeted AI literacy programs, verification skills training, and responsible AI use policies based on student behavioral profiles.
Originality: lies in the development of a behavioral classification model in the use of generative AI that integrates the dimensions of academic productivity, information verification, and academic integrity through a clustering approach.

Introduction

The development of generative artificial intelligence (generative AI), particularly through the emergence of ChatGPT and various large language models (LLMs), has transformed the learning landscape in higher education (Ali et al., 2024; Alqahtani et al., 2023). This technology enables students to obtain instant conceptual explanations, generate ideas, develop writing outlines, summarize information, and even help complete various academic assignments more efficiently (Alawida et al., 2023; Dwivedi et al., 2023; Kasneci et al., 2023). In the context of higher education, generative AI is no longer viewed as an experimental technology but has become part of students' daily learning practices. Numerous studies have shown that students view ChatGPT as a useful tool for improving comprehension of course material, supporting complex thinking, accelerating assignment completion, and increasing academic productivity (Chan & Lee, 2023; Ding et al., 2023; Jo, 2024; Mahapatra, 2024; Ravšelj et al., 2025; Rodríguez et al., 2023).

However, the increasing adoption of Generative AI has also raised new issues in higher education. The ease of obtaining instant answers has the potential to encourage student dependence on AI, thereby reducing critical and reflective thinking. Furthermore, the quality of AI output cannot always be guaranteed, as inaccurate, biased information, and even hallucinated scientific references are still found (Day, 2023). Furthermore, the use of AI in completing academic assignments has also raised concerns about the boundary between legitimate learning assistance and violations of academic integrity, including the phenomenon of AI-giarism, the use of AI that exceeds academic ethics without adequate disclosure (Chan, 2025; Cotton et al., 2024; Eke, 2023; Nashwan et al., 2023). These conditions indicate that the use of Generative AI is not only related to the intensity of technology use, but also concerns how students use it responsibly.

The literature on generative AI in higher education shows that existing research tends to develop in several separate directions. The first group of studies focuses on technology acceptance, including perceived usefulness, trust, intention to use, and factors influencing ChatGPT adoption (Amin et al., 2025; Rodríguez et al., 2023; Shahzad et al., 2024; Strzelecki, 2024; Tiwari et al., 2024). This perspective is largely based on technology acceptance theory, which explains that perceived usefulness and ease of use are key determinants of technology adoption. The second group of studies focuses more on academic integrity, including student perceptions of AI-based plagiarism, misuse of chatbots in assessments, and the ethical implications of AI use in higher education (Chan, 2025; Chiang et al., 2022; Cotton et al., 2024; Crawford et al., 2023; Damiano et al., 2024; Fajt & Schiller, 2025; Lund et al., 2025; Ofem et al., 2025). Meanwhile, a third group of studies has begun to highlight the importance of verifying information and using AI responsibly as part of AI literacy, as students need to re-evaluate the accuracy of AI-generated information before using it in academic activities (AlBlooshi, 2026; Enriquez et al., 2024).

These findings demonstrate that students' generative AI usage behavior is multidimensional. Two students may use ChatGPT equally frequently but exhibit very different behavioral characteristics. Some students utilize AI as a cognitive aid to explore ideas, then independently verify information sources and reconstruct the results. Conversely, others tend to accept AI output directly without double-checking or considering the boundaries of academic integrity (Chan, 2025; Enriquez et al., 2024; Lund et al., 2025). In fact, research by Gruenhagen et al. (2024) shows that students do not always perceive the use of chatbots to assist with assessment completion as a violation of academic integrity. This indicates that the frequency of AI use alone is insufficient to explain the quality of students' usage behavior.

Furthermore, information verification is becoming increasingly important, as various studies have shown that Generative AI output can still contain factual errors, information bias, and unpublished scientific references (Day, 2023). Furthermore, various AI-generated text detection tools lack sufficient accuracy to serve as the sole basis for determining academic misconduct (Wulff et al., 2023). Therefore, policy approaches that rely solely on prohibitions on AI use or automatic detection are unable to accommodate the diversity of student behaviors in utilizing this technology (Day, 2023; Lund et al., 2025; Wulff et al., 2023). Conversely, higher education requires a more comprehensive understanding of student behavior patterns so that policy interventions can be tailored to the characteristics of each user group.

Based on the literature review, a research gap has received little attention. Most previous studies have examined academic productivity, information verification behavior, and academic integrity separately. Research that integrates these three dimensions into a single approach to classifying student behavior remains very limited. Therefore, there is no empirical description of the types of generative AI usage behavior based on the combination of academic productivity, information verification tendencies, and adherence to academic integrity principles. However, such a classification can yield more meaningful information than simply measuring the level of technology acceptance or the frequency of AI use. Therefore, this study offers novelty by applying a cluster analysis approach to identify student behavioral profiles in the use of generative AI across three main dimensions: academic productivity, information verification behavior, and academic integrity. Unlike previous studies, which primarily explain factors influencing AI adoption or students' perceptions of AI, this study seeks to map the heterogeneity of user behavior, yielding a more comprehensive typology of generative AI use in the context of higher education.

Conceptually, this research is based on the technology acceptance theory perspective, which explains that perceived benefits drive technology use (Rodríguez et al., 2023; Shahzad et al., 2024), combined with the concept of responsible AI Use which emphasizes the importance of AI literacy, the ability to verify information, and the responsible use of AI (AlBlooshi, 2026; Chan, 2023; Enriquez et al., 2024). In addition, this research refers to the theory of academic integrity, which positions academic honesty as the primary foundation for the use of digital technology in higher education environments (Cotton et al., 2024; Eke, 2023; Lund et al., 2025; Xu et al., 2024). This study aims to identify and classify patterns of generative AI use by students through cluster analysis based on the dimensions of academic productivity, information verification behavior, and academic integrity. Specifically, this study aims to identify the behavioral profile of students' use of generative AI, determine the optimal number of clusters, and interpret the characteristics of each cluster as a basis for developing AI literacy strategies in higher education.

This research has both theoretical and practical significance. From a theoretical perspective, this study broadens understanding of generative AI usage behavior by integrating three dimensions that have largely been studied separately. This approach is expected to produce a more representative classification model of student behavior in explaining the complexity of AI use in academic environments. From a practical perspective, the research results are expected to serve as a basis for universities in designing more adaptive AI use policies, including the development of AI literacy programs, information verification literacy, the development of guidelines for the use of AI in academic assignments, the implementation of AI use statements, and the strengthening of a culture of academic integrity according to the characteristics of each student group (Chan, 2023; Enriquez et al., 2024; Lund et al., 2025). This research is expected to contribute to the development of studies on the use of generative AI in higher education by providing empirical evidence regarding the typology of student behavior. The resulting classification will not only enrich the literature on AI usage behavior in academic contexts but also provide a stronger foundation for institutional policy-making oriented towards the productive, critical, responsible, and integrity-based use of generative AI.

Method

This study uses a quantitative cross-sectional survey design to identify patterns of generative AI use among university students using cluster analysis. This design was chosen because it enables data collection over a specific time period to describe the behavioral characteristics of generative AI use as they occurred during the study. The unit of analysis in this study is active university students who have experience using generative AI applications in academic activities, such as completing assignments, searching for information, developing ideas, or assisting in the learning process. The study population included active students from various study programs in the Science and Technology (Saintek) and Social and Humanities (Soshum) groups. The sampling technique used was purposive sampling, namely selecting respondents based on criteria relevant to the research objectives. The inclusion criteria used included: (1) being an active student, (2) having used at least one Generative AI application for academic purposes, and (3) being willing to complete the questionnaire in full. Data collection was carried out in the even semester of the 2025/2026 academic year with a total of 200 students from the second to eighth semesters as respondents. The Generative AI applications most frequently used by respondents included ChatGPT, Microsoft Copilot, and Claude, so these three applications represent the context of AI use in this study.

The research instrument was a closed-ended questionnaire designed using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The formulation of the questions centers on three main constructs that underlie the classification of generative AI usage behavior: academic productivity, information verification behavior, and academic integrity, as presented in Table 1. The selection of these three constructs was based on various previous studies showing that the use of generative AI in higher education is not only influenced by perceived benefits or intensity of use, but is also closely related to the ability to verify information, responsible use of AI, and students' understanding of the limits of academic integrity (Chan, 2025; Enriquez et al., 2024; Gruenhagen et al., 2024; Lund et al., 2025).

Table 1 research variables operationalization

Variables	Indicators	Items code
Academic productivity	AI helps in understanding difficult material	AP1
	AI helps in drafting initial assignment ideas	AP2
	AI helps in creating outlines for writing or reports	AP3
	AI helps in completing assignments more efficiently	AP4
	AI helps in improving language and writing structure	AP5
Information verification	Students double-check the accuracy of AI output	IV1
	Students compare AI answers with trusted sources	IV2
	Students verify the authenticity of references provided by AI	IV3
	Students do not immediately use AI answers without understanding the content	IV4
	Students seek clarification if AI output is doubtful	IV5
Academic integrity	Students avoid directly copying AI output	AI1
	Students maintain the use of personal thought and analysis	AI2
	Students understand the limits of AI usage in academic tasks	AI3
	Students are willing to declare AI usage if required	AI4
	Students do not use AI in ways that violate academic regulations	AI5

Prior to the main analysis, the instrument's quality was first evaluated through validity and reliability tests. The validity of each statement item was analyzed using Pearson product-moment correlation (item-total correlation) to assess each indicator's ability to represent the construct being measured. Meanwhile, construct reliability was evaluated using Cronbach's alpha to assess the internal consistency of indicators within each research variable. The validity and reliability test results are presented in detail in the research results section. The data analysis was carried out in stages. The first stage was the data cleaning and filtering process to ensure that all respondents met the research criteria and that there were no incomplete data. Next, a composite score for each construct was calculated as the average of its constituent indicators. Given that cluster analysis is highly sensitive to differences in scale and variance between variables, all composite scores were then transformed into Z-scores (standardization). This standardization aims to ensure that each variable has a balanced contribution to the cluster formation process, preventing the dominance of certain variables due to differences in measurement units.

The optimal number of clusters was determined before the respondent grouping process. This study employed three evaluation methods commonly used in cluster analysis: the Elbow method, the Silhouette score, and the Davies–Bouldin index. The Elbow method was used to identify points of significant decline in the within-cluster sum of squares (WCSS) to determine the optimal number of clusters. Furthermore, the Silhouette Score was used to evaluate the cohesiveness of members within a cluster and the degree of separation between clusters, with values closer to 1 indicating better cluster quality. Meanwhile, the Davies–Bouldin index was used to measure the ratio of within-cluster variation to between-cluster distance; a smaller index value indicates a more optimal clustering result. The simultaneous use of these three methods aims to increase objectivity in determining the best number of clusters so that decisions do not rely solely on a single evaluation measure. After the optimal number of clusters was determined, the respondent classification was performed using the K-Means clustering algorithm. This algorithm was chosen because it effectively groups objects based on similar characteristics in numerical data and is widely used in research on technology user behavior. The analysis produced several key pieces of information, namely the optimal number of clusters, the evaluation value of each cluster determination method, the centroid value for each research dimension, the distribution of the number of members in each cluster, and a substantive interpretation of the characteristics of each group of generative AI usage behaviors.

To maintain consistency and objectivity in interpreting research results, several decision-making criteria were established. First, an indicator is declared valid if it has a Pearson correlation (r-stat) greater than the r-table value of 0.138 at a significance level of $\alpha = 0.05$, with a total of 200 respondents. Second, a construct is declared reliable if it has a Cronbach's alpha value greater than 0.70. Third, the number of clusters is determined by the congruence of results from the Elbow method, Silhouette score, and Davies–Bouldin index, as well as the ease of substantive interpretation of each group's characteristics. Fourth, each cluster is named based on the empirical pattern of centroid values across the three research dimensions, so that the determination of behavioral types is based on the characteristics of the generated data rather than solely on conceptual assumptions. This approach allows for a more objective, representative classification of generative AI behaviors and is more relevant to the development of higher education policy.

Results and discussion

Statistical description & respondent profile

Descriptively, the aggregated composite scores for the 200 respondents showed that the Academic Productivity dimension had a mean of 4.14 (median = 4.20; std = 0.69; min = 2.00; max = 5.00), indicating a very high perception of AI utility among students. The Information Verification dimension recorded a mean of 3.36 (median = 3.20; std = 0.95; min = 1.60; max = 5.00), showing more moderate variations in fact-checking behavior. Meanwhile, the Academic Integrity dimension had a mean of 3.62 (median = 4.00; std = 1.03; min = 1.20; max = 5.00), with the highest standard deviation, highlighting polarization or significant inequality among students in adherence to academic ethical boundaries when using AI.

The first part of the results reported the respondent profile. This information was important for providing context on generative AI usage in the research, including study programs, semesters, and the dominant applications used by respondents. The characteristics of the respondents in this study are presented in Table 2 to provide an overview of the student profiles in the study sample. The descriptions include academic background, study program, semester, gender, type of generative AI application used, and the intensity of its use in academic activities. This information is important for demonstrating that the study sample represents students with diverse academic backgrounds and varying levels of experience with generative AI in the learning process.

Table 2 research respondent profile

Aspect	Category	Frequency	Percentage (%)
Research institution/location	Saintek & soshum fields	200	100.0
Study program	Social sciences and humanities (Soshum)	100	50.0
	Science and technology (Saintek)	100	50.0
Semester range	Semester 2	31	15.5
	Semester 3	32	16.0
	Semester 4	39	19.5
	Semester 5	18	9.0
	Semester 6	30	15.0
	Semester 7	17	8.5
	Semester 8	33	16.5
Gender	Female (P)	115	57.5
	Male (L)	85	42.5
Generative AI application used	ChatGPT	153	76.5
	Copilot	30	15.0
	Claude	17	8.5
Usage intensity for academic tasks	Often	93	46.5
	Very often	76	38.0
	Rarely	31	15.5

Source: primary data, processed (2026)

Based on Table 2, this study involved 200 students from the Science and Technology (Saintek) and Social and Humanities (Soshum) groups, with a balanced composition between the two groups, namely 100 respondents each (50.0%). The distribution of respondents by semester shows that 4th semester students are the largest group (19.5%), followed by 8th semester (16.5%), 3rd semester (16.0%), 2nd semester (15.5%), 6th semester (15.0%), 5th semester (9.0%), and 7th semester (8.5%). By gender, female students were the majority, with 115 (57.5%), while male students numbered 85 (42.5%). In terms of generative AI applications used to support academic activities, ChatGPT was the platform most widely used by respondents, namely 153 students (76.5%), followed by Microsoft Copilot, with 30 students (15.0%), and Claude, with 17 students (8.5%). Meanwhile, based on the intensity of generative AI use in academic activities, the majority of respondents reported frequently using AI (46.5%), followed by very frequently (38.0%), while only 15.5% reported rarely using generative AI. Overall, the respondent profile indicates that most students have considerable experience using generative AI to support their learning and complete academic assignments.

Instrument validity and reliability testing

Following the respondent profile, the results reported the instrument quality. This stage was crucial because cluster-based classification would be more meaningful if it were built on valid and reliable indicators. Prior to cluster analysis, the quality of the research instrument was evaluated using validity and reliability tests to ensure that each indicator accurately and consistently measured the intended construct. The results of the validity test, using Pearson product-moment correlation, and the reliability test, using Cronbach's alpha coefficient, are presented in Table 3.

Table 3 instrument validity and reliability test results

Variables	Items code	r-stat	r-table	Results	Cronbach's alpha	Results
Academic productivity	AP1	0.817	> 0.138	Valid	0.878	Reliabel
	AP2	0.838	> 0.138	Valid		
	AP3	0.801	> 0.138	Valid		
	AP4	0.830	> 0.138	Valid		
	AP5	0.814	> 0.138	Valid		
Information verification	IV1	0.863	> 0.138	Valid	0.924	Reliabel
	IV2	0.897	> 0.138	Valid		
	IV3	0.873	> 0.138	Valid		
	IV4	0.861	> 0.138	Valid		
	IV5	0.882	> 0.138	Valid		
Academic integrity	AI1	0.920	> 0.138	Valid	0.946	Reliabel
	AI2	0.889	> 0.138	Valid		
	AI3	0.924	> 0.138	Valid		
	AI4	0.885	> 0.138	Valid		
	AI5	0.912	> 0.138	Valid		

Source: primary data, processed (2026)

As shown in Table 3, all items (15 indicators) across the academic productivity, information verification, and academic integrity variables had item-total correlation coefficients (r-stat) far exceeding the critical r-table value (0.138) and were therefore declared Valid. Cronbach's alpha values for the academic productivity (0.878), information verification (0.924), and academic integrity (0.946) constructs were all above the strict threshold of 0.70. This confirmed that the instrument possessed excellent internal consistency and was fit for use in cluster modeling.

Determination of optimal cluster count

The next stage was determining the optimal number of clusters. This study did not rely on a single criterion but used a combination of the Elbow method (WSSE), Silhouette score, and Davies–Bouldin index. Combined reporting was required to provide cluster count decisions with a stronger quantitative basis and to avoid relying solely on the visualization of a single technique. Before performing the K-Means clustering analysis, the optimal number of clusters was determined to ensure that the resulting classification accurately represented the underlying data structure. Three complementary cluster validation methods, the Elbow method, Silhouette score, and Davies–Bouldin index, were employed to evaluate the quality of alternative clustering solutions. The results of these evaluations are presented in Table 4 and Figure 1.

Table 4 cluster count evaluation black box testing

Alternative cluster count (k)	Elbow / WSSE value	Silhouette score	Davies–bouldin Index	Interpretative notes
2	314.39	0.476	0.881	Separation not yet optimal; intra-cluster variance remains high.
3	132.41	0.599	0.560	Sharpest elbow point, highest Silhouette, lowest DB Index (Optimal).
4	112.11	0.446	0.868	Decrease in WSSE levels off; Silhouette drops drastically.
5	93.67	0.337	1.109	Risk of overfitting; sub-cluster separation is not substantive.
Selected cluster count	3	0.599	0.560	The 3-cluster solution proved most robust mathematically.

Source: primary data, processed (2026)

Figure 1 evaluation of the number of clusters
Source: primary data, processed (2026)

Based on the results presented in Table 4 and the cluster evaluation curves, the optimal clustering solution was identified as three clusters (k = 3), as this configuration demonstrated the most consistent and superior performance across all validation criteria. The Elbow method revealed a distinct inflection point at k = 3, where the WSSE value decreased substantially from 314.39 at k = 2 to 132.41 at k = 3. However, increasing the number of clusters beyond this point yielded only marginal reductions in WSSE, suggesting that additional clusters did not meaningfully improve the explanation of the data structure. This finding was further supported by the Silhouette score, which achieved the highest value of 0.599 at k = 3, indicating that this solution produced the most cohesive clusters with the clearest separation between groups. In addition, the Davies–Bouldin index reached its lowest value of 0.560 at k = 3, confirming that this configuration provided the optimal balance between minimizing within-cluster variation and maximizing inter-cluster separation. The agreement among these three independent evaluation approaches indicates that the three-cluster solution represents the most statistically reliable and interpretable structure. Therefore, the k = 3 configuration was selected as the final clustering model for the subsequent K-Means analysis to identify distinct profiles of Generative AI usage among university students.

Centroid profile and cluster interpretation

After determining that three clusters represented the optimal solution, the next stage of analysis focused on interpreting the characteristics of each cluster based on the centroid values for the three research dimensions. The centroid values represent the average scores for each cluster on academic productivity, information verification, and academic integrity, measured on a five-point Likert scale. These values provide an empirical basis for identifying and describing distinct patterns of generative AI usage behavior among university students. The centroid results for each cluster are presented in Table 5.

Table 5 centroid values per cluster (1–5 likert scale)

Cluster	Academic productivity (AP)	Information verification (IV)	Academic integrity (AI)	Temporary general character
Cluster 1	2.81	2.69	4.39	Low use, low verification, high integrity
Cluster 2	4.33	2.54	2.46	High use, low verification, low integrity
Cluster 3	4.41	4.32	4.38	High use, high verification, high integrity

Source: primary data, processed (2026)

Based on the centroid values in Table 5, the three identified clusters exhibit distinct patterns of generative AI usage among university students across the dimensions of academic productivity, information verification, and academic integrity. Cluster 1 is characterized by relatively low levels of AI utilization, with an academic productivity score of 2.81 and an information verification score of 2.69, while showing a high level of academic integrity with a score of 4.39. This pattern indicates that students in this group tend to use generative AI less frequently and engage in limited verification practices, yet maintain strong adherence to academic integrity principles. Cluster 2 exhibits the opposite pattern, with the highest level of AI-supported productivity among the three dimensions, reflected by an academic productivity score of 4.33, but accompanied by low information verification (2.54) and academic integrity (2.46) scores. This suggests that students in this cluster extensively use generative AI to improve efficiency in academic tasks but show weaker tendencies to evaluate AI outputs critically and to maintain responsible usage practices. Meanwhile, cluster 3 represents the most balanced and responsible usage profile, with high scores across all dimensions: academic productivity (4.41), information verification (4.32), and academic integrity (4.38). These results indicate that students in this cluster can maximize the benefits of generative AI while applying verification strategies and maintaining ethical academic behavior. Overall, the centroid distribution demonstrates clear differences in students' generative AI usage profiles, ranging from limited users with strong integrity awareness to productivity-oriented users with insufficient control mechanisms to responsible users who integrate productivity, verification, and integrity into their AI-assisted academic practices.

Table 6 number of members and interpretation of each cluster

Cluster	Number of members	Percentage (%)	Cluster name	Substantive interpretation
Cluster 1	30	15.0	Limited-ethical users (*pengguna terbatas berintegritas*)	Utilized AI minimally/limitedly, lacked deep information verification, yet strictly adhered to ethical standards and academic integrity.

Cluster	Number of members	Percentage (%)	Cluster name	Substantive interpretation
Cluster 2	80	40.0	High-risk pragmatic users (*pragmatis berisiko etik*)	Relied intensively on AI for instant task productivity, but ignored source verification and was prone to plagiarism/academic violations.
Cluster 3	90	45.0	Productive-critical-ethical users (*produktif-kritis berintegritas*)	The dominant group that optimized AI for high productivity while applying strict information verification and maintaining academic integrity.

Source: primary data, processed (2026)

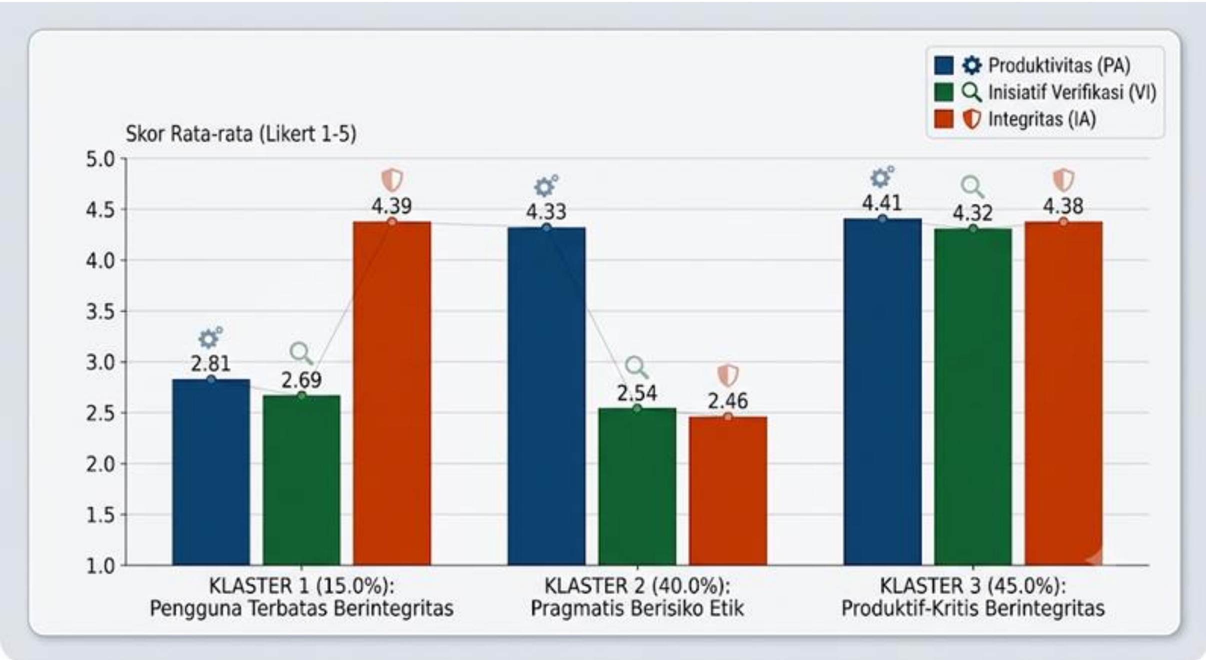

Figure 2 empirical cluster centroid profile
Source: primary data, processed (2026)

The results presented in Tables 5 and 6 reveal three distinct behavioral typologies of generative AI usage among university students based on the combined dimensions of academic productivity, information verification, and academic integrity. Cluster 1, identified as limited-ethical users, represents 15.0% of the total sample (n = 30). This group demonstrated relatively low engagement with generative AI, reflected by an academic productivity score of 2.81 and an information verification score of 2.69, while maintaining the highest academic integrity score among all clusters (4.39). The findings indicate that students in this cluster tend to use AI tools minimally or only for limited academic assistance. Their relatively low verification behavior may be associated with their limited dependence on AI-generated information rather than an intentional disregard for accuracy. Nevertheless, this group demonstrates strong ethical awareness, as reflected in their high commitment to avoiding direct copying of AI-generated content and maintaining personal responsibility in academic work.

Cluster 2, categorized as high-risk pragmatic users, comprises 40.0% of respondents (n = 80) and represents the group with the greatest potential ethical concern. Students in this cluster showed high academic productivity scores (4.33), indicating that they actively utilize generative AI to improve efficiency and accelerate the completion of academic tasks. However, this high level of utilization was not accompanied by adequate information verification (2.54) or academic integrity practices (2.46). This pattern suggests that members of this cluster tend to prioritize the functional benefits of AI, such as obtaining quick answers and completing assignments more efficiently, while paying less attention to evaluating the accuracy of AI outputs, verifying references, or considering ethical boundaries. Consequently, this group may be more susceptible to inappropriate AI use, including excessive reliance on AI-generated content and potential violations of academic integrity principles.

Cluster 3, referred to as productive-critical-ethical users, represents the largest proportion of respondents, accounting for 45.0% of the sample (n = 90). This cluster demonstrates the most balanced and desirable pattern of Generative AI utilization, characterized by high academic productivity (4.41), strong information verification practices (4.32), and high academic integrity (4.38). Students in this group can maximize the benefits of generative AI as a learning support tool while maintaining critical evaluation and ethical academic behavior. Their usage pattern reflects a responsible integration of AI technology, in which AI serves as a cognitive support mechanism rather than a substitute for independent reasoning and scholarly judgment. Overall, the three-cluster solution highlights the diversity of student behaviors in adopting generative AI, demonstrating that the quality of AI usage is determined not merely by the intensity of use but by the combination of productivity, critical verification, and ethical responsibility.

Based on that, policy recommendations derived from the research results were compiled in Table 7 by targeting the specific characteristics of the three empirical clusters.

Table 7 higher education policy recommendations based on classification results

Policy area	Recommendation	Objective	Main target
AI literacy	Conduct AI literacy programs emphasizing AI's function as a thinking aid (*mind-tool*), not a replacement for thinking.	Increase productive yet reflective utilization.	Cluster 2 (high-risk pragmatic) and Cluster 1 for empowerment.
Information verification literacy	Train students in *lateral reading*, fact-checking claims, and verifying AI DOI/reference authenticity against index databases (Scopus/Sinta).	Lower the risk of false information spread (*hallucination trap*).	Cluster 2 (low VI score: 2.54) and Cluster 1.
AI Usage Guidelines in Assignments	Establish AI zoning matrices (Green: Full allowed; Yellow: Limited to outlining/proofreading; Red: Strictly prohibited) per course learning outcome.	Provide clear ethical boundaries and eliminate regulatory ambivalence.	All students and course lecturers.
Ai usage declaration	Mandate attachment of an *AI Disclosure Statement & Prompt Log* on final project/paper validation pages.	Increase transparency, process tracking, and accountability.	All university students.
Strengthening academic integrity	Reform student codes of ethics by including clauses on *AI-assisted pen-for-hire* and conducting ethical dilemma discussions.	Clarify that integrity includes claim authenticity and cognitive effort.	Cluster 2 (critical integrity score: 2.46).
Assessment redesign	Shift from rote essay-based exams to *authentic assessment* (oral presentations, debates, case study analysis, and reflective journals).	Reduce incentives and dependency gaps for instant AI answers.	Courses with high misuse vulnerability.

Policy area	Recommendation	Objective	Main target
Lecturer support	Provide AI-integrated syllabus repositories, *anti-fragile assessment* guides, and AI invigilation workshops.	Align evaluation expectations and prevent lecturer-student miscommunication.	All lecturers and educational staff.

Source: primary data, processed (2026)

Based on the classification results presented in Table 7, the recommended higher education policies emphasize a targeted and balanced approach to promoting productive, critical, and ethical use of generative AI among students. The findings suggest that policy interventions should not focus solely on restricting AI use but rather on strengthening students' capacity to use AI responsibly. For cluster 2 (high-risk pragmatic users), the main priorities include enhancing AI literacy, training in information verification, reinforcing academic integrity, and clarifying AI usage guidelines to reduce reliance on unverified AI outputs and prevent potential academic misconduct. Meanwhile, cluster 1 (limited-ethical users) requires empowerment strategies to improve their ability to utilize AI as a learning support tool while maintaining their existing ethical awareness. For all students and academic stakeholders, universities should establish transparent AI-use guidelines, implement AI disclosure statements, redesign assessments to promote more authentic and reflective learning activities, and provide lecturers with support through AI-integrated teaching resources and training programs. Overall, these recommendations demonstrate that institutional AI governance should adopt a differentiated strategy based on student usage profiles, combining technological competence, critical evaluation skills, and academic integrity to ensure responsible adoption of generative AI in higher education.

Discussion

The findings of this study demonstrate that generative AI use among university students is not a homogeneous phenomenon but comprises distinct behavioral patterns shaped by the interplay among productivity, information verification, and academic integrity. The descriptive results indicate that students generally perceive generative AI as highly beneficial for academic productivity, as reflected by the high mean score of academic productivity (M = 4.14). This finding confirms previous studies showing that students primarily adopt generative AI because of its ability to improve learning efficiency, support idea generation, explain complex concepts, and accelerate academic task completion (Dwivedi et al., 2023; Kasneci et al., 2023; Mahapatra, 2024; Rodríguez et al., 2023). However, the lower average score for information verification (M = 3.36) compared with productivity suggests that students' ability to evaluate AI-generated information critically has not developed at the same pace as their adoption of AI tools. This finding supports concerns raised by Day (2023); Enriquez et al. (2024), who emphasized that the rapid adoption of generative AI in higher education may create a gap between technological usage competence and critical AI literacy. Students may become proficient in obtaining information from AI systems without necessarily possessing sufficient skills to evaluate accuracy, detect hallucinations, or verify AI-generated references.

The variation observed in academic integrity (M = 3.62; SD = 1.03) provides further evidence that ethical understanding remains uneven among students. The relatively high standard deviation indicates significant differences in how students perceive and apply ethical boundaries when using generative AI for academic purposes.

This finding reinforces previous research highlighting that AI adoption in higher education is not merely a technological acceptance issue but also a matter of responsible digital behavior (Cotton et al., 2024; Eke, 2023; Lund et al., 2025). While some students appear to integrate AI as a supportive learning tool while maintaining personal responsibility, others may interpret AI assistance as a shortcut for completing academic tasks. Therefore, measuring only AI adoption frequency or perceived usefulness is insufficient to explain the quality of AI usage behavior among university students.

The cluster analysis provides stronger evidence of this behavioral heterogeneity by identifying three distinct user profiles. The emergence of the limited-ethical users, high-risk pragmatic users, and productive-critical-ethical users demonstrates that students who use the same AI technology may possess fundamentally different approaches toward learning, verification, and ethical responsibility. This finding extends previous technology acceptance research, which has primarily focused on explaining why students adopt AI based on perceived usefulness, ease of use, or behavioral intention (Amin et al., 2025; Shahzad et al., 2024; Strzelecki, 2024). While these studies successfully explain technology adoption, the present study demonstrates that adoption alone does not capture whether AI usage contributes positively to academic development. Two students may both frequently use ChatGPT, yet one may use it as a cognitive partner for exploration and reflection, while another may rely on it as a replacement for independent thinking (Loos et al., 2023; Ravšelj et al., 2025).

The first cluster, limited-ethical users (15.0%), represents students who demonstrate strong academic integrity despite relatively low levels of AI utilization. Their high academic integrity score (4.39) suggests that ethical awareness may exist independently from technological engagement. This group appears to maintain conventional academic values, such as avoiding direct copying and preserving personal intellectual contribution, but has not fully developed productive strategies for integrating AI into learning activities. This finding provides an important perspective that responsible AI adoption does not automatically emerge from increased AI usage intensity. Instead, universities must also empower ethically oriented students with sufficient AI literacy so that effective technological capabilities accompany responsible attitudes. In line with Chan (2023); Enriquez et al. (2024), AI literacy should not only emphasize risk avoidance but also teach students to use AI as a tool for deeper reasoning, creativity, and knowledge construction.

The second cluster, high-risk pragmatic users (40.0%), is the most critical finding of this research, as it reveals a mismatch between productivity benefits and responsible AI practices. Although this group achieved a high academic productivity score (4.33), their Information Verification (2.54) and academic integrity (2.46) scores were substantially lower. This indicates that these students primarily perceive AI as an efficiency-enhancing technology but lack sufficient mechanisms for evaluating and controlling its outputs. This pattern aligns with concerns reported by Nashwan et al. (2023); Cotton et al. (2024); Chan (2025), who warned that Generative AI may create new forms of academic misconduct when students prioritize task completion over learning processes. The findings also support Gruenhagen et al. (2024), who found that students do not always perceive AI-assisted academic work as a violation, suggesting that ethical boundaries around AI use remain ambiguous. Therefore, the challenge for higher education institutions is not simply to prevent AI use but to reshape students' understanding of appropriate AI-supported learning practices.

The third cluster, productive-critical-ethical users (45.0%), represents the most desirable AI usage profile and provides empirical evidence that productive AI adoption can coexist with critical thinking and academic integrity. This group achieved consistently high scores across all dimensions: academic productivity (4.41), information verification (4.32), and academic integrity (4.38). These findings support the argument proposed by Kasneci et al. (2023) that generative AI can enhance learning outcomes when integrated through appropriate pedagogical approaches rather than used as a replacement for human cognition. Students in this cluster appear to demonstrate characteristics of responsible AI users who treat AI as a cognitive assistant while maintaining independent judgment. Their behavior reflects the principles of responsible AI Use, where technological capability must be accompanied by transparency, verification, and ethical accountability (AlBlooshi, 2026; Enriquez et al., 2024).

The identification of these three clusters also contributes theoretically by integrating perspectives from technology acceptance theory, responsible AI Use, and academic integrity frameworks. Previous studies have generally examined these perspectives separately: technology acceptance research explains adoption behavior, responsible AI studies emphasize verification and ethical usage, while academic integrity research focuses on misconduct prevention. This study extends these perspectives by demonstrating that AI usage behavior is multidimensional and can be empirically classified by the interaction among benefits, critical evaluation, and ethical responsibility. The clustering approach therefore provides a more comprehensive explanation of student AI behavior than single-variable approaches based on frequency of use or acceptance intention.

From an institutional perspective, the findings suggest that AI governance in higher education requires differentiated interventions rather than universal restrictions. The existence of the high-risk pragmatic users cluster indicates that universities should prioritize AI literacy programs focusing on critical evaluation, source verification, and ethical decision-making. This recommendation is consistent with Lund et al. (2025), who argued that AI policies should move beyond prohibition-oriented approaches toward competency-based governance. Similarly, the presence of productive-critical-ethical users demonstrates that AI integration policies should support and expand responsible practices rather than limit innovation. Universities should therefore develop AI guidelines that combine clear boundaries, AI disclosure mechanisms, authentic assessment redesign, and lecturer capacity building.

Overall, this study demonstrates that the central issue in generative AI adoption is not whether students use AI, but how they use it. The findings challenge the assumption that high AI usage intensity automatically leads to either positive learning outcomes or academic risks. Instead, responsible AI adoption depends on the integration of three complementary capabilities: the ability to leverage AI for productivity, the ability to critically verify AI-generated information, and the commitment to preserve academic integrity. By identifying distinct behavioral profiles, this research provides an empirical foundation for developing more adaptive higher education policies that promote generative AI as a tool for intellectual enhancement rather than a substitute for human learning and scholarly responsibility.

Conclusions

Generative AI usage among university students represents a multidimensional behavioral phenomenon that cannot be explained solely by the frequency or intensity of technology use. Through K-Means clustering based on three key dimensions: academic productivity, information verification, and academic integrity, the study successfully identified three distinct user profiles: limited-ethical users, high-risk pragmatic users, and productive-critical-ethical users. The findings reveal that the largest proportion of students (45.0%) belong to the productive-critical-ethical users group, demonstrating that many students are capable of utilizing generative AI to enhance academic productivity while maintaining verification practices and ethical responsibility. However, the identification of the high-risk pragmatic user group (40.0%) highlights a significant concern, as some students benefit substantially from AI assistance yet exhibit insufficient verification behavior and weaker awareness of academic integrity. These findings confirm that responsible adoption of Generative AI depends not only on technological accessibility but also on students' critical literacy and ethical understanding.

This study contributes theoretically and practically by providing an empirical classification model that integrates three dimensions frequently examined separately in previous research: technology utilization, information verification capability, and academic integrity. The clustering approach expands existing discussions on Generative AI adoption by demonstrating that students with similar levels of AI usage may exhibit substantially different behavioral patterns. Practically, the findings provide a foundation for higher education institutions to design differentiated AI governance strategies, including targeted AI literacy programs, verification training, transparent AI usage guidelines, disclosure mechanisms, and assessment redesign. Nevertheless, this study has several limitations. First, the research employed a cross-sectional survey design, which captures student behavior at a specific point in time and cannot fully explain changes in AI usage patterns over time. Second, the sample was obtained using purposive sampling with 200 respondents, which may limit the generalizability of the findings to broader student populations. Third, the study relied on self-reported questionnaire responses, which may be influenced by respondents' perceptions, social desirability bias, or differences in understanding ethical AI usage.

Future research should address these limitations by adopting longitudinal research designs to examine how students' generative AI usage behaviors evolve as AI technologies, institutional policies, and academic practices continue to develop. Further studies may also employ larger and more diverse samples across multiple universities, disciplines, and cultural contexts to improve the external validity of the proposed behavioral classification model. In addition, future research could integrate objective behavioral data, such as AI usage logs, assignment analysis, or learning performance indicators, to complement self-reported measures and provide a more comprehensive understanding of actual AI practices. Expanding the analytical framework by incorporating additional factors, such as AI literacy level, digital competence, learning motivation, and disciplinary differences, may further strengthen the explanation of why students develop different patterns of generative AI adoption in higher education.

References

Alawida, M., Mejri, S., Mehmood, A., Chikhaoui, B., & Isaac Abiodun, O. (2023). A Comprehensive Study of ChatGPT: Advancements, Limitations, and Ethical Considerations in Natural Language Processing and Cybersecurity. *Information*, *14*(8), 462. https://doi.org/10.3390/info14080462

AlBlooshi, S. (2026). Artificial intelligence in higher education, opportunities, and challenges: a review. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1683968

Ali, D., Fatemi, Y., Boskabadi, E., Nikfar, M., Ugwuoke, J., & Ali, H. (2024). ChatGPT in

Teaching and Learning: A Systematic Review. *Education Sciences*, *14*(6), 643. https://doi.org/10.3390/educsci14060643

Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., bin Saleh, K., Alowais, S. A., Alshaya, O. A., Rahman, I., Al Yami, M. S., & Albekairy, A. M. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in Social and Administrative Pharmacy*, *19*(8), 1236–1242. https://doi.org/10.1016/j.sapharm.2023.05.016

Amin, M. Al, Kim, Y. S., & Noh, M. (2025). Unveiling the drivers of ChatGPT utilization in higher education sectors: the direct role of perceived knowledge and the mediating role of trust in ChatGPT. *Education and Information Technologies*, *30*(6), 7265–7291. https://doi.org/10.1007/s10639-024-13095-y

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, *20*(1), 38. https://doi.org/10.1186/s41239-023-00408-3

Chan, C. K. Y. (2025). Students' perceptions of 'AI-giarism': investigating changes in understandings of academic misconduct. *Education and Information Technologies*, *30*(6), 8087–8108. https://doi.org/10.1007/s10639-024-13151-7

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are Gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their Gen X and millennial generation teachers? *Smart Learning Environments*, *10*(1), 60. https://doi.org/10.1186/s40561-023-00269-3

Chiang, F., Zhu, D., & Yu, W. (2022). A systematic review of academic dishonesty in online learning environments. *Journal of Computer Assisted Learning*, *38*(4), 907–928. https://doi.org/10.1111/jcal.12656

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, *61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Crawford, J., Cowling, M., & Allen, K.-A. (2023). Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI). *Journal of University Teaching and Learning Practice*, *20*(3). https://doi.org/10.53761/1.20.3.02

Damiano, A. D., Lauría, E. J. M., Sarmiento, C., & Zhao, N. (2024). Early Perceptions of Teaching and Learning Using Generative AI in Higher Education. *Journal of Educational Technology Systems*, *52*(3), 346–375. https://doi.org/10.1177/00472395241233290

Day, T. (2023). A Preliminary Investigation of Fake Peer-Reviewed Citations and References Generated by ChatGPT. *The Professional Geographer*, *75*(6), 1024–1027. https://doi.org/10.1080/00330124.2023.2190373

Ding, L., Li, T., Jiang, S., & Gapud, A. (2023). Students' perceptions of using ChatGPT in a physics class as a virtual tutor. *International Journal of Educational Technology in Higher Education*, *20*(1), 63. https://doi.org/10.1186/s41239-023-00434-1

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of*

Information Management, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eke, D. O. (2023). ChatGPT and the rise of generative AI: Threat to academic integrity? *Journal of Responsible Technology*, *13*, 100060. https://doi.org/10.1016/j.jrt.2023.100060

Enriquez, B. G. A., Ballesteros, M. A. A., Jordan, O. H., Roca, C. L., & Tirado, K. S. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: effect of intent to use, verification of information and responsible use. *BMC Psychology*, *12*(1), 255. https://doi.org/10.1186/s40359-024-01764-z

Fajt, B., & Schiller, E. (2025). ChatGPT in Academia: University Students' Attitudes Towards the use of ChatGPT and Plagiarism. *Journal of Academic Ethics*, *23*(3), 1363–1382. https://doi.org/10.1007/s10805-025-09603-5

Gruenhagen, J. H., Sinclair, P. M., Carroll, J.-A., Baker, P. R. A., Wilson, A., & Demant, D. (2024). The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. *Computers and Education: Artificial Intelligence*, *7*, 100273. https://doi.org/10.1016/j.caeai.2024.100273

Jo, H. (2024). From concerns to benefits: a comprehensive study of ChatGPT usage in education. *International Journal of Educational Technology in Higher Education*, *21*(1), 35. https://doi.org/10.1186/s41239-024-00471-4

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … 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

Loos, E., Gröpler, J., & Goudeau, M.-L. S. (2023). Using ChatGPT in Education: Human Reflection on ChatGPT's Self-Reflection. *Societies*, *13*(8), 196. https://doi.org/10.3390/soc13080196

Lund, B. D., Lee, T. H., Mannuru, N. R., & Arutla, N. (2025). AI and Academic Integrity: Exploring Student Perceptions and Implications for Higher Education. *Journal of Academic Ethics*, *23*(3), 1545–1565. https://doi.org/10.1007/s10805-025-09613-3

Mahapatra, S. (2024). Impact of ChatGPT on ESL students' academic writing skills: a mixed methods intervention study. *Smart Learning Environments*, *11*(1), 9. https://doi.org/10.1186/s40561-024-00295-9

Nashwan, S. A. Bin, Sadallah, M., & Bouteraa, M. (2023). Use of ChatGPT in academia: Academic integrity hangs in the balance. *Technology in Society*, *75*, 102370. https://doi.org/10.1016/j.techsoc.2023.102370

Ofem, U. J., Owan, V. J., Iyam, M. A., Udeh, M. I., Anake, P. M., & Ovat, S. V. (2025). Students' perceptions, attitudes and utilisation of ChatGPT for academic dishonesty: Multigroup analyses via PLS–SEM. *Education and Information Technologies*, *30*(1), 159–187. https://doi.org/10.1007/s10639-024-12850-5

Ravšelj, D., Keržič, D., Tomaževič, N., Umek, L., Brezovar, N., A. Iahad, N., Abdulla, A. A., Akopyan, A., Aldana Segura, M. W., AlHumaid, J., Allam, M. F., Alló, M., Andoh, R. P. K., Andronic, O., Arthur, Y. D., Aydın, F., Badran, A., Balbontín-Alvarado, R., Ben Saad, H., … Aristovnik, A. (2025). Higher education students' perceptions of ChatGPT: A global study of early reactions. *PLOS ONE*, *20*(2), e0315011.

https://doi.org/10.1371/journal.pone.0315011
Rodríguez, J.-M. R., Montoya, M.-S. R., Fernández, M. B., & Lara, F. L. (2023). Use of ChatGPT at University as a Tool for Complex Thinking: Students' Perceived Usefulness. *Journal of New Approaches in Educational Research*, *12*(2), 323–339. https://doi.org/10.7821/naer.2023.7.1458

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*(1), 46. https://doi.org/10.1186/s41239-024-00478-x

Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, *32*(9), 5142–5155. https://doi.org/10.1080/10494820.2023.2209881

Tiwari, C. K., Bhat, M. A., Khan, S. T., Subramaniam, R., & Khan, M. A. I. (2024). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education*, *21*(3), 333–355. https://doi.org/10.1108/ITSE-04-2023-0061

Wulff, D. W., Naumeca, A. A., Bjelobaba, S., Foltýnek, T., Dib, J. G., Popoola, O., Šigut, P., & Waddington, L. (2023). Testing of detection tools for AI-generated text. *International Journal for Educational Integrity*, *19*(1), 26. https://doi.org/10.1007/s40979-023-00146-z

Xu, X., Wang, X., Zhang, Y., & Zheng, R. (2024). Applying ChatGPT to tackle the side effects of personal learning environments from learner and learning perspective: An interview of experts in higher education. *PLOS ONE*, *19*(1), e0295646. https://doi.org/10.1371/journal.pone.0295646