ISTANBUL UNIVERSITY PRESS

Acta Infologica

Acta Infologica,
ACIN 2025, 9 (1): 147–166

https://doi.org/10.26650/acin.1670197
Submitted: 04.04.2025
Revision Requested: 29.04.2025
Last Revision Received: 03.05.2025
Accepted: 04.05.2025
Published Online 20.06.2025

Research Article

Open Access

Generative AI in Higher Education: Students' Perspectives on Adoption, Ethical Concerns, and Academic Impact

Gökçe Karahan Adalı [1] & Asiye Bilgili [2]

[1] Haliç University, Faculty of Business Administration, Management Information Systems, İstanbul, Türkiye
[2] İstanbul Beykent University, Faculty of Engineering and Architecture, Department of Computer Engineering, İstanbul, Türkiye

Abstract

This study explores the adoption patterns of Generative Artificial Intelligence (GenAI) tools among 226 university students from various departments in Turkish higher education institutions, revealing unexpected relationships between age, discipline, and ethical concerns.Through quantitative analysis of university students' survey responses, three distinct clusters of GenAI users' re indentified: high adopters with low ethical concerns, moderate adopters with high ethical awareness, and low adopters with moderate ethical considerations. Notably, the findings challenge the prevalent assumption about younger students' technology adoption, revealing a strong positive correlation between age and AI tool preferences ($r=.858$, $p<.01$). The study also revealed significant gender and disciplinary variations, with female and non-STEM students expressing stronger ethical concerns ($p<.05$ and $p<.01$, respectively). While students recognized GenAI's potential to enhance academic productivity, they expressed concerns about misinformation, plagiarism, and AI-enabled inequalities. These findings suggest the need for differentiated approaches to AI integration in higher education, considering age-based adoption patterns and discipline-specific variations. The results call for targeted institutional policies addressing ethical literacy, disciplinary needs, and equitable AI access. This research contributes to the growing discourse on GenAI in higher education by providing evidence-based insights for developing more nuanced and effective AI integration strategies.

Keywords Generative AI · Higher Education · Ethical Concerns · Technology Adoption

Citation: Karahan Adalı, G. & Bilgili, A. (2025). Generative AI in higher education: Students' perspectives on adoption, ethical concerns, and academic impact. *Acta Infologica*, *9*(1), 147-166. https://doi.org/10.26650/acin.1670197

Corresponding author: Gökçe Karahan Adalı gokceadali@halic.edu.tr

Introduction

Artificial intelligence (AI) has developed significantly over the years, and one of the most notable examples of these developments is Generative Artificial Intelligence (GenAI) (Chakraborty et al., 2024). GenAI is a field of AI that uses large language models (LLMs) and other deep learning models to generate new content like text, images, audio, and video. Technology has revolutionized several fields, including education, medicine, business, and the arts, by generating data based on human input (Eysenbach, 2023). The ability of GenAI to create high-quality and human-like content has raised both enthusiasm and concerns regarding its implementation in educational contexts (Moorhouse et al., 2023). While the first AI applications were based on algorithms that mimicked human intelligence and performed tasks that typically required human cognitive abilities, GenAI goes beyond these capabilities. Thanks to these capabilities, GenAI has found application in various fields, such as art, entertainment, and education (Kirk & Givi, 2025).

Generative AI in Education

GenAI has been introduced as a novel educational technology that supports the learning of students. GenAI, which pushes the boundaries of artificial intelligence and offers new possibilities for human-computer interaction, has managed to attract the attention of researchers and technology enthusiasts (Chen et al., 2024). Applications of GenAI, especially in the field of education, are of particular importance because of its potential to transform and enrich learning processes (Kumar et al., 2025).

Such technologies can simplify academic work, personalize instructional processes, and optimize learning efficiency (Chaudhry & Kazim, 2024; Zhai, 2023). However, the ethical, academic integrity, and pedagogical consequences of such technologies are controversial (Fisher & Haake, 2024).

Use of Generative AI in Education

The application of GenAI in the classroom can transform pedagogy. Students engage with such tools to complete homework, conduct research, brainstorm, and summarize information (Montenegro-Rueda et al., 2023; Sun et al., 2024). The primary benefits of GenAI in education include the following:

- Personalized Learning: AI-generated content can be tailored to an individual's own learning rhythm (Zhai, 2023).
- More Engaging and Interactive Learning: AI-powered chatbots and content generators can facilitate interactive interaction with students (Fisher & Haake, 2024).
- Development of Language and Writing Skills: AI can assist students in improving their academic writing (Ali et al., 2024; Moorhouse et al., 2023).

However, the universal use of GenAI in learning is accompanied by challenges and ethical concerns, such as the following:

- Academic Integrity: Excessive reliance on these tools may lead to academic dishonesty (Xames & Shefa, 2023; Sun et al., 2024).
- Information Reliability: AI-generated information may at times not be dependable, and this may affect the academic performance of learners (Clark et al., 2024; Jo, 2024).
- Teacher Roles and Pedagogical Approaches: Educators should redesign their instructional models to accommodate AI technologies effectively (Fisher & Haake, 2024; Sandu et al., 2024).

With the rapid development of technology, students need to quickly access the right information in the field of education and effectively support their learning processes. With the recent spread of generative artificial intelligence tools such as ChatGPT, Claude, and Bard, the integration of these technologies into educational environments and the level of their adoption by students have become critical research topics (Saaida, 2023). In order for these technological transformations to be successfully realized in higher education and to be used effectively by students, it is necessary to first understand students' perceptions and attitudes toward these tools.

While generative artificial intelligence tools add a new dimension to the interaction between computers and students, they create an interdisciplinary field that focuses on the integration of this interaction into academic processes. These tools are affected by the continuous development of technology because their structures and areas of use are gradually expanding. In this field, which aims to shape technology according to student needs, the aim is not to have students adapt to technology but to adapt technology to student needs and expectations.

Literature Review

The evolution of Generative AI is deeply rooted in the foundational advancements of the 20th century. Alan Turing's theoretical contributions, particularly the concept of the Turing Machine and the Turing Test, laid the philosophical and computational groundwork for artificial intelligence (Turing, 1950). In the 1950s, the development of the Perceptron by Frank Rosenblatt introduced one of the first neural network models, enabling machines to learn from input data (Rosenblatt, 1958). During the 1960s and 1980s, symbolic AI, also known as "Good Old-Fashioned AI," dominated the field, relying on hand-coded rules and logical inference (Russell & Norvig, 2021). However, the limitations of symbolic systems led to a shift toward connectionist approaches, especially after the introduction of backpropagation algorithms in the 1980s (Rumelhart, Hinton, & Williams, 1986). These milestones not only expanded AI's computational capacity but also set the stage for today's data-driven, generative models that use deep learning and large-scale language processing.

Albadarin et al. (2024) systematically examined 14 empirical studies on the use of ChatGPT in education, and their research results showed that ChatGPT has a bidirectional effect on educational processes. While ChatGPT has positive contributions, such as providing instant feedback to students as a virtual intelligent assistant, improving writing and language skills, and providing personalized learning support, it also points out that if used excessively, it can weaken students' creativity, collaborative learning, and critical thinking skills. In the study examining the benefits and limitations of using ChatGPT in higher education, we found that ChatGPT can provide personalized educational experiences thanks to its natural language processing, text generation capacity, and performance evaluation opportunities. However, important problems such as content quality, possible bias in responses, risk of plagiarism, and content originality were also emphasized (Ali et al., 2024). In the study examining the negative effects of privacy concerns, fear of technology, and guilt on the intention to use chatbots, it was determined that this privacy concern is of critical importance due to the intensive sharing of personal data in interactions with AI chatbots. This study examined how fear of technology (technophobia), fear, and anxiety toward advanced technologies affect the intention to use such technologies, and it was determined that negative attitudes toward advanced technologies, such as AI chatbots, prevent their use. It was observed that the feeling of guilt arising from the thought of being dependent on AI in learning or work processes reduces the intention to use (Jo, 2024). This systematic literature review revealed the multifaceted effects of ChatGPT in the field of education. According to the research findings, appropriate use of ChatGPT significantly improves students' academic performance and acts as a motivating tool for students in terms of practical application of information and communication technologies. In the context of communication departments in German universities, Henke (2025) observed a significant increase in the adoption of GenAI tools between 2023 and 2024, particularly for tasks such as text generation and translation, indicating a shift toward mainstream integration. However, it was determined that there is a need for comprehensive training to prevent misuse and that it has led to new discussions in traditional teaching methods, methodology and evaluation processes. It was emphasized that ethical use and appropriate supervision are of critical importance in this process (Montenegro-Rueda et al., 2023). In the study examining the possibility of transformation of large language models such as ChatGPT in the learning environment in higher education, it was found that despite some challenges, students viewed ChatGPT as an effective academic aid and that it can potentially create more inclusive learning environments. In addition, there was emphasis on how institutional backing and ethical issues play a key role in the effective adoption of AI tools in educational environments, and how matters such as data safety, plagiarism, and potential biases must be tackled proactively (Sandu et al., 2024).

Johnston et al. (2024) conducted a vast survey at Liverpool (n=2555) and discovered that, while 93% of students were familiar with generative AI tools, the intention to implement them was not identical.
While 70.4% of them opposed the use of AI to compose complete essays, the majority appreciated tools like Grammarly for assistance. Confidence in writing was most prominent, where students who were confident in writing were less likely to utilize AI tools. The study sought to address the need for specific institutional policies rather than bans so that the usage of AI technologies was made accessible to all student groups equitably. A study by Chan and Hu (2023) involving a survey of 399 Hong Kong university students found a predominantly positive attitude toward GenAI, with students recognizing its potential for personalized learning, research assistance, and writing help. Worries were raised about data privacy, ethical implications, and AI-generated misinformation. The study recommends that policymakers develop AI integration plans that weigh technological benefits against ethical use in higher education.

Similarly, research by Song and Wang (2024) on 487 Chinese design college students and identified that over 60% of them used AI tools primarily to collect data, brainstorm, and offer conceptual design assistance. Students identified AI as a tool for enhancing creativity and productivity although in-depth integration was limited. Furthermore, AI anxiety was rather prevalent among students who were not exposed to such technologies. The writers highlighted the importance of literacy in AI in creative endeavors, arguing that education in AI can prepare students to employ AI as a design tool rather than as a substitute. A global study by Ravšelj et al. (2025) revealed that while students recognize the utility of ChatGPT for tasks like summarization and idea generation, they also express concerns regarding its reliability and ethical implications in academic settings. Khlaif et al. (2024) explored university instructors' perspectives in the Middle East, finding that while educators acknowledge the potential of GenAI tools to enhance assessment practices, they also raise concerns about academic integrity and the necessity for clear institutional policies.

Recent studies have explored the determinants of higher education students' adoption of Generative AI technologies. For instance, Sergeeva et al. (2025) employed the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework to empirically investigate these factors, highlighting the roles of performance expectancy and social influence in students' adoption behaviors.

When the studies conducted in this field are examined; it is seen that the focus is on the use of generative artificial intelligence tools in higher education, student perceptions, attitudes, purposes of use, ethical concerns, and academic honesty (Michel-Villarreal et al., 2023; Ogunleye et al., 2024; Xames & Shefa, 2023).

With the use of GenAI tools in higher education, a new form of relationship has emerged between learning-teaching processes and artificial intelligence. This relationship is important in terms of understanding how students use these tools to fulfill their academic duties and their attitudes toward these tools. In this context, examining university students' perceptions and attitudes toward generative artificial intelligence tools can contribute to the development of strategies for the effective and ethical use of these technologies in higher education. At the same time, it is believed that understanding students' motivations and concerns for using these tools will guide the shaping of future education policies and practices. Accordingly, the research questions determined within the scope of the study are as follows:

Main Research Question:

What are the perceptions, attitudes, and purposes of university students' use of ChatGPT and similar generative AI tools?

RQ1: How do university students perceive generative AI tools in academic processes?

RQ2: What are the students' positive and negative attitudes toward the use of these tools?

RQ3: For what academic purposes do students use generative AI tools?

RQ4: What kind of experiences do users have when using these tools?

RQ5: What are students' views on the ethical use of generative AI tools?

RQ6: How did the respondents evaluate the use of these tools in the context of academic honesty?

These research questions provide a comprehensive framework to fill the gaps identified in the literature and to understand the educational dimension of generative AI tools from a student perspective.

Method

This research was designed using the descriptive survey model, which is a quantitative research method. A cross-sectional research design was used in the study, which aimed to determine the perception, attitude, and usage patterns of university students toward generative artificial intelligence tools.

Study Group

The study group of the research was determined using maximum diversity sampling, a purposeful sampling method. This method aimed to understand the change in attitudes toward artificial intelligence tools among different disciplines and demographic characteristics by ensuring the participation of students from different departments and demographic groups. The study group consisted of university students who were studying at different universities and faculties and actively used generative artificial intelligence tools. A total of 226 students participated in the study. Table 1 provides the demographic information about the participants.

Table 1
Demographic Information

		N	%
Gender	Female	126	56
	Male	100	44
Age	18-20	108	47.8
	21-23	87	38.5
	24–26	21	9.3
	27 and older	8	3.6

When the demographic characteristics of the participants are examined, it is seen that 56% (n=126) are female and 44% (n=99) are male. When evaluated in terms of age distribution, 47.8% (n=108) of the students were in the 18-20 age range, 38.5% (n=87) were in the 21-23 age range, 9.3% (n=21) are in the 24-26 age range, and 3.6% (n=8) are 27 years old and over. These demographic data show that most sample (86.3%) is concentrated in the traditional university age group of 18-23.

Students from 16 different associate and undergraduate departments participated in the study. The fact that 55.2% of the participants were from the informatics field reflects the more widespread use of artificial intelligence tools in these disciplines. However, this study aimed to compare the attitudes and perceptions of students in various disciplines toward artificial intelligence tools. For this reason, the research did not solely focus on information technology students but included participants from diverse academic backgrounds. While information technology students are known to use these tools more frequently, including students from other disciplines, was critical for evaluating the impact of artificial intelligence tools on general education processes from a broader and interdisciplinary perspective.

When examining the distribution of students by department, the highest participation rate was observed in the Management Information Systems department (33.6%, n=76), followed by Computer Engineering (15%, n=34), Business Administration (11.9%, n=27), Public Relations and Promotion (10.2%, n=23), and International Trade and Business (6.2%, n=14). Departments such as Electrical and Electronics Engineering (4.4%, n=10), Political Science and International Relations (4%, n=9), and Software Engineering (3.5%, n=8) showed medium-level participation. Meanwhile, departments like Industrial Engineering (2.2%, n=5), Computer Technology and English Translation and Interpreting (1.8%, n=4), and Computer Programming (1.3%, n=3) had lower participation rates. Lastly, Radio, Television and Cinema, Mechanical Engineering, and American Culture and Literature had the least representation, each with 0.4% (n=1). This distribution highlights the strong participation from information technology and business-related fields, while also ensuring representation from various academic disciplines to achieve a comprehensive perspective.

Data Collection Tools

The questions asked the participants were prepared within the scope of the study as a result of the literature review. This consists of questions covering basic dimensions such as students' purposes and frequency of use of generative artificial intelligence tools, perceived benefits and difficulties, impact on academic processes, ethical concerns and security concerns. The survey form comprised sections that included demographic information and various dimensions regarding the use of generative artificial intelligence, in line with the purposes of the research. In terms of the ethical compliance of the research, an application was made to the Haliç University Social and Human Sciences Ethics Committee, and the ethics committee approval was obtained with the decision numbered (10) dated (25.12.2024). The voluntary participation of the participants was taken as a basis in the research process, and the confidentiality of their personal data was guaranteed.

Data Analysis

In order to ensure methodological transparency and to clearly demonstrate how each research question is addressed, the following table presents the alignment between the research objectives, corresponding data sources, and statistical techniques employed in the study. Table 2 shows the mapping of each research question to the relevant data and analysis techniques.

Table 2

Mapping of Research Questions to Data Sources and Analysis Methods

Research Question	Relevant Survey Items	Analysis Method
RQ1	Q12, Q14, and Q16:	Descriptive, Correlation
RQ2	Q17–Q20	Factor, Cluster
RQ3	Q8, Q9, and Q10:	Descriptive
RQ4	Q11, Q13	Correlation
RQ5	Q21–Q24	Factor, ANOVA
RQ6	Q25–Q27	Factor

The persuasiveness of the findings obtained in the study is directly related to validity and reliability. All questions asked to the participants were included in the validity and reliability analyses conducted within the scope of the study. Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity test were used to assess the suitability of the data set for factor analysis. The test results are shown in Table 3.

Table 3

KMO and Bartlett's Test

KMO and Bartlett's test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.713
Bartlett's test of sphericity Approx. Chi-Square		1497.971
	df	435
	Sig.	.000

The KMO value was found to be 0.713. This value is in the range of 0.70-0.79, it shows that the sample adequacy is at a "good" level. When the Bartlett sphericity test results were examined, the Chi-square value was found to be 1497.971 (p<.001). The significance of the Bartlett test (p<.001) shows that the relationships between the variables are suitable for factor analysis. According to these results, the data set met the necessary assumptions for factor analysis, and the analysis was continued. In the study, a grouping factor analysis was performed to examine the relationship between several variables measuring a certain phenomenon. The Total Variance Explained Table indicates how many factors the variables are grouped under. The results are shown in Table 4.

Table 4
Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings	
	Total	% Variance	Cumulative %	Total	% Variance
1	5.479	18.263	18.263	5.479	18.263
2	3.289	10.965	29.227	3.289	10.965
3	2.199	7.330	36.557	2.199	7.330
4	1.907	6.358	42.915	1.907	6.358
5	1.398	4.661	52.546	1.398	4.661
6	1.281	4.269	56.815	1.281	4.269
7	1.070	3.565	64.437	1.070	3.565
8	.962	3.205	67.643		
9	.925	3.083	70.725		
10	.917	3.057	73.783		
11	.806	2.687	76.470		
12	.779	2.596	79.067		
13	.687	2.290	81.357		
14	.617	2.058	83.415		
15	.599	1.996	85.410		
16	.552	1.841	87.251		
17	.508	1.692	88.943		
18	.461	1.538	90.482		
19	.422	1.408	91.890		
20	.394	1.313	93.203		
21	.342	1.139	94.342		
22	.323	1.077	95.419		
23	.287	.958	96.377		
24	.274	.914	97.291		
25	.258	.859	98.151		
26	.224	.746	98.896		
27	.180	.600	99.496		
28	.151	.504	100.000		
29					
30					

Because of the factor analysis, 7 factors with eigenvalues greater than 1. These factors explain 64.437% of the total variance. The first factor explains 18.263% of the total variance, the second factor explains 10.965%, and the third factor explains 7.330%. The contributions of other factors to the variance are 6.358%, 4.970%, 4.661%, 4.269%, 4.057%, and 3.565%, respectively.

Table 5 shows the Rotated Component Matrix indicating which question statement falls under each factor.

Table 5

Rotated Component Matrix

	Component								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Which grade are you studying?				.846					
How do you perceive the use of Large Language Models (LLM) and AI tools and their impact on academic integrity and the quality of education?					.475			-.565	
On average, how many hours do you spend studying or working on academic assignments per week?			.405						
Which device do you most frequently use for academic purposes?				-.404					
Have you used Generative AI tools previously?								.521	
Indicate the reasons for not using Generative AI tools.									.895
How often do you use generative AI tools?			-.715						
How familiar are you with generative AI tools?			.763						
Which generative AI tools do you most frequently use?						-.697			
In which of the following ways do you use LLMs or other Generative AI tools? [Problem-solving and brainstorming (e.g., generating ideas, finding solutions to specific challenges)]	.582					.463			
In which of the following ways do you use LLMs or other Generative AI tools? [Learning about AI (e.g., experimenting with AI tools to understand how they work)]	.815								
In which of the following ways do you use LLMs or other Generative AI tools? [Academic purposes (e.g., writing essays, generating study materials, summarizing texts)]	.471					.426	.425		
In which of the following ways do you use LLMs or other Generative AI tools? [Creative content creation (e.g., writing stories, creating art, generating music or poetry)]	.767								
In which of the following ways do you use LLMs or other Generative AI tools? [Programming and coding assistance (e.g., debugging code, generating scripts, learning programming languages)]			.531			.429			
In which of the following ways do you use LLMs or other Generative AI tools? [Data analysis and visualization (e.g., generating graphs, summarizing datasets, statistical analysis)]	.660								
In which of the following ways do you use LLMs or other Generative AI tools? [Language learning (e.g., improving grammar, practicing conversational skills, translating texts)]	.765								
In which of the following ways do you use LLMs or other Generative AI tools? [Professional tasks (e.g., writing emails, preparing reports, brainstorming ideas)]	.770								
In which of the following ways do you use LLMs or other Generative AI tools? [Personal use (e.g., exploring AI capabilities, entertainment, chatting with AI for fun)]	.713								
In which of the following ways do you use LLMs or other Generative AI tools? [Social media content (e.g., creating posts, captions, hashtags, or managing online presence)]	.730								

	Component								
	1	2	3	4	5	6	7	8	9
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [As a helpful tool]					.723				
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [As a double-edge sword]		.578			.413				
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [As a way to level the playing field]					.693				
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [As a means for students to cheat]		.773							
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [As an unfair advantage]		.768							
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [With concern for the human element]		.739							
How do students perceive the use of LLMs and AI tools and their impact on academic integrity and the quality of education? [With risk of misleading information]		.768							
Indicate the extent to which you agree or disagree with the following statements.								.621	

Because of the factor analysis, 7 factors were identified. The first factor includes 9 items covering different usage purposes of AI, and the factor loadings range from .471 to .815. The second factor includes 5 items covering ethical concerns regarding AI use, and the factor loadings range from .578 to .773. The third factor includes 3 items regarding AI usage competence, and the factor loadings range from .405 to .763. The fourth factor includes AI tool preference and academic use (factor loadings: .426-.697), and the fifth factor includes 2 items reflecting positive perceptions toward AI (factor loadings: .413-.723). The sixth and seventh factors include AI usage experience and reasons for not using it. Table 6 shows the themes of the factors and Cronbach's Alpha values to show whether any variable creates distrust of the factor.

Table 6

Themes of the Factors

Factor	Theme	Number of Items	Cronbach's Alpha
F1	AI Usage Purposes	9	.874
F2	Ethical Concerns	5	.821
F3	AI Usage Competence	3	.421
F4	AI Tool preferences	3	.691
F5	Positive AI Perception	2	.450
F6	AI Usage Experience	1	Reliability analysis is not performed for single-item factors.
F7	Reasons for not using AI	1	

Reliability analysis of the structure obtained because of factor analysis was performed. While F1 (α = .874) and F2 (α = .821) showed high reliability, F4 (α = .714) had acceptable reliability. The reliability coefficients of F3 were below the expected level. Because F6 and F7 were single-item factors, reliability analysis was not performed. The Cronbach's Alpha value was still lower than the critical value (.70) in case of deletion of questions that decreased reliability for F6 and F7 factors were removed from the analysis.

One-Sample Kolmogorov-Simirnov test was performed to determine whether the tests to be performed after this stage were parametric or nonparametric, and the results are shown in Table 7.

Table 7

Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
F1	.085	194	.002	.981	194	.009
F2	.083	194	.002	.982	194	.016
F4	.196	194	.000	.919	194	.000

According to the analysis results, both Kolmogorov-Smirnov (*p*=.002) and Shapiro-Wilk (*p*=.009) test results were found to be significant for the F1 (AI Usage Purposes) factor. Similarly, Kolmogorov-Smirnov (*p*=.002) and Shapiro-Wilk (*p*=.016) tests for the F2 (Ethical Concerns) factor gave significant results. Normality distribution was also examined for F6 (AI Usage Experience) and F7 (Reasons Not to Use AI), and all test results had p values less than .05 and the data did not conform to a normal distribution. For this reason, we decided to use nonparametric tests in further analyses.

Results

Spearman's correlation analysis was performed to determine the relationship between the variables, as shown in Table 8.

Table 8

Spearman's correlation analysis

		AI Usage Purposes	Ethical Concerns	AI Tool preferences	Age	Gender	Which department are you studying in?	On average, how many hours do you spend studying or working on academic assignments per week?
AI Usage Purposes	Correlation Coefficient	1.000	-.005	-.011	-.024	.072	-.125	.041
	Sig. (2-tailed)	.	.949	.873	.735	.301	.074	.562
	N	209	195	207	207	208	207	206
Ethical Concerns	Correlation Coefficient	-.005	1.000	.186**	.164*	-.101	-.177*	.164*
	Sig. (2-tailed)	.949	.	.008	.019	.150	.012	.020
	N	195	204	203	203	204	202	202
AI Tool preferences	Correlation Coefficient	-.011	.186**	1.000	.858**	-.090	-.573**	.130

		AI Usage Purposes	Ethical Concerns	AI Tool preferences	Age	Gender	Which department are you studying in?	On average, how many hours do you spend studying or working on academic assignments per week?
	Sig. (2-tailed)	.873	.008	.	.000	.182	.000	.055
	N	207	203	224	224	223	221	220
Age	Correlation Coefficient	-.024	.164*	.858**	1.000	-.157*	-.455**	.106
	Sig. (2-tailed)	.735	.019	.000	.	.019	.000	.116
	N	207	203	224	224	223	221	220
Gender	Correlation Coefficient	.072	-.101	-.090	-.157*	1.000	.104	-.133*
	Sig. (2-tailed)	.301	.150	.182	.019	.	.121	.048
	N	208	204	223	223	225	222	222
Which department are you studying in ?	Correlation Coefficient	-.125	-.177*	-.573**	-.455**	.104	1.000	-.018
	Sig. (2-tailed)	.074	.012	.000	.000	.121	.	.796
	N	207	202	221	221	222	223	220
On average, how many hours do you spend studying or working on academic assignments per week?	Correlation Coefficient	.041	.164*	.130	.106	-.133*	-.018	1.000
	Sig. (2-tailed)	.562	.020	.055	.116	.048	.796	.
	N	206	202	220	220	222	220	222

The analysis findings demonstrate significant relationships between various variables. When examining the relationships between students' ethical concerns and other variables, it was found that as ethical concerns increased, AI tool preferences also increased (r= .164, p<.05). Similarly, ethical concerns were found to increase with age (r= .164, p<.05) and weekly study hours (r= .164, p<.05). Additionally, ethical concerns varied significantly across different academic departments (r= -.177, p<.05). Regarding AI tool preferences, the most notable finding is the strong positive correlation with age (r= .858, p<.01), indicating that AI tool usage preferences significantly increase with age. Conversely, a strong negative correlation was observed between academic department and AI tool preferences (r= -.573, p<.01) suggests substantial variations in AI usage preferences across different academic disciplines. Analysis of demographic variables revealed a weak negative correlation between age and gender (r= -.157, p<.05) and a moderate negative correlation between age and academic department (r= -.455, p<.01). Furthermore, a weak negative correlation was identified between gender and weekly study hours (r= -.133, p<.05), indicating gender-based differences in study duration patterns.

Notably, the AI usage purposes variable showed no significant correlation with any other variables (p>.05), suggesting that AI usage purposes develop independently of other factors. These findings indicate that attitudes and behaviors toward AI usage are associated with various factors, including age, academic department, ethical concerns, and study habits. The strong influence of age and academic department variables on AI tool preferences suggests that these factors should be considered when developing strategies for AI technology integration into educational processes.

The factor and correlation analyses revealed the fundamental factors influencing students' attitudes and behaviors in AI usage while also uncovering the relationships between these factors. To gain a deeper understanding of these relationships and determine students' AI usage profiles, cluster analysis was performed. K-means cluster analysis using factor scores revealed three distinct student groups. The Elbow method and Silhouette score tests confirmed three clusters as the optimal number (Silhouette score = 0.421).

The relationships between age, gender, and ethical concerns identified in the correlation analysis showed similar patterns in the cluster analysis. For instance, the positive correlation between age and ethical concerns (r= .164, p<.05) aligns with the older age and high ethical concerns profile observed in Cluster 0. Similarly, the strong positive correlation between AI tool preferences and age (r= .858, p<.01) was reflected in the clustering results, particularly in Cluster 1, where younger students showed greater propensity for AI usage. These two analytical methods provided complementary findings, enabling a more comprehensive understanding of students' AI usage profiles. While factor and correlation analyses revealed relationships between variables, cluster analysis demonstrated how these relationships manifested across specific student groups.

Cluster Method

Factor scores were computed by adding Likert-scale values for each of the selected constructs: AI Usage Purposes, Ethical Concerns, AI Tool Preference, Demographic Characteristics, Gender, AI Usage Experience, and Reasons Not to Use AI. Standardization was performed using Z-score normalization to enable variable comparison. The optimal number of clusters was determined using both the Elbow Method and Silhouette Score. The Elbow Method indicated a significant decline in WCSS up to K=3, after which the rate of decrease flattened. The highest Silhouette Score (0.421) was also observed at K=3, confirming that this number provided the most distinct and well-separated clusters. The k-means algorithm with K=3 was used and resulted in the following characteristics for each cluster: Table 9 shows the statistical characteristics of the three identified clusters.

Table 9

Summary Statistics of Cluster Characteristics

Cluster	AI Usage Score	Ethical Concerns Score	AI Tool preferences	Predominant Demographic
0	−0.105	0.147	−0.519	Older, Female
1	0.031	−0.531	1.438	Younger, Balanced Genders
2	0.078	0.197	−0.421	Predominantly Male

Cluster 0: Moderate AI usage with high ethical concerns

Students in this group possessed the highest average AI utilization score (-0.105) but the highest ethical concerns (0.147), showing that such students, particularly among a bit older and female participants, are defensive toward AI use, most likely due to expected threats to academic honesty. Their AI tool preference was the lowest among clusters (-0.519) and is consistent with their cautious attitude.

Cluster 1: High AI Usage-Low Ethical Concerns

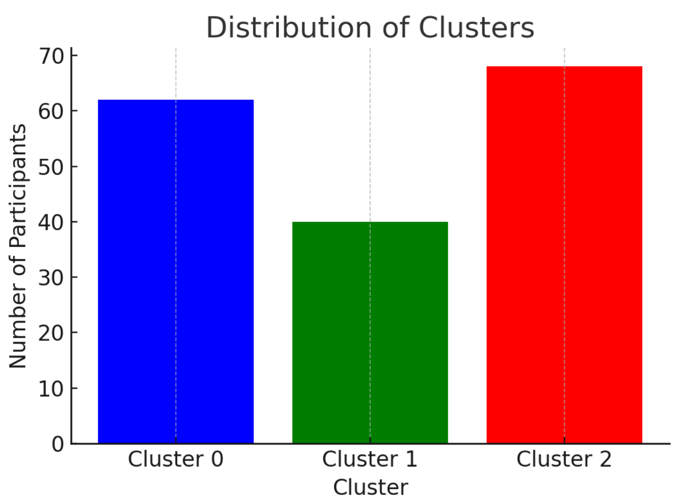
This cluster represents the student group with a moderate usage score of AI (0.031) coupled with greater ethical issues (-0.531) about the influence of AI on academic honesty. Indicating that these students are most enthusiastic about AI and view it as a useful tool, not an ethical matter. Their favor for AI tools was very high (1.438), which indicates frequent usage. Stronger possibility of female and more senior learners. This cluster has wary adoption of AI due to concerns about academic integrity.

Cluster 2: Low AI Usage-Moderate Ethical Concerns

This cluster had the lowest AI use score (0.078) and moderate ethical concerns (0.197), reflecting a less active but not necessarily anti-AI group. Their preference for AI tools (-0.421) is quite low, reflecting little reliance on AI-based tools, with a predominance of male participants. The students in this group represent the most engaged users of AI and have the lowest ethical concerns about using AI tools. They actively utilized AI for intellectual and professional purposes and were easier to use with AI technology. This cluster includes young students with an equivalent gender split. These results reflect diverse perspectives on AI adoption and ethical concerns among students.

Figure 1

Distribution of Clusters



The distribution of participants across the three clusters indicates varying trends in AI adoption (Figure 1). This suggests that although a large majority of students possess ethical concerns and conservative AI adoption (Cluster 0), an equally large majority are not engaged with AI (Cluster 2). The relatively high presence in Cluster 1 reflects the growing number of students actively employing AI tools with limited ethical issues. To understand these trends further, it is essential to examine them from a demographic perspective.

AI Usage Concerns and Preferences Across Demographic Levels

To further investigate whether there is a difference in design students' use of AI at the demographics level, statistical methods were applied to explore AI participation patterns and ethical concerns by groups of different demographics. The data were divided by gender and academic discipline, and one-way ANOVA and independent sample t-tests were conducted to compare means to establish differences. Findings indicated that female students had statistically higher ethical issues regarding AI application, particularly on the topic of misinformation and cheating (*p*<.05, Table 10). Male students, on the contrary, would be more likely to answer that insufficient knowledge or technical expertise prevented the implementation of AI. These tendencies suggest that AI literacy courses must be designed to address ethical concerns and skill deficits.

Table 10

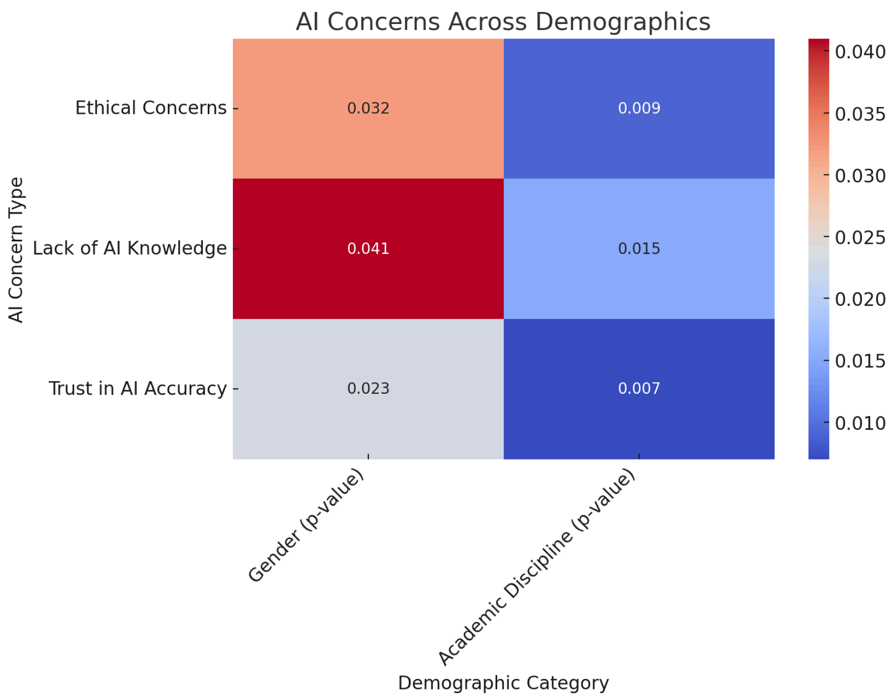
Statistical Significance of AI Concerns Across Demographics

Variable	Gender (*p*)	Academic Discipline (*p*)
Ethical Concerns	.032	.009
Lack of AI Knowledge	.041	.015
Trust in AI Accuracy	.023	.007

Academically, the findings revealed that non-technical students (e.g., social sciences and humanities) are more interested in the authenticity and ethical issues of AI-created content, and there are considerable differences found in their replies compared to STEM students (*p*<.01, Table 10). Technology and computer science students, however, showed extreme confidence in AI tools with few ethical issues. These variations highlight the importance of discipline-specific AI training to guarantee accountable and informed AI use across all areas of scholarship.

Figure 2

AI Concerns Across Demographics



The heatmap (Figure 2) illustrates the statistical significance of the variation in AI concerns by academic discipline and gender. The p-values for gender indicate significant variation in ethical concerns (*p*=.032), lack of AI knowledge (*p*=.041), and trust in AI accuracy (*p*=.023), suggesting that men and women perceive these concerns differently. Similarly, academic disciplines also show statistically significant differences in all AI issues, with the lowest p-value observed for AI trust in accuracy (*p*=.007), which describes participants from different fields having varying trust in AI systems. In total, these findings illustrate the influence of demographic variables on AI-related issues and highlight the need for tailored approaches to AI education and policy adoption.

Figure 3

AI Usage Preferences according to Demographics and Discipline

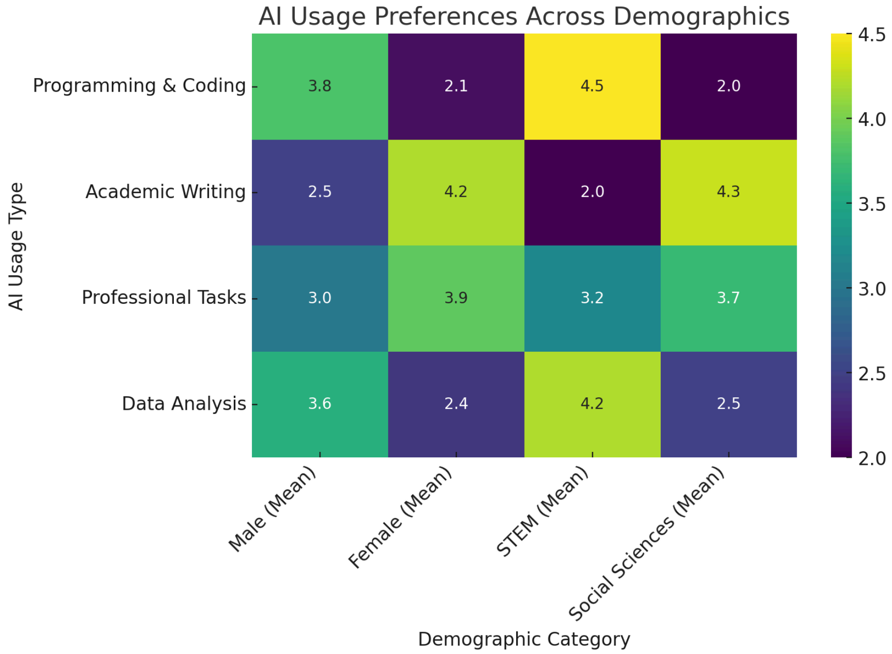


Figure 3 shows AI usage preference among different groups of demographics, including gender and stream of study (STEM and Social Sciences). These values are the mean scores for the four themes of AI usage: programming and coding, university-level writing, tasks at work, and data analysis. The results indicate clear demographic variations in AI preference. Men are more inclined toward AI in programming and coding (mean=3.8) and data analysis (mean=3.6) compared to women, who score much lower in these areas (mean=2.1 and 2.4). Women are more interested in AI for academic writing (mean=4.2) and professional work (mean=3.9) than men.

In academic discipline terms, STEM participants are most interested in using AI for programming and coding (mean=4.5) and data analysis (mean=4.2), whereas Social Sciences participants are most active in using academic writing (mean=4.3) but show lower interest in AI for technical work like programming (mean=2.0) and data analysis (mean=2.5). The results suggest that trends in AI use are shaped by gender as well as academic discipline, reflecting differences in requirements and comfort levels with AI according to discipline.

Discussion and Conclusion

This study provides comprehensive insights into university students' perceptions, attitudes, and usage patterns toward generative AI tools. In addition, it also reveals important findings that contribute to our understanding of AI integration in higher education.

Correlation analysis revealed high correlations between ethical concerns and the selection of AI tools, age, and other variables such as work habits. More precisely, the significant positive correlation between ethical awareness and preference for AI tools ($r=.164$, $p<.05$) implies that students with higher ethical awareness are more careful when applying AI tools. This finding is supported by Johnston et al.'s (2024) research that confirmed that students' attitudes toward AI tools are shaped primarily by their ethical concerns. The strong positive correlation between age and preferred AI tools (r=.858, *p*<.01) is one of the interesting results, i.e., older learners are more likely to use AI tools. This differs from some previous studies showing that young learners are more sensitive to technology, but it is similar to Chan and Hu's (2023) findings that demonstrate that adult learners learn more deliberately from AI tools. The cluster analysis demonstrated three distinct student profiles, which are quite valuable for revealing various student groups in relation to interacting with AI technology. High ethical problems and medium levels of AI usage appeared together in Cluster 0 as a vigilant pattern, while Cluster 1 indicates an open personality represented by high use and low levels of ethical concerns. The outcome aligns with the work by Song and Wang (2024), where equal diverging student uses of AI were revealed.

Demographic differences in patterns of AI usage showed that female students had more ethical concerns, in particular, misinformation and academic dishonesty. This finding contributes to the growing body of evidence on gender differences in technology uptake and suggests critical implications for designing inclusive AI learning strategies.

The differences among disciplines, where STEM students showed more technical inclination and fewer ethical concerns than non-STEM students, suggest the need for discipline-based approaches to AI integration in education. This aligns with Montenegro-Rueda et al.'s (2023) research on the differential impacts of AI by academic discipline.

This study provides significant information about the complex adoption of generative AI in tertiary education. The findings revealed that students' use of AI tools was influenced by several factors, such as age, gender, study field, and ethical considerations. The classification of different user profiles using cluster analysis provides a foundation for different AI adoption strategies among students.

The results of this study are as follows:

- The relationship between ethical concerns and AI use is more complex than previously described. However, despite this complexity, high ethical awareness does not reduce the use of AI.
- Although existing literature generally suggests that younger students are more prone to using artificial intelligence, our findings demonstrate that older students exhibit higher levels of AI tool adaptation.
- Significant disciplinary and gender differences in AI adoption patterns suggest the need for customized approaches to AI integration in education.
- The emergence of different user profiles suggests that a single AI policy approach to education may be ineffective.

These findings have important implications for education policy and practice. Accordingly, institutions should:

- Develop discipline-specific guidelines for AI integration.
- Address ethical concerns while promoting responsible AI use.
- Consider demographic factors when designing AI policies.
- Provide targeted support to different student groups based on their usage patterns and concerns.

While this study focuses on students' present involvement with Generative AI, these opinions must be interpreted within the history of AI advances as a whole. The shift from symbolic systems of reasoning to statistical and neural ones over the last few decades has, in essence, changed what is possible with AI. Today's GenAI technologies, such as ChatGPT, are the end point of a lengthy development beginning in theoretical abstractions and evolving into productive, generative systems through cumulative innovation. Understanding this history not only serves to contextualize the educational relevance of GenAI today but also highlights the importance of historical awareness in shaping future AI policy and pedagogy. Future research should examine longitudinal changes in student attitudes toward AI, investigate the effectiveness of various AI integration strategies across disciplines, and examine how ethical frameworks can be developed to guide AI use in academic settings.

The limitations of this study include its cross-sectional nature and its focus on a specific geographic context. The findings also provide valuable insights for educators, administrators, and policymakers seeking to integrate AI technologies into higher education while maintaining academic integrity and promoting effective learning outcomes.

Ethical approval	Ethics committee approval for this research was obtained from the Haliç University Social and Human Sciences Research Ethics Committee (Date: 25.12.2024, No: 10).
Informed Consent	Written informed consent was obtained from all participants who participated in this study.
Peer Review	Externally peer-reviewed.
Author Contributions	Conception/Design of Study- G.K.A., A.B.; Data Acquisition- G.K.A., A.B.; Data Analysis/Interpretation- G.K.A., A.B.; Drafting Manuscript- G.K.A., A.B.; Critical Revision of Manuscript- G.K.A., A.B.; Final Approval and Accountability- G.K.A., A.B.
Conflict of Interest	The authors have no conflict of interest to declare.
Grant Support	The authors declared that this study has received no financial support.

Author Details

Gökçe Karahan Adalı

[1] Haliç University, Faculty of Business Administration, Management Information Systems, İstanbul, Türkiye

0000-0001-8567-4626 gokceadali@halic.edu.tr

Asiye Bilgili

[2] İstanbul Beykent University, Faculty of Engineering and Architecture, Department of Computer Engineering, İstanbul, Türkiye

0000-0002-9776-5119

References

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of the empirical research on ChatGPT in education. *Discover Education*, https://doi.org/10.1007/s44217-024-00138-2

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

Chakraborty, D., Kar, A. K., Patre, S., & Gupta, S. (2024). Enhance online grocery shopping trust through generative AI chatbots. *Journal of Business Research*, https://doi.org/10.1016/j.jbusres.2024.114737

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1), doi:10.1186/s41239-023-00411-8

Chaudhry, S., & Kazim, H. (2024). AI-driven learning: Enhancing student engagement and critical thinking. *Journal of Educational Technology*, *35*(2), 98-112. https://doi.org/10.1016/j.jet.2024.02.005

Clark, T., Johnson, R., & Wang, M. (2024). Generative AI in learning environments: A framework for ethical use. *Computers and Education*, *180*, 104432. https://doi.org/10.1016/j.compedu.2024.104432

Eysenbach, G. (2023). The Role of ChatGPT, Generative Language Models, and Artificial Intelligence in Medical Education: A Conversation With ChatGPT and a Call for Papers. *JMIR Medical Education*, *9*(1), e46885. https://doi.org/10.2196/46885

Fisher, R., & Haake, J. (2024). The ethics of AI integration in higher education: Emerging trends and concerns. *AI & Society*, *39*(3), 567-580. https://doi.org/10.1007/s00146-023-01567-9

Henke, J. (2025). New normal: The increasing adoption of generative AI in university communication departments. *Journal of Science Communication*, *24*(2), A07. https://doi.org/10.22323/2.24020207

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

Johnston, B., Strachan, R., & Mangat, M. (2024). Student perspectives on the use of generative artificial intelligence technologies in higher education. *International Journal for Educational Integrity*, *20*(1), Article 149, doi:10.1007/s40979-024-00149-4

Khlaif, Z. N., Ayyoub, A., Hamamra, B., Bensalem, E., Mitwally, M. A. A., Hattab, M. K., & Shadid, F. (2024). University teachers' views on the adoption and integration of generative AI tools for student assessment in higher education. *Education Sciences*, *14*(10), 1090. https://doi.org/10.3390/educsci14101090

Kirk, C. P., & Givi, J. (2025). The AI-authorship effect: Understanding authenticity, moral disgust, and consumer responses to AI-generated marketing communications. *Journal of Business Research*, https://doi.org/10.1016/j.jbusres.2024.114984

Kumar, A., Shankar, A., Hollebeek, L. D., Behl, A., & Lim, W. M. (2025). Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption. *Journal of Business Research*, https://doi.org/10.1016/j.jbusres.2024.115160

Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and Opportunities of Generative AI in Higher Education as Explained by ChatGPT. *Education Sciences*, *13*(9), 856. https://doi.org/10.3390/educsci13090856

Moorhouse, B. L., Kohnke, L., & Zou, D. (2023). ChatGPT in education: Opportunities, challenges, and future directions. *Educational Technology Research and Development*, *71*(1), 85-99. https://doi.org/10.1007/s11423-023-10109-8

Montenegro-Rueda, M., Fernández-Cerero, J., Fernández-Batanero, J. M., & López-Meneses, E. (2023). Impact of the Implementation of ChatGPT in Education: A Systematic Review. *Computers*, *182*, 104463. https://doi.org/10.1016/j.compedu.2023.104463

Ogunleye, B., Zakariyyah, K. I., Ajao, O., Olayinka, O., & Sharma, H. (2024). A Systematic Review of Generative AI for Teaching and Learning Practice. *Education Sciences*, *14*(6), 636. https://doi.org/10.3390/educsci14060636

Ravšelj, D., Keržič, D., Tomaževič, N., Umek, L., & Brezovar, N. (2025). Higher education students' perceptions of ChatGPT: A global study of early reactions. *PLOS ONE*, *20*(3), e0267890. https://doi.org/10.1371/journal.pone.0267890

Rosenblatt, F. (1958). The Perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, *65*(6), 386–408. https://doi.org/10.1037/h0042519

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, *323*(6088), 533–536. https://doi.org/10.1038/323533a0

Russell, S., & Norvig, P. (2021). Artificial intelligence: A Modern Approach* (4th ed.). Pearson.

Saaida, M. B. (2023). AI-Driven transformations in higher education: Opportunities and challenges. *International Journal of Educational Research and Studies*, 29-36, DOI 10.5281/zenodo.8164414

Sandu, R., Gide, E., & Elkhodr, M. (2024). The role and impact of ChatGPT in educational practices: insights from an Australian higher education case study. *Discover Education*, *2*(1), 14. https://doi.org/10.1007/s44217-024-00014-7

Sergeeva, O. V., M. R. Zheltukhina, T. Shoustikova, L. R. Tukhvatullina, D. A. Dobrokhotov, & S. V. Kondrashev. (2025). Understanding higher education students' adoption of generative AI technologies: An empirical investigation using UTAUT2. *Contemporary Educational Technology*, *17*(2), ep. 571. https://doi.org/10.30935/cedtech/16039

Shoufan, A. (2023). Students' perception of AI-generated content: A critical review. *International Journal of Educational Technology in Higher Education*, *20*(1), 12. https://doi.org/10.1186/s41239-023-00358-9

Song, Y., & Wang, M. (2024). A Survey and Research on the Use of Artificial Intelligence by Chinese Design- College Students. *Buildings*, *62*(3), 567–589, doi:10.3390/buildings14092957

Sun, H., & Li, P. (2024). AI, academic integrity, and pedagogical shifts: The new landscape of higher education. *Journal of Applied Learning and Teaching*, *5*(3), 45-60. https://doi.org/10.37074/jalt.2024.5.3.9

Turing, A. M. (1950). Computing machinery and intelligence. *Mind*, *59*(236), 433–460. https://doi.org/10.1093/mind/LIX.236.433

Xames, M. D., & Shefa, J. (2023). ChatGPT for research and publication: Opportunities and challenges. *Journal of Applied Learning and Teaching*, 390-395, 4(2), 123-134. https://doi.org/10.37074/jalt.2023.4.2.7

Zhai, X. (2023). Exploring the role of AI in personalized learning: A systematic review. *International Journal of Artificial Intelligence in Education*, *33*(1), 1-27. https://doi.org/10.1007/s40593-023-00291-4