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Generative Artificial Intelligence in Higher Education: Analysing the Impact of Perceived Ease of Use and Usefulness on AI Technology Adoption Among University Students in Azerbaijan

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STATEMENT OF AUTHENTICITY

I have read ADA's policy on plagiarism and certify that, to the best of my knowledge, the content of this thesis, entitled (The Awareness and Use of Artificial Intelligence: Exploring Perspectives of University Students in Azerbaijan), is all my work and does not contain any unacknowledged work.

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ABSTRACT

This study investigated the use of Generative Artificial Intelligence tools by university students in Azerbaijan through the lens of the Technology Acceptance Model. The research explored student perceptions of ease of use and usefulness of Generative artificial intelligence tools, their influence on actual usage, and student perspectives on the future role of artificial intelligence in education.

The findings revealed positive correlations between perceived ease of use, perceived use, and actual uses. Regression analysis confirmed that both perceive ease of use and perceived use significantly predict students' actual use of Generative AI tools. The data obtained on student motivations for using artificial intelligence tools identified information access, comprehension, study efficiency, and assessment preparation as key factors. Notably, a significant portion of students reported using artificial intelligence for critical thinking tasks at least occasionally.

These findings support Technology Acceptance Model and suggest that user-friendly and valuable artificial intelligence tools can be effectively integrated into educational settings. The study highlights the potential of artificial intelligence to enhance learning experiences and student outcomes. Based on these findings, the research recommends strategies for universities to promote responsible artificial intelligence integration in curricula, assessment practices, and ethical considerations.

Keywords: Generative AI, Technology Acceptance Model, Higher Education, Student Perceptions, Learning Outcomes

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Chapter 1: Introduction

Education, as a cornerstone of human development and societal progress, has been constantly evolving to meet the demands of a changing world. Recently, there has been a lot of interest in the use of chatbots and Artificial Intelligence (AI) systems in academia. AI technologies have the potential to change research and education, by automating time-consuming and repetitive operations, supporting data analysis, and opening new possibilities for learning and assessment (Chen et al., 2020). The implementation of AI-based learning in Azerbaijani institutions is still in its early stages, despite the country's significant efforts toward achieving its national development goals and its prioritization of the application of AI in several sectors, including education (Aliyev et al., 2021). For instance, a recent study highlighted the use of AI-powered chatbots on government portals to summarize progress reports and provide citizens with insights into program effectiveness (Gasimli & Mehraliyeva, 2023). Although positive strides have been made, such as the use of AI-powered chatbots for summarizing government program reports, challenges persist regarding ethical considerations, social interaction, and staff preparedness (Chatterjee & Sreenivasulu, 2019). To bridge this gap and optimize AI integration within Azerbaijani universities, a deeper understanding of university students' awareness and utilization of Generative AI is crucial.

Background Information

The implementation of AI in education has evolved significantly over the years, transforming the way teaching and learning is conducted. Initially, AI was introduced to education in the form of computer-assisted instruction (CAI) in the 1960s (Crompton & Song, 2021). These early systems were very simple, giving learners drill-and-practice activities. As technology developed, AI in education advanced to become intelligent tutoring systems that could adjust to the demands of each individual student (Anderson &

Evans, 1995). In recent years, AI in education has entered a new era, with the development of powerful machine learning and natural language processing. Personalized material and recommendations are generated by adaptive learning platforms, such as Knewton, by utilizing AI to evaluate student performance data (Liu, 2019).

For instance, AI-powered chatbots are also being used to assist students with inquiries, such as Georgia State University's "Pounce" chatbot, which provides information and support 24/7 (Goel, 2020). This enables them to offer personalized learning pathways and interventions. A group of Stanford University academics created the open-source AI project Alpaca, which can comprehend and carry out activities in accordance with user instructions (Stanford CRFM, 2023). Alpaca is a convincing ChatGPT substitute since it is more affordable to imitate and displays behaviour similar to text-davinci-003 on the self-instruct evaluation set. Additionally, AI in education offers personalized learning online courses to each student based on their learning profile, such as Course Era and edX (Hwang et al., 2020). AI-driven grading and assessment tools have streamlined the evaluation process for educators, in platforms such as but not limited to Gradescope, which is also true for some Azerbaijani universities that utilize tools such as Turn-it-in to check plagiarism when assessing students (Holmes et al., 2018).

According to UNESCO (2023), the Ministry of Science and Education of Azerbaijan has implemented AI and Cyber Security to increase the experience of specialists in this field. Additionally, during the Covid era, several e-learning portals such as Microsoft Teams, Blackboard, and Google Classroom with artificial intelligence embedded in them were adopted to support the e-learning environment and are still in use (Nuraliev et al., 2022).

Research Problem Statement

In Azerbaijan, many universities are using new technology with AI to help students learn. We don't fully understand why some students use this technology more than others. This research will look at how easy students think the technology is to use, and how helpful they think it is ‘perceived ease of use’, and ‘perceived usefulness ‘respectively. By understanding these factors, we can improve how AI technology is used in universities in Azerbaijan.

The research problem is analyzing the impact of perceived ease of use and usefulness of generative AI on technology adoption among university students.

The research aims to fill this gap by empirically investigating these relationships using inferential statistics and regression analysis, thereby providing insights into how these factors collectively shape students' engagement with AI in their education.

Research Objectives

1. To analyses theoretically the perceived ease of use and usefulness of AI technologies in education among university students in Azerbaijan.
2. To analyses the relationship between Technology Acceptance Model (TAM factors) with the actual usage of AI technologies by university students in Azerbaijan.

These objectives aim to shed light on the underlying factors that influence university students' decisions to adopt and utilize AI technologies in their education. By understanding these determinants, we can develop strategies to promote effective integration of AI tools within Azerbaijani universities, ultimately enhancing the learning experience for students.

Research Questions

1. How do perceived ease of use and perceived usefulness (TAM factors) influence the actual usage of AI technologies among university students in Azerbaijan?
2. How do university students in Azerbaijan perceive the usefulness (PU) of Generative AI in their education
3. What are the patterns and trends in AI technology adoption among university students in Azerbaijan when analysed through the lenses of TAM.

Significance

The significance of this study lies in its potential to enhance understanding of AI technology adoption in education. By analysing the roles of perceived ease of use and perceived usefulness the research can provide valuable insights for educators, policy makers, and technology developers in Azerbaijan. This could lead to more effective implementation of AI in educational settings, improving learning experiences and outcomes for students. Additionally, this study contributes to the broader field of educational technology by offering a context-specific understanding of AI adoption in a rapidly evolving technological landscape.

The novelty of this research lies in its in-depth analysis of AI technology use among Azerbaijani university students, a largely unexplored area. It innovatively integrates the Technology Acceptance Model, offering fresh perspectives on how student perceptions impact AI utilization in educational settings.

Chapter 2: Literature Review

The existing literature reviewed focused on the current state of Generative AI in education globally and within Azerbaijan. This literature review is divided into sections exploring the application of AI in education, focusing on student perspectives and factors influencing their acceptance of AI tools and delves into the Technology Acceptance Model as key theoretical framework for understanding student adoption of AI technologies. It examines existing research on student attitudes towards AI in education, highlighting both the perceived benefits and challenges.

2.1. Generative AI in Education

AI can be broadly classified into two types which are narrow AI and general AI. Narrow AI refers to the ability of machines or systems to perform specific tasks that require human intelligence, such as speech recognition, image recognition, and natural language processing (Kuusi & Heinonen, 2022). General AI can be defined as the ability of machines or systems to perform tasks that normally require human intelligence, such as reasoning, learning, decision making, and problem solving (Russell & Norvig, 2010). While general AI is still a hypothetical concept, narrow AI has been widely applied and developed in various domains, including education this includes generative AI, such as ChatGPT. Lim et al., (2023) define generative AI as a deep learning technique that creates text, images, and audio content based on a user's regular linguistic patterns and thought processes.

Generative AI is being applied in education to enhance teaching and learning processes, by providing personalized feedback, adaptive instruction, intelligent tutoring, and automated assessment (Luckin & Holmes, 2016). Chan & Hu (2023) investigated student perceptions of generative AI in higher education. Their findings suggest that students recognize the potential of generative AI to personalize learning experiences, which in turn, could enhance student motivation and engagement. However, the adoption and integration of Generative AI in education is not a straightforward or simple process. It depends on various factors, such as the availability and accessibility of AI technologies, the quality and usability of AI applications, the attitudes and perceptions of educators and learners, and the social and cultural contexts of education (Xu et al., 2021). Therefore, it is important to understand how and why different stakeholders, especially students, accept and use AI in their education.

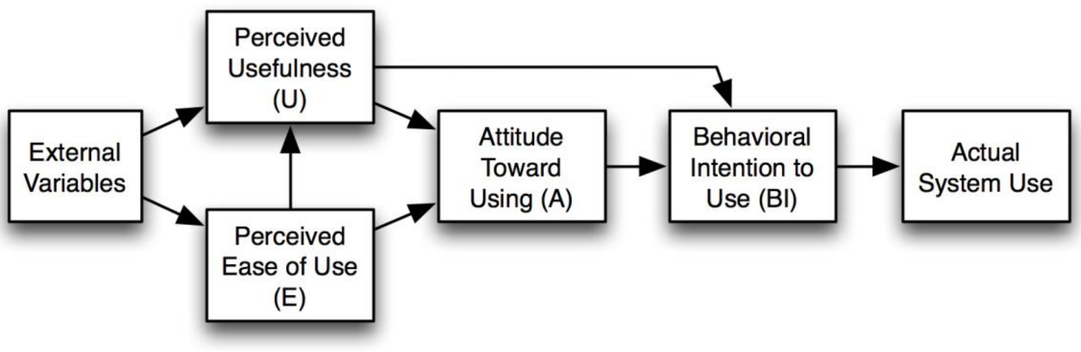
2.2. Theoretical background and hypotheses development

2.2.1. Technology Acceptance Model Theory

One of the most widely used theoretical frameworks for studying technology acceptance and usage is the Technology Acceptance Model (TAM) (Davis,1989). TAM's primary goal is investigating the elements influencing users' acceptance of the product development model in the context of the organizational environment. The TAM model has developed into a reliable tool for predicting the acceptance of various technologies (AL-Emran et al., 2018). The revised TAM model is shown in Figure 1.

Figure 1

Technology Acceptancy Model (TAM)



Source: Davis (1989)

TAM proposes that the actual usage of a technology is determined by the behavioural intention to use it, which in turn is influenced by two key beliefs: ‘perceived usefulness’ and ‘perceived ease of use’. ‘Perceived usefulness’ refers to the degree to which a user believes that using a technology will enhance his or her performance or outcomes, while ‘perceived ease of use’ refers to the degree to which a user believes that using a technology will be free of effort or difficulty (Davis, 1989). When individuals feel that a technology will be beneficial to them, they are more likely to accept it. On the other hand, individuals are likely to have negative intentions about using technology if they believe it to be of little use (Kao & Huang, 2023). Several study themes have been put out in earlier studies on technology acceptance to identify the factors that influence people's acceptance of new technology. Empirical studies applying the TAM to Generative AI in higher education have investigated various aspects of technology acceptance. For example, research has explored the acceptance of AI in semi-structured decision-making situations, such as evaluating undergraduate dissertations, and found that while technology acceptance is adaptive, it requires modifications in AI's transparency to be accepted (Greiner et al., 2023). Another study focused on the transformative impact of Generative AI on higher education, highlighting the complexities in decision and policy making where staff and students exhibit a wide spectrum of views on the use of GenAI (Malik et al., 2023).

Despite being developed in the USA; TAM has been applied and assessed in a variety of situations and empirical research. The TAM has been extensively utilized to examine human-robot and/or human-AI interactions since it is intended to examine people's psychological systems regarding new technology (Del Giudice, 2023). Additionally, it has been widely applied and extended to various contexts and technologies, including AI in education (Sánchez-Prieto et al., 2020). According to research by Rafique et al. (2020), perceived usefulness and perceived ease of use were direct and significant determinants of the intention to use mobile library applications. The study looked at the acceptability of mobile library applications with an extended TAM. Perceived usefulness in this study refers to the belief that generative AI will improve students' academic achievement or make their work easier, demonstrating the tool's usefulness as a study tool. Perceived ease of use reflects the idea that generative AI is simple to use and interact with, which encourages adoption.

However, TAM alone may not be sufficient to capture the complexity and diversity of technology acceptance and usage behaviour, especially in the context of AI, which involves not only cognitive but also affective and social aspects of human-machine interaction (Hong, 2022). Therefore, it is necessary to incorporate other factors or constructs that may moderate or mediate the relationships between TAM variables and technology usage.

2.2.2 Applications of TAM in Educational Settings

In the context of educational technology, TAM has been extensively applied to explore student acceptance of various digital learning tools and platforms. Rafique et al., (2020) investigated the acceptance of mobile library applications among university students using an extended TAM model. The study found that perceived usefulness and perceived ease of use were direct and significant determinants of the intention to use mobile library applications. Perceived usefulness in this context referred to the students' belief that the app would enhance their academic performance or make learning tasks easier. This study extended TAM to include factors such as subjective norms and perceived enjoyment, which were also found to influence technology acceptance.

In the context of online learning, another study applied TAM to understand the acceptance of mobile technologies for learning among university students (Huang et al., 2020). The study highlighted that perceived ease of use had a stronger effect on behavioural intention to use mobile learning technologies compared to perceived usefulness. This indicates that when it comes to learning technologies, ease of use may be a more critical factor for students.

In addition, Lim et al., (2023) examined the adoption of e-learning systems in higher education using TAM. Their research extended the model by integrating trust and perceived risk, demonstrating that these additional factors significantly impact students' acceptance of e-learning systems. The findings suggested that increasing students' trust in e-learning systems and reducing perceived risks could enhance their acceptance and use of these technologies.

In the context of AI technologies specifically, a study by Al-Abdullatif, (2023) explored the acceptance of AI-based Chatbots among university students. The study extended TAM by including factors such as perceived privacy risk and perceived ethicality. The results indicated that while perceived usefulness and perceived ease of use remained significant predictors of technology acceptance, perceived privacy risk negatively affected students' intentions to use AI-based tools, highlighting the importance of addressing privacy concerns in AI adoption.

These studies underscore the versatility of TAM in understanding the factors that drive technology adoption in educational settings. Emphasizing the need to consider additional factors that may influence technology acceptance, particularly in the context of emerging technologies like AI. By understanding these dynamics, educators and policymakers can better facilitate the adoption of AI technologies in education, enhancing learning experiences and outcomes for students.

2.3 Students’ perspectives on AI in higher education

A quantitative study on Students’ Attitude Towards the Use of Artificial Intelligence and Machine Learning to Measure Classroom Engagement Activities was carried out, according to (Kairu, 2020) the study on 385 students shows that 39.06% agreed that AI would have a positive impact on education, and 49.48% agreed that it would influence learning. Students also recognized AI’s potential to track student progress (35.79%), enhance teacher-student interactions (47.78%), and measure classroom engagement (55.21%). The impact of

AI is increasingly felt in the education sector, where it serves as an auxiliary tool to enhance the teaching and learning process. Alamri & Alamiah (2021) research showed that students' tendency to accept artificial intelligence is positively influenced by perceived ease of use. This is because technology that is easy to use enhances students' perception of its effectiveness, which in turn influences their adoption of artificial intelligence. Perceived ease of use has a major influence on students' adoption of artificial intelligence technology, according to another study that revealed students felt more satisfied and productive when using applications that are easy to use (Joo et al., 2017). Despite the increasing interest in artificial intelligence and its potential applications in various aspects of society, including education, there is limited research specifically focused on the awareness and use of artificial intelligence among university students in Azerbaijan. Therefore, this literature review aims to fill this gap by exploring the perspectives of university students in Azerbaijan regarding artificial intelligence.

2.4 Challenges and Opportunities of Using AI

AI is used in education in different ways. For instance, AI is integrated into several instructional technologies such as chatbots, intelligent tutoring, and automated grading systems (Clark, 2020). These AI-based systems offer several opportunities to all stakeholders throughout the learning and instructional process (Chen et al., 2020). Previous research conducted on the educational use of AI presented AI’s support for student collaboration and personalization of learning experiences (Luckin et al., 2016), scheduling of learning activities and adaptive feedback on learning processes (Koedinger et al., 2012), reducing teachers’ workload in collaborative knowledge construction (Roll & Wylie, 2016), predicting the probability of learners dropping out of school or being admitted into school profiling students’ backgrounds, monitoring student progress and summative assessment such as automated essay scoring (Maloca et al., 2019). Though, use of artificial intelligence brings a lot of opportunities in the long run, a noteworthy challenge to the successful adoption of AI in higher education is staff and faculty preparedness (Owoc, et al., 2019). Studies have demonstrated that staff and faculty need professional development opportunities and strong support networks for successful integration (Indrawati & Kuncoro, 2021). Additionally, social connection and a feeling of community might be at risk as it necessary for the process of learning in a higher education (Pisica et al., 2023). AI is unable to perceive the entire range of emotions that impact students' behaviour and their motivation to accomplish goals which might affect the capabilities of students in their academic achievement. There are also ethical concerns pertaining to data privacy and security in the context of AI-driven transformations in higher education (Chatterjee & Sreenivasulu, 2019). Concerns about students being motivated to cheat are common because of increasing number of accurate software and chatbots (ChatGPT) that can generate assignments that are necessary for their academic success and hence, this temptation presents ethical challenges (Pisica et al., 2023).

2.5 Limitations

The literature review has presented and discussed the definition and scope of AI and its applications in education, the benefits, and challenges of AI technologies in education, the theoretical background of TAM and its extensions and applications in education and AI, and the empirical studies on the factors influencing the acceptance and use of AI technologies in education, especially among university students. The literature review has shown that AI technologies have great potential and promise for enhancing and transforming education, and that TAM ais useful and relevant constructs for understanding and predicting the acceptance and use of AI technologies by the educators and learners. However, the literature review has shown that there are few empirical studies that have investigated the acceptance and use of AI technologies in education, especially among university students in Azerbaijan, and that most of the studies are based on surveys and self-reported data, which may not reflect the actual behaviour and outcomes of using AI technologies. Therefore, there is a need for more empirical studies that use different methods and data sources to provide more evidence and insights on the acceptance and use of AI technologies in education, especially among university students in Azerbaijan. Additionally, the literature review has shown that most of the studies that have investigated the acceptance and use of AI technologies in education, especially among university students, are conducted in specific contexts and cultures, such as Singapore, Saudi Arabia, and China, which may not be representative or generalizable to Azerbaijan. Therefore, there is a need for more studies that explore the acceptance and use of AI technologies in education, especially among university students, in Azerbaijan, which is the focus of this research, and compare the findings and implications across different contexts and cultures.

Chapter 3: Research Methodology

The research methodology, including of questionnaire development, data gathering, and hypothesis development, is covered in this chapter. Skewness and Kurtosis analysis, scale reliability statistics, and the limitations of quantitative data collected are all included in the reliability of the empirical research findings.

To reach the target audience, a quantitative approach with the use of regression analysis was conducted for this research, as it aimed to measure and test the factors influencing the acceptance and use of AI technologies by university students in Azerbaijan, using statistical analysis of the collected numerical data. Regression analysis which is a type of statistical technique that allows the researcher to examine the relationship between one or more independent variables (such as ‘perceived usefulness, perceived ease of use’), and a dependent variable (such as ‘actual usage of AI technologies’), and to estimate the magnitude and direction of the effects of the independent variables on the dependent variable (Knight, 2018). The research focused on four constructs which are Perceived Ease Of Use (PEOU), Perceived Usefulness (PU), Attitude towards Generative AI, Behavioural intention towards Generative AI, and Actual use (AU) of Generative AI with the goal of analysing the Generative AI technology use among Azerbaijani university students. In other words, the purpose of this research was to determine whether there is a statistically significant difference these constructs. The research hypothesis is described below in Table 1.

3.1 Development of hypothesis

Table 1

Development of hypothesis

H1: There is a significant relationship between the Perceived Ease of Use of generative AI tools and their Perceived Usefulness in higher education. *This hypothesis tests whether users who find generative AI tools easy to use in an educational context also perceive them as useful for their study.*
H2: There is a significant relationship between the Perceived Usefulness of generative AI tools in higher education and the Actual Use of these tools. *This tests the idea that if students perceive generative AI tools as useful for their educational needs, they are more likely to use them in their academic activities.*
H3: There is a significant relationship between the Perceived Ease of Use of generative AI tools in higher education and the Actual Use of these tools. *This hypothesis explores whether the ease of using generative AI tools directly influences their actual usage in the academic setting.*

The first hypothesis (H1) examined the relationship between PEOU and PU of generative AI tools in higher education. According to TAM, users are more likely to perceive a technology as useful if they find it easy to learn and navigate (Davis, 1989). In this context, this hypothesis suggests that if students find Generative AI tools easy to use, they are more likely to view them as valuable for their studies. The second hypothesis (H2) focused on the connection between PU and actual use of generative AI tools. TAM theorizes that a positive perception of a technology's usefulness increases a user's intention to adopt it (Davis, 1989). Here the hypothesis is that if students find these tools beneficial for their learning, they are more likely to integrate them into their academic activities. The third hypothesis (H3) explored the relationship between PEOU and AU of generative AI tools. While TAM emphasizes the indirect influence of PEOU on behavioural intention through PU (Davis, 1989), this hypothesis delves deeper to see if PEOU has a direct effect on students' actual use of Generative AI tools. The research was interested in whether students who find these tools easy to use are more likely to use them in their studies, regardless of their perceived usefulness.

It is obvious that the relationship between PEOU and PU, as well as PU and AU of technologies, has been established in various TAM-based studies (Davis, 1989; Lee et al., 2006). However, the specific context of Generative AI in higher education presents a unique opportunity to explore these relationships within the under-researched educational landscape of Azerbaijan. While TAM's core principles are likely generalizable, the specific features and functionalities of Generative AI tools may influence student perceptions in unforeseen ways. Furthermore, the cultural and educational environment in Azerbaijan might have a distinct impact on how students perceive and adopt these technologies compared to findings from studies conducted elsewhere. Therefore, investigating the relationships between PEOU, PU, and AU of GAI tools specifically among Azerbaijani university students is crucial.

3.2 Data Collection and Questionnaire Design

The data collection in this study was collected through a questionnaire. Questionnaires are a common research method due to their effectiveness in gathering data from a large number of respondents (Bachman & Schutt, 2015). This is a type of research design that involved collecting data from a sample of subjects which were ADA university students in this case, using a survey to obtain information about their characteristics, opinions, attitudes, behaviours, or experiences (Strunk & Mwavita, 2020). The survey design was chosen, as it allows a researcher to collect data from the sample of students using to measure their ‘perceived usefulness’, ‘perceived ease of use’, and ‘actual usage of AI technologies’, as well as their gender, age, experience, and voluntariness. The questionnaire was administered online, using google forms which allowed the researcher to create, distribute, and analyse the questionnaire. About 13 different groups of classes were visited at ADA university to allow efficiency in the collection of data.

The survey was divided into 2 sections, the first section focused on the respondents' demographic information (Appendix A), while the remaining section was based on a hypothesis related to a specific type of factor of TAM. The respondents were given a brief introduction to the outlined survey goal before responding to the questions in the google survey form which were distributed to available instructors and the reason for conducting a survey. The questionnaire consisted of multiple-choice and Likert-scale questions that measured the variables of interest, based on the existing instruments that have been validated and used in previous studies, such as the Technology Acceptance Model (TAM) questionnaire by Davis (1989). The survey was brief and straightforward, taking about 10 minutes to complete. The Likert scale questions aimed to make the survey simple to understand and complete while also collecting accurate and useful data. The researcher employed a 5-point Likert scale to analyse the participants', with a value from 1 (strongly disagree) until 5 (strongly agree) with the indicated statement. Likert scales are frequently used in questionnaires to evaluate attitudes and opinions (Likert, 1932). A 4-item (PEOU1-PEOU4) questionnaire section was used in the second section to investigate how students find the easiness of use of Generative AI technologies. *(There is a significant relationship between the Perceived Ease of Use of generative AI tools in higher education and the Actual Use of these tools)*. The questionnaire was designed to analyse how students find it easy to learn to use generative AI tools for studying (PEOU1), proficiency at employing generative AI (PEOU2), interaction with generative AI tools (PEOU3), overall attitude towards how generative AI tools is easy to use (PEOU4). The questions were based on Davis (1989); Chocarro, Cortiñas & Marcos-Matás (2021); Li (2023); Faruk et al. (2023) research, and participants were asked to use a Likert scale to indicate their level of agreement / disagreement with the statements. Table 2 shows the design of the PEOU questionnaire.

Table 2

Questionnaire design for Perceived Ease of Use

Construct	Item code	Measurement items	Source
Perceived Ease of Use	PEOU1	It is easy for me to learn to use generative AI tools for studying.	Davis (1989); Chocarro, Cortiñas & Marcos-Matás (2021); Li (2023); Faruk et al. (2023)
	PEOU2	I can quickly become proficient at employing generative AI tools in my learning process.	
	PEOU3	My interaction with generative AI tools is easy for me to understand.	
	PEOU4	Overall, I think that generative AI tools are easy to use.	

The third section of the questionnaire included a questionnaire section with four items (ATT1-ATT4) aimed to investigate student's attitude towards Generative AI's usefulness. display remarketing in connection to their purchasing decisions. *(There is a significant relationship between the Perceived Usefulness of generative AI tools in higher education and the Actual Use of these tools.)*. The questionnaire was designed to measure participants' feeling towards using generative AI for studying (ATT2), attitude towards Generative AI's engagement (ATT3), and overall attitude towards Generative AI tools (ATT4). The questionnaire was developed using the 7-point Likert Scale questions based on Voss's (2003) research. The format of the questionnaire for the purchase decision dimension is shown in Table 3 below.

Table 3

Questionnaire design for attitude context

Attitude towards Generative AI	ATT1	I like using generative AI tools for my study.	**Davis (1989); Venkatesh & Davis (2000); Sohn & Kwon (2020); Li (2023)**
	ATT2	I have a positive feeling towards using generative AI for studying.	
	ATT3	I find the use of generative AI tools to be an engaging method of learning.	
	ATT4	Overall, my attitude towards generative AI tools is positive.	

To examine the actual use of Generative AI the sixth section included 4 items (AU1-AU4) that targeted student's utilization of AI. *(There is a significant relationship between the Perceived Ease of Use of generative AI tools in higher education and the Actual Use of these tools)*. The purpose of the questionnaire was to assess the actual usage of Generative AI in academic performance (AU1), learning productivity (AU2), collaboration with peers (AU3), and efficiency in the learning process (AU4).

Table 4

Questionnaire design for Actual use of Generative AI

Actual use of Generative AI	AU1	I utilize generative AI tools to enhance my academic performance.	**Venkatesh & Davis (2000); Sohn & Kwon (2020); Sohn & Kwon (2020); Li (2023); Rohan et al. (2023)**
	AU2	The features of generative AI tools have been instrumental in boosting my learning productivity.	
	AU3	Generative AI tools aid in my collaboration with classmates on academic projects.	
	AU4	I use generative AI tools to increase the efficiency of my learning process.	

The questions in the purchasing decision dimension questionnaire were developed based on Davis (1989); Venkatesh & Davis (2000); Sohn & Kwon (2020); Li (2023) research. Participants were then asked to repeatedly express their level of agreement / disagreement with the statements using a Likert scale. The questionnaire's design is shown in Table 4 above.

3.2.1 Sampling

The population of interest for this research were ADA university students, who were the potential users and beneficiaries of AI technologies in education. The sampling method for this research was convenience sampling, which is described as a type of nonprobability sampling that involves selecting subjects who are easily accessible and available for the research (Creswell, 2017). Convenience sampling is often used in educational research, as it is simple and economical, and allows the researcher to collect data quickly and efficiently (Roni et al., 2020). For this research, the convenience sample consisted of university students available from Ada University which happened to be bachelor's students only. Table 5 below explores the characteristics of the 277 ADA university students who participated in the survey.

Table 5

Demographic Profile of Respondents

Variables	**Item**	**Respondents (n=277)**	
		Frequency	Percentage
Gender	Male	135	48.74%
	Female	142	51.26%
Age Group (years)	17 - 25*	277	100.00%
Education Level	Bachelor's Degree**	277	100.00%

Note: * Due to the limited range of participant ages, a specific age group will be presented instead of the originally planned four categories. ; ** All participants were Bachelor's degree students, limiting the analysis to this level.

It's important to acknowledge that the initially planned breakdowns for age group and education level had to be adjusted due to limitations in the collected data. The data for this survey was collected from 302 university students at ADA University. However, after analysing the responses, 25 students were identified as outliers based on a test question included in the survey. Outliers are data points that fall outside the expected range and can potentially skew the results of analysis (Seo, 2006). Due to the outlier removal and a limited range of ages observed in the data, only one age group is represented (17-25 years old) in the final sample. The remaining 277 participants constitute the final sample for this study. The sample consisted of nearly equal proportions of 48.74% male and 51.26% female students. The survey was intended to gather data from a broader range of university students, including those enrolled in Bachelor's, Master's, and Ph.D. programs. However, the final sample consisted solely of bachelor's degree students. Table 6 provides insights into the distribution of respondents across different programs of study.

Table 6

Program of Study of Respondents

Program of Study	Frequency	Percentage
BSIT (Bachelor of Science in Information Technology)	55	19.86%
BAPA (Bachelor of Arts in Public Affairs)	39	14.08%
BSCS (Bachelor of Science in Computer Science)	38	13.72%
BAIS (Bachelor of Arts in International Studies)	38	13.72%
BBA (Bachelor of Business Administration)	33	11.91%
BSF (Bachelor of Science in Finance)	32	11.55%
BSE (Bachelor of Science in Economics)	19	6.86%
BACDM (Bachelor of Arts in Communication and Digital Media)	11	3.97%
BSCE (Bachelor of Science in Computer Engineering)	7	2.53%
BSMATH (Bachelor of Science in Mathematics)	5	1.81%

Table 7 below shows the frequency distribution of bachelor's students according to their faculties.

Table 7

Categorized Program of Study of Respondents

Academic Field	Frequency	Percentage
Computer and Information Sciences	100	36.10%
Social Sciences and Humanities	88	31.77%
Business and Economics	84	30.32%
Science and Mathematics	5	1.81%

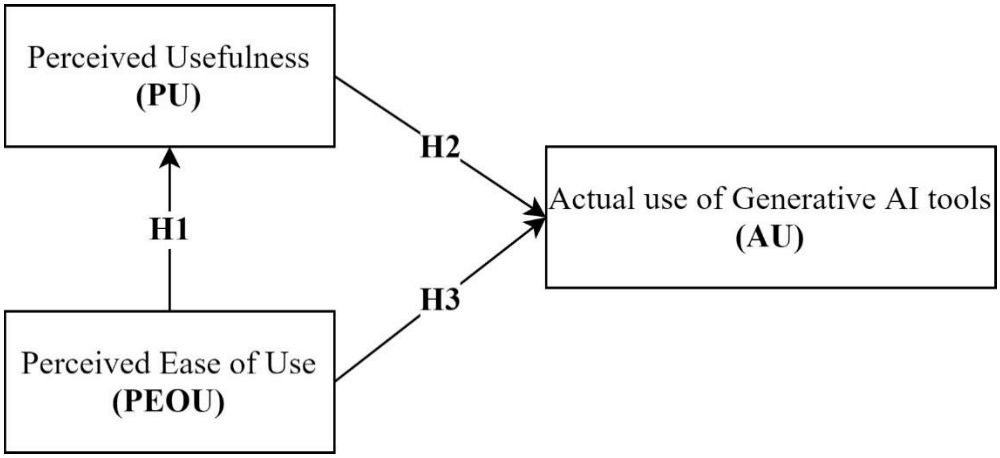
The data reveal a diverse range of academic disciplines represented among the respondents, with the highest proportions enrolled in programs such as Bachelor of Science in Information Technology (BSIT), Bachelor of Arts in Public Affairs (BAPA), and Bachelor of Science in Computer Science (BSCS). Computer and Information Sciences (36.10%) had the highest representation, while Science and Mathematics (1.81%) had the lowest.

3.3 Data Analysis

The data analysis methods for this study were descriptive and inferential statistics. The descriptive statistics were used to analyse the quantitative data from the surveys, using Jamovi. Descriptive statistics were used to describe the characteristics and distribution of the data, and to identify any outliers or errors in the data (Chappell & Voykhansky, 2022). These include measures of central tendency, dispersion, and frequency, such as mean, standard deviation, and percentage which were included in the findings. Inferential statistics was used to compare the differences and relationships between the groups and variables, and to determine the significance and effect size of the results (Strunk & Mwavita, 2020). Inferential statistics were testing hypotheses and drawing conclusions about the population based on the sample data, using statistical techniques, using t-test and regression analysis. In this research the dependent variable was the "actual use of AI technologies" in education. Whilst the independent variables were the factors that may influence the dependent variable. These could include "perceived ease of use" and "perceived usefulness" of AI technologies, as well as "self-efficacy" in using these technologies. The analysis is guided by the conceptual model depicted in the Figure 2. The figure depicts a conceptual model based on the Technology Acceptance Model (TAM). TAM proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are key factors influencing a user's intention to adopt a new technology (Davis, 1989). The technology being examined is generative AI (GAI) tools for higher education. These two factors interact to shape users' attitudes and intentions towards adopting and utilizing the technology in question.

Figure 2

Conceptual Model of the Technology Acceptance of Generative AI Tools in Higher Education



Additionally, multiple regression analysis was used to analyse the relationships between the dependent and independent variables, after controlling for the effects of exposure level and the confounding variables, and to determine the significance and effect size of the results.

3.3.1 Reliability of the analysis

In empirical research, reliability analysis is important because it offers a way to evaluate the stability and consistency of measurements or data gathering tools. The objective of the researcher in this study was to guarantee the reliability and accuracy of the data they collect to enable insightful interpretations and conclusions. Reliability analysis also helps to find problematic items or indications that could add bias into the measurement or undermine the instrument's overall reliability (Nimon et al.,2012). The questionnaire was pretested and piloted before the main data collection to ensure reliability and validity (Strunk & Mwavita, 2020). Additionally, a test question was added to the questionnaire to check some outliers that were among the respondents. In reliability testing, skewness, and kurtosis act as important statistical tools to evaluate how data is spread out. By analysing these measures, researchers can identify if the data aligns with a normal distribution or deviates away from it. Understanding this information is essential for choosing the most appropriate statistical tests and guaranteeing a reliable interpretation of the findings. Research by Hair et al. (2010) and Byrne (2010) suggests that a normal distribution typically exhibits skewness values between -2 and +2, and kurtosis values ranging from -7 to +7. The obtained data in this research paper was evaluated separately for each question code and factor. The analysis showed that the data exhibited skewness and kurtosis values within the acceptable range of -2 to +2. This suggests a normal distribution for the collected data, which aligns with the assumptions of most statistical tests for reliable interpretation of the results. Table 8 provides descriptive statistics and scale reliability measures for items related to Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Actual Use (AU) of Generative AI tools in higher education.

Table 8

Items descriptives

Items	Mean	Median	SD	Min.	Max.	Skewness		Kurtosis	
						Skewness	*SE*	*Kurtosis*	*SE*
PEOU1	5.56	6	1.33	1	7	-0.76	0.15	0.09	0.29
PEOU2	5.07	5	1.46	1	7	-0.37	0.15	-0.62	0.29
PEOU3	5.68	6	1.25	1	7	-1.01	0.15	0.80	0.29
PEOU4	5.94	6	1.09	1	7	-1.16	0.15	1.76	0.29
PU1	5.53	6	1.42	1	7	-0.95	0.15	0.46	0.29
PU2	5.46	6	1.4	1	7	-0.88	0.15	0.31	0.29
PU3	5.68	6	1.38	1	7	-1.00	0.15	0.57	0.29
PU4	5.48	6	1.41	1	7	-1.01	0.15	0.78	0.29
AU1	5.23	5	1.54	1	7	-0.76	0.15	-0.05	0.29
AU2	5.11	5	1.47	1	7	-0.75	0.15	0.16	0.29
AU3	4.88	5	1.64	1	7	-0.55	0.15	-0.60	0.29
AU4	5.4	6	1.46	1	7	-1.02	0.15	0.67	0.29

Cronbach's alpha and McDonald's omega are popular tools for measuring a survey's internal consistency. In this study, both coefficients were used to ensure the reliability and accuracy of the Likert scale questions used in the survey. This study employed Cronbach's alpha to assess the internal consistency of questions measuring the same construct. This analysis helped identify items that may require revision or removal due to low consistency with the overall construct. McDonald's omega was then utilized to provide a more accurate estimation of the scale's true reliability. Omega achieves this by incorporating the strength of association between individual items and the underlying construct, while also accounting for item-specific measurement errors that can inflate alpha coefficients. Ranging from 0 to 1, both Cronbach's alpha (Cronbach, 1951) and McDonald's omega coefficients reflect the internal consistency of a scale's variables. Higher values indicate greater internal accuracy. While a cut-off of 0.70 is considered acceptable for initial research phases, particularly during scale development (Lance et al., 2006), more established research, whether basic or applied, typically requires coefficients of 0.80 or above. The analysis yielded a coefficient of 0.933, which indicates good reliability according to established benchmarks while the result of McDonald’s omega was equal to 0.935 which is also considered as the reliable value. According to Taber (2018), sufficient levels of dependability are indicated by Cronbach's alpha values ≥ 0.70. Furthermore, the 1.07 calculated standard deviation indicates that the data is relatively close to the true value. According to the statistical rule of thumb, results that lie within plus or minus two standard deviations are typically seen as more reliable. Table 9 below shows the reliability of the survey.

Table 9

Scale Reliability Statistics

	Mean	**SD**	**Cronbach's α**	**McDonald's ω**
Scale	5.42	1.07	0.933	0.935

It's also notable that each factor's values came in higher than the suggested cut-off number of 0.80. This suggests that the study's factors are accurate and consistent measures of the corresponding constructs. The internal consistency and dependability of the survey results were indicated by the range of Cronbach's alpha coefficients, which was 0.819 to 0.896. Additionally, the McDonald's omega coefficients, which ranged from 0.824 to 0.862, showed a similar pattern, as indicated for the factors of PU, PEOU, and AU in Table 10 that is given below.

Table 10

Scale Reliability Statistics

Factor	Cronbach's α	McDonald's ω
PU	0.859	0.862
PEOU	0.819	0.824
AU	0.896	0.842

3.4 Ethical considerations and Limitations

To ensure that all participants in the data collection are respected, I obtained the ethical approval and the informed consent from the relevant authorities and the subjects, respectively, before conducting the research. The research used a convenience sample, which involves selecting the participants who are easily accessible and available for the research, instead of using a probability sample, which involves selecting the participants based on a random or systematic procedure. I acknowledged that, this would introduce sampling bias and error, which would affect the external validity and generalizability of the research results. Despite the valuable information provided by this study, there are several limitations that should be considered. The study was conducted at ADA University in Azerbaijan, and the findings may not be generalizable to other universities or student populations in Azerbaijan. The sample size was also relatively small, which may limit the generalizability of the findings. The data collected in this study relied on self-reported responses from students, which may be subject to bias or inaccuracies. Future research could incorporate objective measures of AI technology usage to validate self-reported data. Additionally, the study utilized a cross-sectional design, which limits the ability to draw causal conclusions about the relationships between PEOU, PU, and actual usage of Generative AI tools. Longitudinal studies could provide more robust evidence of these relationships over time. Although English was the dominant primary language among the respondents, there were also significant percentages of students using Azerbaijani, Russian, and Turkish as their primary languages. The potential language barrier may have influenced students' interactions with Generative AI tools. The study was conducted at ADA University, which may have its own unique characteristics and context that may not be representative of other universities in Azerbaijan.

Chapter 4: Findings and Discussion

The aim of this research paper is to shed light on the easiness of use of Generative AI and the usefulness of it among students. To achieve this objective, the researcher has adopted empirical research which in incorporated quantitative approach to investigate these relationships using inferential statistics and regression analysis, thereby providing insights into how these factors collectively shape students' engagement with AI related to the research topic was conducted to provide secondary data.

This final chapter reveals the key findings from the survey responses and discussion of the findings from the quantitative study that investigated the factors influencing the acceptance and use of generative AI tools among Bachelor students at ADA University in Azerbaijan. To further contextualize the conclusions, the research paper's findings will be compared with earlier works on the subject authored by different authors. The chapter ends with a review of the study's limitations and suggestions for further research initiatives.

4.1 The Patterns and Trends in AI technology Adoption

Before delving deeper into the hypothesis of the study it was important to assess the frequency of use with which students utilize Generative AI tools for educational purposes, the total experience level, the devices used, and the language utilized. Table 11 dives deeper into the quantitative data collected through the survey, specifically focusing on the valuable insights into the adoption rate of Generative AI among the student’s population.

Table 11

Frequency of Generative AI Use for Education

Frequency of Use	Count	Percentage (%)
Daily basis	138	49.82
Twice in a week	60	21.66
Occasionally (a few times a month)	34	12.27
Once in a week	30	10.83
Rarely or never	15	5.42

The table reveals a positive trend in Generative AI use for education. Nearly half of the respondents (49.82%) reported using these tools daily, followed by 21.66% using them twice a week. This indicates a significant portion of the student body has integrated Generative AI into their regular learning routines. Furthermore, a combined total of 34.1% (12.27% occasionally + 10.83% once a week) use Generative AI tools on a somewhat frequent basis. This suggests a potential for further growth in adoption rates as students become more familiar and comfortable with these technologies. However, a small minority (5.42%) reported using Generative AI tools rarely or never. This could be due to factors such as lack of awareness, perceived complexity, or limited access to relevant resources.

Table 12 provides an overview on the overall experience level of the students at ADA University regarding Generative AI tools. Understanding the students' familiarity with Generative AI can provide context for their reported usage frequency (*as seen in Table 10*).

Table 12

Total Experience Level with the Use of Generative AI

Experience Level	Count	Percentage (%)
less than 2 years	103	37.18
less than 1 year	96	34.66
less than 6 months	55	19.86
more than 2 years	23	8.3

The data in Table 12 suggests that most of the students (71.84%) have less than two years of experience using Generative AI. Over one-third (34.66%) had less than a year of experience, suggesting they are still exploring its functionalities. Interestingly, a notable proportion of respondents (19.86%) reported having experience with Generative AI for less than 6 months, indicating a cohort of relatively new users. This indicates that a significant portion of the student body is still in the early stages of exploring and utilizing Generative AI. However, a small group (8.3%) reported having more than two years of experience. This suggests a growing community of students who are becoming more adept and comfortable with these technologies.

Table 13 analyses the types of devices that students at ADA University prefer to use when interacting with Generative AI tools. This information is crucial for understanding the accessibility and integration of Generative AI into students' learning environments.

Table 13

Device Usage Among Respondents for Generative AI Tools

Device	Count	Percentage (%)
Laptop	234	84.48
Smartphone	168	60.65
Desktop Computer	65	23.47
Tablet	25	9.03

The data collected shows the dominance of laptops (84.48%) as the primary device for using Generative AI tools. This aligns well with the findings on experience level (Table 12), suggesting that students might be accessing these tools through web-based platforms or software programs typically used on laptops. Smartphones also hold a significant position (60.65%), indicating a trend towards mobile access. This could be particularly relevant for quick tasks or on-the-go learning situations using Generative AI apps. The considerably lower usage of desktop computers (23.47%) and tablets (9.03%) suggests these might not be the preferred choices for interacting with Generative AI tools. This could be due to factors like screen size, processing power, or software availability on these devices.

Table 14 focuses on the primary language used by the students who participated in the survey. This information is relevant for understanding the potential language barriers or preferences that might influence their interaction with Generative AI tools.

Table 14

Primary Language of Usage of Respondents

Primary Language of Usage	Frequency	Percentage
English	260	93.86%
Azerbaijani	61	22.02%
Russian	38	13.72%
Turkish	35	12.64%
Others: (German, French, Persian, Spanish) *	4	1.44%

*Note: * students had to write separately other languages of use*

The data reveals that English is the dominant primary language (93.86%) among the respondents. This suggests that the majority of students are likely comfortable using Generative AI tools that have English-language interfaces or instructions. However, there are also notable percentages of students using Azerbaijani (22.02%), Russian (13.72%), and Turkish (12.64%) as their primary languages. This indicates a multilingual student body with diverse language needs. The small group using other languages (1.44%) highlights the potential for a broader range of language requirements.

4.2 Hypotheses Analysis

This section analyses the correlation of the three hypotheses of the research. The analysis will begin with the first hypothesis which investigates the relationship between students' PEOU of Generative AI tools and their PU in a higher education context. In simpler terms, the hypothesis aims to understand if students who find these tools easy to use also find them valuable for their studies. Table 14 analyses this relationship. The table presents two key correlation coefficients: Pearson's r (0.688) and Spearman's rho (0.700). Both coefficients measure the association between PEOU and PU. The values of both coefficients (above 0.6) indicate a strong positive correlation. This means that when students perceive Generative AI tools as easier to use (higher PEOU), they also tend to perceive them as more useful for their studies (higher PU). Conversely, if students find these tools difficult to use, they are less likely to see their value in education.

Table 15

Correlation Analysis of Perceived Ease of Use and Perceived Usefulness

Correlation	Pearson's r	**0.688*** **
	p-value	< .001
	Spearman's rho	0.700***
	p-value	< .001
Confidence interval	95% CI Upper	1.000
	95% CI Lower	0.633
Note: H_a is positive correlation		
Note: * p < .05, ** p < .01, *** p < .001, one-tailed		

The p-values associated with both correlations are less than 0.001, which is a very low value. This statistically significant result suggests that the observed correlation is highly unlikely to be due to chance. In other words, there's strong evidence to support a genuine connection between PEOU and PU. In terms of confidence interval, the 95% confidence interval provides a range within which the true correlation coefficient likely falls. The upper bound reaching 1.000 indicates a potentially perfect positive correlation, while the lower bound being significantly above zero further strengthens the evidence for a substantial and positive relationship.

A simple regression analysis was carried out by the researcher using Jamovi software using the second hypothesis which examines the relationship between students' PU of Generative AI tools in higher education and their actual use AU of these tools in academic activities. In simpler terms, the hypothesis investigates if students who find these tools valuable for their studies are more likely to integrate them into their learning practices. Table 16 utilizes simple regression analysis to assess the impact of PU on AU, where PU is the predictor variable and AU is the dependent variable.

Table 16

Simple regression results using Perceived Usefulness as a predictor of Actual use of Generative AI

Model Coefficients – AU					**Model Fit Measures**				
Predictor	Estimate	SE	T	P	R	R^2	Adjusted R^2	AIC	RMSE
Intercept	0.250	0.2425	1.03	< .304	0.78	0.608	0.607	692	0.834
PU	0.886	0.0428	20.7	< .001					

The derived regression equation is represented as follows:

$$AU = 0.250 + 0.886 \times PU$$

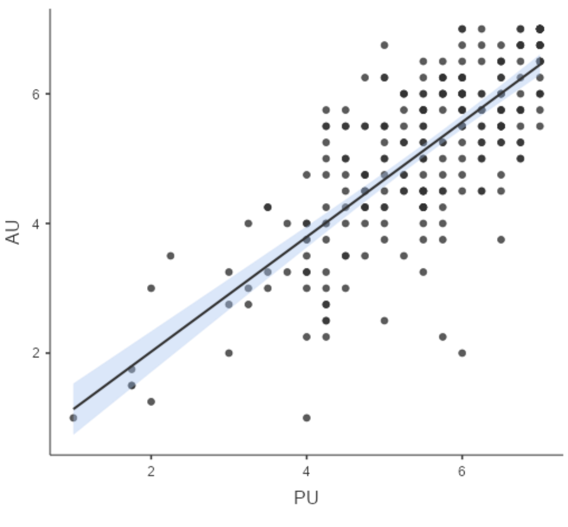
Here, 0.250 is the estimated intercept, and 0.886 is the estimated coefficient for the relationship between PU and AU.

The table 16 focuses on PU as the main predictor of AU. The positive coefficient (0.886) for PU indicates a positive relationship between these variables. This value indicates that for every one-unit increase in students' perceived usefulness of Generative AI tools, their actual use is predicted to increase by 0.886 units on whatever scale was used to measure AU. This suggests a strong positive association between PU and AU. This aligns with the hypothesis, suggesting that students who perceive Generative AI tools as more useful are more likely to use them in their academic work. The R^2 value (0.608) indicates that 60.8% of the variance in students' actual use of Generative AI tools (AU) can be explained by the perceived usefulness (PU) of these tools. This suggests a moderately strong positive relationship between the two variables. While R^2 (0.608) indicates that PU explains a moderate portion of the variance in AU, the adjusted R^2 (0.607) suggests this is a relatively good fit for a simple regression model with one predictor variable.

Statistical Significance. The p-value associated with the PU coefficient is less than 0.001, indicating a statistically significant result. This implies that the observed relationship is highly unlikely to be due to random chance and strengthens the evidence for a genuine connection between PU and AU. The regression equation derived from the analysis ($AU = 0.250 + 0.886 \times PU$) indicates that PU significantly predicts AU ($\beta = 0.886$, $p < .001$). This suggests that students who perceive Generative AI tools as more useful are more likely to actually use them in their academic activities. The coefficient of determination ($R^2 = 0.608$) indicates that 60.8% of the variance in AU can be explained by PU. Therefore, Hypothesis 2, which suggests a significant relationship between PU and AU, is supported by the regression analysis. The scatterplot on Figure 3 depicts a positive relationship between perceived usefulness (PU) and actual use (AU) of Generative AI tools among students at ADA University.

Figure 3

Scatterplot of Perceived Usefulness as a predictor of Actual use of Generative AI



The scatterplot on Figure 3. strengthens the evidence supporting the second hypothesis. It visually demonstrates the positive influence of perceived usefulness on students' actual use of Generative AI tools in their academic activities. There would be a cluster of data points showing a positive trend. This means that as the PU increases (moving to the right on the X-axis), AU also increases (moving up on the Y-axis).

Another simple regression analysis was carried out to examine the relationship between students' perceived ease of use (PEOU) of Generative AI tools and their actual use (AU) in academic activities. In other words, the third hypothesis explores if students who find these tools easier to use are more likely to integrate them into their learning practices. Table 17 presents the results of a simple regression analysis, where PEOU is the independent variable influencing the dependent variable, AU.

Table 17

Simple regression results using Perceived Ease of Use as predictor of Actual use of Generative AI

Model Coefficients – AU					**Model Fit Measures**				
Predictor	Estimate	SE	T	P	R	R^2	Adjusted R^2	AIC	RMSE
Intercept	0.144	0.3120	0.46	< .645	0.70	0.492	0.491	763	0.950
PEOU	0.901	0.0551	16.3	< .001					

The derived regression equation is represented as follows:

$$AU = 0.144 + 0.901 \times PEOU$$

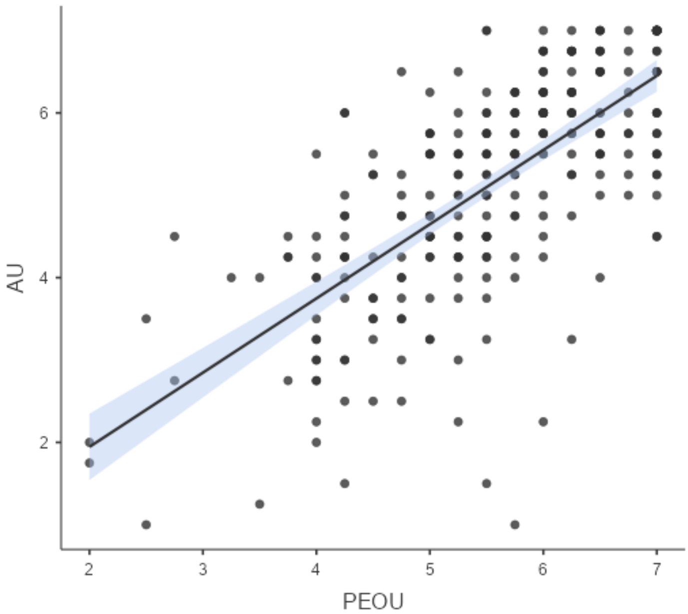
Here, *0.144* is the estimated intercept, and *0.901* is the estimated coefficient for the relationship between PEOU and AU.

The regression coefficient in terms of estimator value of 0.901 indicates a strong positive association between PEOU and AU. For every one-unit increase in students' perceived ease of use, their actual use is predicted to increase by 0.901 units on the scale used to measure AU. The coefficient estimate for PEOU was 0.901 with a standard error (SE) of 0.0551. The low standard error suggests a high degree of precision in the estimate. The t-value (16.3) is highly significant ($p < 0.001$), indicating that the relationship between PEOU and AU is statistically significant, it's highly unlikely to be due to chance. R^2 value of 0.492 indicates that approximately 49.2% of the variance in actual use of Generative AI tools can be explained by the perceived ease of use. This value indicates that 49.2% of the variance in students' actual use of Generative AI tools can be explained by their perceived ease of use. While not as strong as the relationship between PU and AU ($R^2 = 0.608$ in Table 16), it still suggests a substantial influence of PEOU on AU. On the other hand, Root Mean Square Error (RMSE) of 0.950 indicates the average difference between the observed actual use and the actual use predicted by the model. Lower values of RMSE indicate better fit of the model to the data.

Interpretation of the Regression Equation. The equation AU = 0.144 + 0.901 × PEOU represents the predicted relationship between PEOU and AU. The intercept value 0.144 suggests that even with a PEOU score of zero (meaning students perceive no ease of use), there might still be a base level of actual use (0.144 units on the AU scale). This could be due to other factors or students using the tools despite challenges. The scatterplot on Figure 4. strengthens the evidence supporting the third hypothesis

Figure 4.

Scatterplot of Perceived Ease of Use as predictor of Actual use of Generative AI



There would be a cluster of data points showing a positive trend. This means that as the perceived ease of use (PEOU) increases (moving to the right on the X-axis), the actual use (AU) also increases (moving up on the Y-axis). According to Figure 5 showing the Scatterplot, PEOU and AU have a positive association, which is consistent with the regression analysis' findings.

Previously the individual relationships between PEOU and AU (Hypothesis 3 in Table 17) and PU and AU (Hypothesis 2 in Table 16) have been explored. Another multiple regression analysis was carried out which is presented Table 18 using both PEOU and PU as predictors of Actual use of Generative AI. Multiple regression allows the investigation on the impact of both PEOU and PU simultaneously while controlling for their potential influence on each other. This provides a more comprehensive understanding of how these factors contribute to students' actual use of Generative AI tools. This analysis aimed to understand the combined effects of both PEOU and PU on students' actual use (AU) of Generative AI tools. Table 18 presents the results of a multiple regression analysis with AU as the dependent variable and PEOU and PU as the independent variables.

Table 18

Multiple regression results using PEOU and PU as predictor of Actual use of Generative AI.

Model Coefficients – CPB					**Model Fit Measures**			**Overall Model Test**			
Predictor	Estimate	SE	t	P	R	R^2	Adjst. R^2	F	df1	df2	P
Intercept	-0.631	0.2644	-2.4	< .018	0.81	0.66	0.658	266	2	274	< .001
PEOU	0.402	0.0623	6.45	< .001							
PU	0.641	0.0551	11.6	< .001							

The multiple linear regression equation, which includes both PEOU and PU as predictors, is:

$$\boldsymbol{AU = -0.631 + 0.402 \times PEOU + 0.641 \times PU}$$

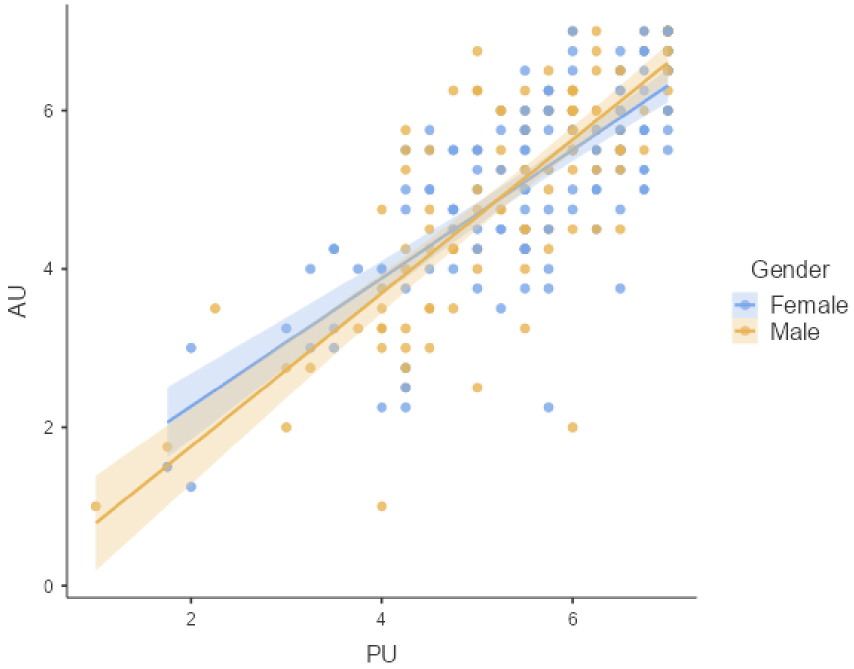
Here, -0.631 is the intercept, 0.402 is the coefficient for PEOU, and 0.641 is the coefficient for PU. This equation can be used to predict AU based on the values of PEOU and PU.

R^2 (0.66) indicates that 66% of the variance in students' actual use of Generative AI tools can be explained by the combined effects of PEOU and PU. This is a significant improvement compared to the R^2 values in Tables 15 (0.608 for PU) and 16 (0.492 for PEOU) when these factors were considered individually. It suggests that including both PEOU and PU provides a more robust explanation for students' actual use. The high F-statistic (266) and very low p-value (<0.001) provide strong statistical evidence that the overall model is significant. In other words, the combined effects of PEOU and PU have a statistically significant impact on students' actual use of Generative AI tools.

Individual Predictor Effects. Even when controlling for PU, PEOU remains a significant positive predictor of AU (coefficient = 0.402, p-value < 0.001). This suggests that students who find Generative AI tools easier to use are still more likely to integrate them into their studies, even if they perceive some value in them. Similar to the individual analysis, PU also remains a significant positive predictor of AU when controlling for PEOU (coefficient = 0.641, p-value < 0.001)). This reinforces that the perceived value students derive from these tools plays a crucial role in driving their actual use. Based on the findings from the multiple regression analysis in Table 18, the Figure 5 visually shows the positive association between PEOU and AU of Generative AI tools, while also acknowledging the influence of other factors, including PU. The symbol coding of the data points in the scatterplot represents the levels of PU. This could visually indicate how PU interacts with PEOU in affecting AU. For instance, data points for students with high PU might show a steeper positive slope compared to those with lower PU, suggesting that PU strengthens the relationship between PEOU and AU.

Figure 5

Gender Association of Variables



4.3 Student Motivations for Using Generative AI Tools in Education

To understand the student motivations for using Generative AI tools in their education, the researcher analysed the frequencies and percentages of their yes and no responses. The key findings are divided into top motivations, and less frequent motivation for using Generative AI.

Top Motivations. The most frequent motivations reported by students are related to quickly accessing information (75.83%) similar to a Google search and understanding complex concepts (68.21%) by breaking down difficult material into simpler terms. This highlights the perceived value of Generative AI for efficient knowledge acquisition and comprehension. Understanding Course Materials (53.31%) and Generating Ideas or Brainstorming (50.99%) further emphasize students' desire to leverage Generative AI for deeper comprehension and creative exploration within their coursework. **Enhancing Efficiency and Skills.** A significant portion of students (over 50%) use Generative AI tools to improve study efficiency (48.68%)

and gain a deeper understanding of course materials (53.31%) beyond classroom lectures. This reflects students' interest in utilizing Generative AI to optimize their study time and refine their academic communication. **Idea Generation and Assessment Preparation**. Students also utilize Generative AI for generating ideas or brainstorming (50.99%) for projects and assignments, as well as preparing for quizzes and assignments (34.77%) by getting practice questions and explanations. This indicates that Generative AI can support students not only in information gathering but also in developing critical thinking and test preparation skills. **Less Frequent Uses.** Tutoring and Personalized Learning (26.16%) and Cognitive Skill Development (23.51%) appear as less common motivations, possibly because these applications might require more advanced Generative AI capabilities or a shift in how students approach learning. Collaborative Learning (15.23%) is the least frequent motivation. This could be due to a preference for traditional group work or the need for further development of Generative AI tools for collaborative learning environments.

The motivations in Table 19 support the findings from previous sections regarding the perceived usefulness of Generative AI. Students see these tools as valuable for tasks like understanding complex concepts, improving study efficiency, and preparing for assessments. The emphasis on quick access to information aligns with the positive relationship between perceived ease of use and actual use (Tables 17 & 18). Easy access might encourage students to explore Generative AI for various tasks. While some motivations (like personalized learning and cognitive skill development) are less frequent, they still highlight the potential for Generative AI to broaden its impact on education in the future. These results are shown in Table 19, which provide useful data about how students see and use these tools in the classroom in summary of frequency and percentage.

Table 19

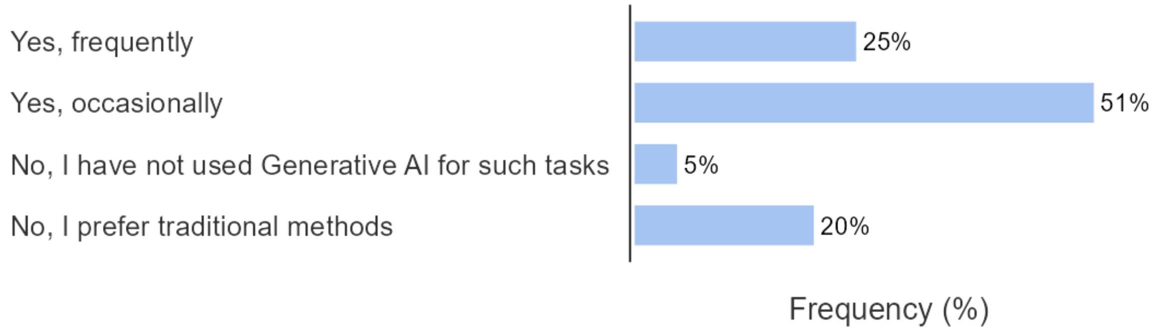
Motivations for Using Generative AI in Education

#	Motivation	Frequency	Percentage (%)
1	Quick Access to Information (like a Google search)	229	75.83%
2	Understanding Complex Concepts: to break down and explain complex material in simpler terms.	206	68.21%
3	Understanding course materials: to ask for further explanation of materials not understood during class attendance	161	53.31%
4	Generating Ideas or Brainstorming: to help brainstorm ideas for projects, essays, or studies.	154	50.99%
5	Improving Study Efficiency: to speed up the study process and increase its efficiency.	147	48.68%
6	Assisting with Research: to analyze data, synthesize information, or provide summaries of research material.	120	39.74%
7	Preparation for Quizzes and Assignments: to get ready for upcoming quizzes and assignments.	105	34.77%
8	Improving Writing or Communication Skills: to enhance writing abilities, including grammar, style, and structure.	101	33.44%
9	Assessment Preparation: to be prepared for exams by generating practice questions and explaining solutions.	92	30.46%
10	Tutoring and Personalized Learning: to provide personalized explanations and tutoring.	79	26.16%
11	Collaborative Learning: to support group projects and promote collaborative learning environments.	46	15.23%

An analysis was carried out to investigate how frequently students use Generative AI tools for tasks that require critical thinking abilities with the use of a bar graph generated from the responses. Figure 6 depicts how frequently students utilize Generative AI tools for tasks requiring critical thinking skills. The data is segmented into four categories. The information suggests that a significant portion of students (76%, combining "Yes, frequently" and "Yes, occasionally") integrate Generative AI into their critical thinking processes. This indicates a growing acceptance and potential value proposition of these tools for complex tasks that go beyond simple information retrieval. The majority of students (51%) use Generative AI occasionally for critical thinking tasks. This might indicate they are still exploring the capabilities of these tools or use them for specific aspects of critical thinking activities. A combined 10% of students (5% not having used and 20% preferring traditional methods) do not leverage Generative AI for critical thinking. This could be due to various reasons, such as unfamiliarity with the tools, scepticism about their effectiveness for complex tasks, or a preference for traditional learning methods.

Figure 6

Student Use of Generative AI for Critical Thinking Tasks

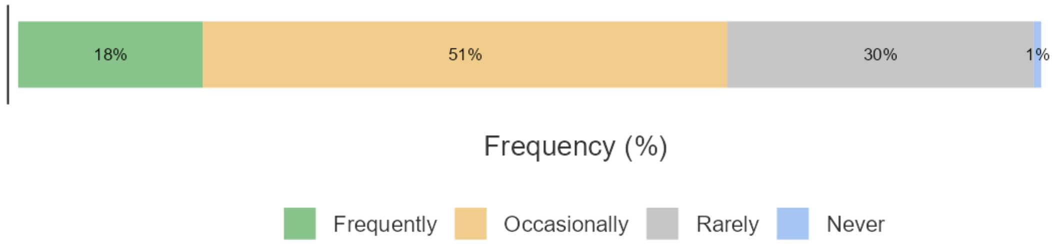


In conclusion, the figure 6 reveals a positive trend in student adoption of Generative AI tools for critical thinking tasks. While a significant portion use them frequently or occasionally, there's also a segment that doesn't.

An analysis was conducted to assess how frequently users perceive responses generated by ChatGPT to be inaccurate. This information is crucial for understanding user trust and potential limitations of large language models like ChatGPT. The largest percentage of users (51%) reported encountering inaccurate responses from ChatGPT only occasionally. This suggests that ChatGPT can often provide seemingly correct outputs, but there's a chance of encountering inaccuracies that users should be aware of. Combining the "Frequently" (18%) and "Occasionally" (51%) categories, we see that a substantial portion of users (69%) perceive ChatGPT to be inaccurate at least some of the time. This highlights the need for continuous improvement in the accuracy and reliability of large language models. It's encouraging to see that a combined 31% of users (30% "Rarely" and 1% "Never") perceive ChatGPT's responses to be accurate most of the time or never inaccurate. This suggests that ChatGPT can be a valuable tool when its limitations are considered, and accuracy is verified through other sources. The findings are presented in the following figure 7 below.

Figure 7

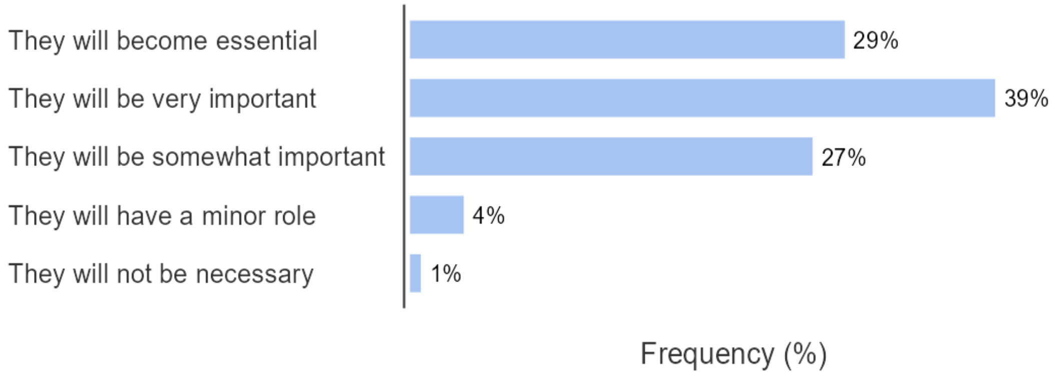
Perceived Inaccuracy of ChatGPT Responses



In addition to investigating student use of Generative AI tools, the researcher also explored their perspectives on the future role of these technologies in education. A combined 95% of students (29% essential + 39% very important + 27% somewhat important) believe AI tools will have at least a somewhat important role in future education. This highlights a clear recognition of the potential these tools hold for enhancing the learning experience. Nearly two-thirds of students (29% essential + 39% very important) anticipate AI tools becoming essential or very important in education. This suggests a future where these tools are seamlessly integrated into various aspects of learning. Only a small percentage of students (4% minor role + 1% not necessary) believe AI tools will have a minor role or not be necessary in education. This indicates that the potential benefits of AI in education are widely recognized by the student population. The following figure 8 depicts the distribution of student responses regarding the perceived importance of AI tools like ChatGPT in future learning environments.

Figure 8

Student Perceptions of the Future Role of AI Tools in Education



In conclusion, the findings of this research show a growing acceptance and utilization of generative AI tools among students at ADA University. PEOU, PU, and motivations for specific tasks emerged as key factors influencing students' engagement with these technologies. The potential of generative AI to support critical thinking skills is also noteworthy. This study has limitations of its focus on a single university in Azerbaijan. Further research could explore the long-term impact of generative AI on student learning outcomes and investigate the development of these tools to cater to multilingual needs and personalized learning approaches.

4.4 Discussion of findings

This study investigated the use of Generative Artificial Intelligence (AI) in higher education through the lens of the Technology Acceptance Model (TAM) among university students in Azerbaijan. The research aimed to analyse student perceptions of AI tools (perceived ease of use and usefulness) and their influence on actual usage, along with exploring student perspectives on the future role of AI in education. The findings obtained from the empirical research conducted to investigate the easiness of use and usefulness of Generative AI among students will be discussed in detail and some of the trends and patterns in usage as well. These findings can assist interested stakeholders to develop advanced AI device investment and adoption strategies in higher education. The findings from the empirical research indicate that students find Generative AI tools relatively easy to use and perceive them as useful in their academic pursuits.

4.4.1 Perceived Ease of Use and Perceived Usefulness

The findings of this study revealed a strong positive correlation between PEOU and PU of Generative AI tools among university students in Azerbaijan. The correlation analysis showed significant Pearson's r (0.688, $p < .001$) and Spearman's rho (0.700, $p < .001$) values, indicating that students who found Generative AI tools easier to use also perceived them as more useful for their studies. This finding is consistent with previous research on technology acceptance (Davis, 1989; Venkatesh & Davis, 2000). According to the TAM, perceived ease of use and perceived usefulness are significant predictors of users' attitudes and intentions towards using a technology (Davis, 1989).

The regression analysis further supported this relationship, showing that both PEOU and PU significantly predict the actual usage (AU) of Generative AI tools among university students. The multiple regression analysis indicated that 66% of the variance in students' actual use of Generative AI tools can be explained by the combined effects of PEOU and PU. These findings suggest that students who perceive Generative AI tools as easier to use and more useful are more likely to integrate them into their academic activities. This finding suggests that both perceived ease of use and perceived usefulness are important predictors of students' actual usage of Generative AI tools in their academic activities.

These findings are consistent with previous research on technology acceptance in educational contexts. For instance, a study by Venkatesh et al. (2003) found that both perceived ease of use and perceived usefulness significantly influence students' intention to use technology in learning. Similarly, Wang & Wang (2018) found that perceived ease of use and perceived usefulness positively influence students' intention to use educational technology.

4.4.2 Perceived Usefulness and Actual Use

The findings revealed a significant positive relationship between perceived usefulness (PU) and actual use of Generative AI tools by university students. This aligns with the fundamental principle of TAM, which states that a technology's perceived usefulness is a key driver of its adoption (Huang et al, 2019; Venkatesh & Davis, 2000). Students who believe AI tools can enhance their learning experience are more likely to integrate them into their academic activities. This is further supported by Table 18, where the most frequent motivations for using AI tools revolved around improving information access, comprehension, study efficiency, and preparation for assessments – all factors contributing to successful learning outcomes. The findings resonate with prior research by Razack, et al, (2021) who found that students in university perceived AI tools as valuable for tasks like summarizing research papers, generating ideas, and checking for plagiarism. Similarly, Wang et al, (2023) reported that university students in China saw AI as beneficial for enhancing learning efficiency and understanding complex concepts.

4.4.3 Perceived Ease of Use and Actual Use

The analysis also confirmed a positive relationship between perceived ease of use (PEOU) and actual use of AI tools. Students who found the tools user-friendly and intuitive were more likely to utilize them. This aligns with TAM's proposition that ease of use facilitates technology adoption (Davis,1986). While PU emerged as a slightly stronger predictor in our study, PEOU still plays a significant role. The results are consistent with Wang et al, (2023), research which reported that students' perceptions of AI tool complexity negatively impacted their willingness to use them. Similarly, (Chaushi et al, 2023) found that user-friendly interfaces and clear instructions were crucial for encouraging AI adoption in educational settings. These findings highlight the importance of user-centered design principles when developing and implementing AI tools for education. Intuitive interfaces, comprehensive tutorials, and readily available support can significantly enhance students' perceived ease of use and ultimately, their willingness to integrate these tools into their learning.

4.4.4 Technology Acceptance Model (TAM) Factors and Actual Usage

The results of the regression analysis provided strong evidence that both perceived ease of use and perceived usefulness significantly predict students' actual usage of Generative AI tools. The positive coefficients for both PEOU and PU indicate that as students perceive Generative AI tools to be easier to use and more useful, they are more likely to integrate them into their learning practices. This finding is consistent with the TAM, which posits that perceived ease of use and perceived usefulness are key determinants of users' attitudes and intentions towards using a technology (Davis, 1989). The scatterplots depicting the relationships between PEOU, PU, and actual usage further support the findings of the regression analysis. Both scatterplots showed a positive association between PEOU and AU, as well as PU and AU. This indicates that as perceived ease of use and perceived usefulness increase, students' actual usage of Generative AI tools also increases.

4.4.5 Student Perspectives on the Future of Generative AI

The overwhelming majority of students (95%) expressed positive outlooks on the future role of AI tools like ChatGPT and Gemini in education. Nearly two-thirds of students anticipate AI tools becoming essential or very important in education. This suggests a widespread student belief in the potential of AI to transform the learning landscape.

These findings suggest that students recognize the potential of AI tools to enhance the learning experience and improve educational outcomes. This is consistent with the growing interest in AI-driven educational technologies and their potential to transform teaching and learning processes (Holmes et al., 2020; Shneiderman, 2021). The study explored the motivations of university students in Azerbaijan for using Generative AI tools in education.

The top motivations reported by students included quick access to information (75.83%), understanding complex concepts (68.21%), and generating ideas or brainstorming (50.99%).

These findings are consistent with previous research on the use of AI in education. For instance, Zhang et al. (2020) found that students use AI tools for tasks such as information retrieval, comprehension, and idea generation. Similarly, Aung et al. (2019) found that students perceive AI tools as valuable for enhancing learning efficiency and effectiveness. These findings underscore the need for universities to develop strategies for effectively integrating AI tools into the curriculum. While student perspectives are optimistic, it's crucial to address potential concerns about over-reliance, accuracy limitations, and ethical considerations. Transparency regarding the capabilities and limitations of AI tools can foster trust and responsible use among students.

4.4.6 Patterns and Trends in AI Adoption

By analysing TAM factors, this study revealed several patterns and trends in AI adoption among university students in Azerbaijan. Notably, a substantial portion of students (76%) used Generative AI tools for critical thinking tasks at least occasionally. This suggests a growing exploration of AI as a tool to support complex cognitive processes beyond simple information retrieval. These findings go beyond studies that primarily focused on AI use for tasks like summarizing text or checking grammar (Huang et al, 2023). The findings suggest a potential shift towards utilizing AI for higher order thinking skills, which aligns with the evolving capabilities of these tools. However, a minority of students (24%) preferred traditional methods or reported never using AI for critical thinking. This highlights the need for further exploration of the specific contexts and tasks where AI can best support critical thinking development. Additionally, addressing concerns about the reliability and accuracy of AI outputs in critical thinking tasks is crucial.

4.5 Implications for Higher Education

The findings of this study have several implications for higher education in Azerbaijan. First, the high adoption rate of Generative AI tools among students suggests that these tools have the potential to enhance learning experiences and improve academic performance. Second, the positive relationship between perceived ease of use, perceived usefulness, and actual usage of Generative AI tools highlights the importance of designing user-friendly and useful AI technologies for educational purposes. Universities can explore revising curricula to incorporate AI tools in a way that complements and enhances existing learning activities. This might involve using AI for tasks like analysing complex data sets, generating practice problems, or providing personalized feedback on student work. In addition, as generative AI tools become more integrated into learning processes, assessment strategies need to be revisited to ensure they accurately measure student learning outcomes and mitigate potential issues like plagiarism. This may involve incorporating assessments that require students to demonstrate critical thinking skills, problem-solving abilities, and the capacity to effectively evaluate and synthesize information generated by AI tools. Lastly, the ethical issues should also be investigated, as generative AI integration in education grows, universities must establish clear guidelines and policies regarding responsible use. This could involve addressing issues like plagiarism detection, data privacy, and potential biases in AI algorithms. Open discussions with students and faculty can help promote trust and transparency in navigating the ethical landscape of AI-driven learning.

4.6 Conclusion

This study investigated university students' perceptions and use of Generative AI tools in Azerbaijan. The findings support the TAM, demonstrating that PEOU and PU significantly influence students' actual use of Generative AI tools. The data collected revealed student motivations for using Generative AI tools, with information access, comprehension, study efficiency, and assessment preparation being key factors. Notably, a significant portion of students utilize Generative AI for critical thinking tasks, suggesting a potential shift towards using these tools for higher order thinking skills. These findings provide useful data for higher education institutions in Azerbaijan. By strategically integrating user-friendly and valuable Generative AI tools, universities can enhance learning experiences and potentially improve student outcomes. However, careful consideration of assessment practices and the development of clear policies for responsible use are crucial to ensure ethical and effective Generative AI integration in educational settings. Further research is recommended to explore the long-term impact of Generative AI on student learning outcomes.

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APPENDICES

1. Demographic characteristics of respondents

Variables	Category
Gender	Male
	Female
Age group	18-25
	26-35
	36-45
	46-55
	Above 56
Education	Bachelor’s degree
	Master’s degree
	Above
Total Experience level of the respondents regarding	less than 6 months
	less than 1 year
	less than 2 years
	more than 2 years
How often do you use Generative AI for education purposes	once in a week
	twice in a week
	daily base
Devices Used	Desktop Computer
	Laptop
	Tablet
	Smartphone
Primary Language of Usage	English
	Russian
	Turkish
	Azerbaijani
	Other (Please specify): ________________

2. Measurement items and their sources

Construct	Item code	Measurement items	Source
Perceived Ease of Use	PEOU 1	It is easy for me to learn to use generative AI tools for studying.	Davis (1989); Chocarro, Cortiñas & Marcos-Matás (2021); Li (2023); Faruk et al. (2023)
	PEOU 2	I can quickly become proficient at employing generative AI tools in my learning process.	
	PEOU 3	My interaction with generative AI tools is easy for me to understand.	
	PEOU 4	Overall, I think that generative AI tools are easy to use.	
Perceived Usefulness	PU1	Using generative AI tools enhances my ability to learn new concepts efficiently.	Davis (1989); Venkatesh & Davis (2000); Sohn & Kwon (2020); Chocarro, Cortiñas & Marcos-Matás (2021) Rohan et al. (2023)
	PU2	Studying with generative AI tools would improve my study efficiency.	
	PU3	Generative AI tools make my study easier without limitation of location and time.	
	PU4	On the whole, generative AI tools are beneficial for my academic activities.	
Attitude towards Generative AI	ATT1	I like using generative AI tools for my study.	Davis (1989); Venkatesh & Davis (2000); Sohn & Kwon (2020); Li (2023)
	ATT2	I have a positive feeling towards using generative AI for studying.	
	ATT3	I find the use of generative AI tools to be an engaging method of learning.	
	ATT4	Overall, my attitude towards generative AI tools is positive.	
Behavioral intention towards Generative AI	BI1	I intended to adopt generative AI tools for my study.	Davis (1989); Venkatesh & Davis (2000); Li (2023)
	BI2	Given the chance, I would integrate generative AI tools into my study practices.	
	BI3	I think generative AI tools are useful for my study.	
	BI4	The likelihood that I would recommend generative AI tools to my friends/classmates is high.	
Actual use of Generative AI	AU1	I utilize generative AI tools to enhance my academic performance.	Venkatesh & Davis (2000); Sohn & Kwon (2020); Sohn & Kwon (2020); Li (2023); Rohan et al. (2023)
	AU2	The features of generative AI tools have been instrumental in boosting my learning productivity.	
	AU3	Generative AI tools aid in my collaboration with classmates on academic projects.	
	AU4	I use generative AI tools to increase the efficiency of my learning process.	