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Determinants of University Students' Attitudes Toward Artificial Intelligence: A Study on Demographic Variables, Usage Habits, and Levels

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Annotation. Using the SATAI scale, this study assesses attitudes towards artificial intelligence among 351 students at Sakarya University of Applied Sciences. Attitudes were positive and significantly more favorable among students with programming skills and frequent AI use. Educational use was associated with stronger behavioural attitudes than curiosity-driven use. The findings support embedding applied AI training in university curricula to strengthen technological awareness and adoption.

Keywords: *attitudes toward artificial intelligence, university students, artificial intelligence in education, technological awareness.*

Introduction

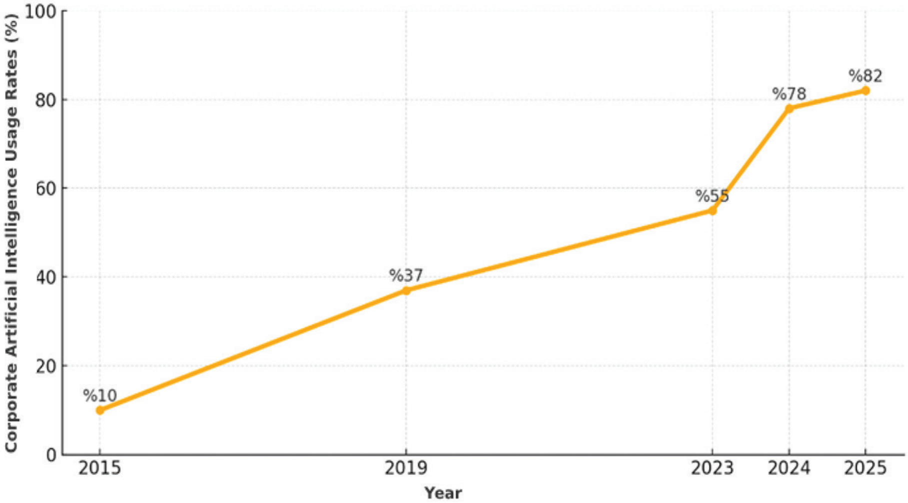
Digital transformation has impacted every area of society due to the exponential growth of technology over the past few decades (Hamut et al., 2021). This is a result of the rapid proliferation of mobile phones, the rise of cloud computing, the surge in IoT products, and an expansion of high-speed internet available for consumption. In addition, many workers are now required to work from home, and students are now learning remotely due to the COVID-19 pandemic, which has also added to the acceleration of digital tools (Koç Baykara, 2023). Additionally, e-commerce is replacing brick-and-mortar stores, cloud-based services are increasing flexibility in businesses, and large data analytics is now essential in corporate decision making (Ersöz & Özmen, 2020).

Since the early twenty-first century, when machine learning technology was still developing from its infancy, the field of Artificial Intelligence (AI) has experienced rapid growth. The recent emergence of advanced language models is an example of this accelerated growth within the AI field. Prior to the mid-2000s, the vast majority of research conducted on the topic of AI consisted of academic studies. However, the introduction of large datasets along with significant improvements in computer capability contributed to the widespread implementation of improved machine learning and deep learning methods during the early 2010s (Şeker et al., 2017). The early 2010s saw tremendous advancements in the field of computer vision, as evidenced by the success of the ImageNet competition and the development of convolutional neural networks such as AlexNet. Simultaneously, Generative Adversarial Networks (GANs) that emerged in 2014 enabled the generation of extremely realistic forms of generated content. The creation of attention-based architectures and transformer-based architectures in 2017 contributed to a significant increase in the application of natural language processing, resulting in the development of highly capable language models, including GPT and BERT. The early 2020s have seen the emergence of models such as GPT-3, DALL-E, and Stable Diffusion that demonstrate unprecedented levels of capability in generating both text and images, thus enabling creative professionals to apply these technologies to enhance their creative processes. In the period spanning 2023–2025, multimodal models, possessing semantic understanding and reasoning capabilities, along with more efficient and compact architectural designs, began to be integrated into nearly all aspects of society and fields of study, including but not limited to medicine, law, education, art, and daily living (Doğan & Türkoğlu, 2019; İşcan & Durgun, 2024).

Figure 1 shows the rapid spread of AI in businesses by illustrating corporate adoption of AI-based technologies between 2015 and 2025. The use of AI in business increased rapidly during the last decade. In 2015, only 10% of corporations used AI-based technology. However, by 2019, nearly 37% of corporations utilized AI- based technology, and by 2023, that number had grown to 55%. It is estimated that nearly 78% of all corporations will utilize AI-based technology in at least some capacity by 2024, and by 2025, it is estimated that nearly 80% of all corporations will utilize AI-based technology in their operations. The data suggests that there has been a rapid growth of the use of AI-based technologies within businesses due to technological advancements and integration into business processes (Exploding Topics, 2024; McKinsey & Company, 2023) and that AI-based technologies are now being used in many different capacities across various industries.

Figure 1

Rates of Corporate Use of AI Tools Worldwide, 2015–2025



Note. Data from Stanford Institute for Human-Centered Artificial Intelligence (2025).

The accelerated growth in this area of AI is a major factor in the integration of AI into many areas of a student's academic life. The widespread use of AI tools (notably Large Language Models), e.g., ChatGPT and Claude, among university students is a relatively new phenomenon which has occurred across campus-based, library-based, and individual study environments (Ahmadi and Tekemen, 2024; Türel et al., 2024). These technology platforms support students in completing a number of basic functions in the course of completing their academic work, for example, preparing their assignments, conducting research, identifying appropriate sources, and creating summaries of the information they find. In addition, these platforms play a major role in supporting students in developing their skills in foreign languages through the explanation of difficult concepts and providing the means to solve problems (Uslu, 2023). In particular, this trend has become increasingly apparent during the post-pandemic era, when there was a great increase in the utilization of digital learning environments, which was accompanied by a tremendous advancement in the use of AI-powered learning assistants, lesson planning applications, and personalized learning platforms. Overall, the technological innovations listed above have significantly increased students' ability to access information and improve their academic development. When students and university libraries need answers to questions or want to gain greater insight into a subject, students, and librarians are currently using AI systems as one of the primary sources of information.

Students in many fields of study use AI tools to accomplish the different needs of each area of study (Uslu, 2023; Yaşar ve Kılıç, 2021). For example, the use of code completion tools like GitHub Copilot by students of Computer Engineering and Software Development allows them to finish their programming assignments faster and helps them find errors that occur in their code (Prather et al., 2024). Medical students aid themselves in analyzing patient cases using clinical diagnostic support systems and medical literature search engines, and law students use AI- powered legal research platforms to look for precedent cases in legal documents. Social science students speed up their research by utilizing AI tools in large data analysis, survey review, and coding of qualitative research data (Aydemir, 2025). Design and fine art students also show the advantages of integrating image generation models such as Midjourney and DALL-E into their design process (Ceyhan Akça et al., 2024). In addition, literature and communication students report a great deal of advantage to the use of enhanced text editors for creating, editing and controlling content. The variety of uses is an indication of the interdisciplinary nature of AI technologies and their ability to be used in a number of ways to accommodate a variety of usages across a number of areas of study.

Above we discussed the major social and academic impacts of advancements in both AI and Information Technology (IT). There have been many studies done which have shown that AI tools are being used more and more in the learning processes of University Students throughout all disciplines. While the previous literature covers general views of students' attitudes toward AI Tools, the current literature lacks detailed, granular research that identifies and analyzes the individual and combined factors influencing those attitudes. Therefore, a model that examines the individual influences of various demographic, educational, and behavioral factors that may impact students' attitudes toward AI Tools would be a step forward for developing appropriate pedagogical practices and institutional policy regarding the use of AI Tools in the higher education setting.

This study will attempt to systematically examine the most influential factors impacting university students' attitudes toward AI and how these attitudes are influenced by demographic, educational, and behavioral factors. The objectives of this study were developed from the above framework through the following research questions:

1. How do university students' attitudes toward artificial intelligence distribute overall?
2. Do students' attitudes toward AI differ significantly based on demographic factors, specifically gender?
3. Are there significant differences in attitudes toward AI among students who have had prior experience with computer programming versus students who have no prior experience with computer programming?
4. Do students' beliefs about the use of AI tools depend upon how often those students use the AI tool(s)?

5. Do students have different beliefs about the AI tools they are going to use for various purposes (e.g., educational vs. curiosity-driven)?
6. Are students' beliefs about AI related to the extent to which students know what AI is, and can use it?
7. Do students in different departments believe differently about the potential of AI?

The next section will systematically review other studies that have been done about the issues that are listed above.

Literature Review

Over the past several years, there has been considerable growth in research being conducted on how to use AI in the classroom, as well as the impact of using AI on the learning experience. The subsequent section of this paper will explain in detail the five major theoretical frameworks that are the basis for this current research project. First, this will involve evaluating the use of AI technology in educational settings and how it affects the way students learn. Second, this will entail a critique of the models and research that have attempted to define how students at the university level accept and adapt to new technology. Third, this will involve comparing the attitudes toward technology that exist among students from different generations. Fourth, this will involve conducting an examination of the attitudes toward AI technology that exist among members of Generation Z. Finally, this will entail conducting an examination of all existing research regarding attitudes toward AI technology that exists among students attending a university.

Technology Acceptance Models

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains how factors like performance expectancy, effort expectancy, social influence, and facilitating conditions contribute to people adopting new technology (Venkatesh et al., 2003). This research uses a number of theories to explain how university students use new technology. For example, Arı et al. (2016) found that the Technology Acceptance Model (TAM) demonstrates how students' perception of a technology's ease-of-use and usefulness affects their intent to adopt a technology. Zhang and Dafoe (2019) studied the attitudes of the American public toward AI and its governance. Their study, which included 2,000 American adults, was the first study to explore the U.S. public's perspective on this topic. Zhang and Dafoe (2019) explored many topics related to AI, including workplace automation, international collaboration, and regulation of AI development. Vasiljeva et al. (2021), however, conducted a comparative study to compare and contrast the views of the public and businesses regarding AI, to identify the most influential factors affecting those views. Using the Technology Organization Environment (TOE) framework as the basis for their model, the researchers used a combination of surveys and semi-structured interviews to collect their data. Their findings indicated a difference in how different industries viewed AI and how companies that had adopted AI differed from those that had not. Thus, they created a foundation for developing recommendations to help organizations successfully implement these technologies.

Studies on Students' Attitudes

This study investigated what influences how people feel about AI for all the research done on this topic in Turkey. It was a thesis study that involved 405 students studying at Erciyes University, Kayseri University, Nuh Naci Yazgan University, and HACI Bektaş Veli University. The results showed that, within the demographic characteristics studied, only the gender variable demonstrated an important difference in how students felt about AI. An important difference in the scores of the attitude of students was found with respect to gender; female and male students differed significantly in terms of attitude. In addition, the same thesis documented that, although students were generally very supportive of using AI in education, communications, and transportation services, students had mixed feelings regarding whether or not AI should be allowed to care for children or provide rights to robots such as citizenship (Kozacıoglu, 2022). Kaya et al. (2022) attempted to explore the perceptions of university students in the Accounting Department at Akdeniz University toward accounting and the use of AI-based on the Technology Readiness Model and Technology Acceptance Model. According to the study's results, students who were more ready for technology were directly related to the students' beliefs regarding the usefulness and ease of use of the AI technologies, which are two of the primary drivers of students' adoption of AI technologies. The study further discovered that there was no statistically significant difference in the adoption of AI technologies among female and male students; therefore, gender did not appear to play a role in the pattern of adoption of AI technologies. Many international studies have also examined students' views toward AI from many different vantage points.

The authors report on an empirical survey of 190 Greek social science students who have demonstrated that attitudes include three components: cognitive, emotional, and behavioral; overall attitude was positively oriented (Katsantonis & Katsantonis, 2022). Park and Hoo examined the relationship between personality traits of individuals and instead of to their attitudes toward AI in their 2022 study. The authors carefully divided the attitudes into two dimensions: emotional components (the positive and negative emotion); and cognitive components (social orientation and functionality) based on the results from a survey of 1,530 South Korean adults. It was found in the study that there is a positive correlation between extroversion and negative emotions and a lower level of functionality.

More recent empirical studies have demonstrated that both peer influence and being visible through social media contribute to the technology adoption behavior of Generation Z university students. Grassini (2023) has shown that because technologies are adopted faster by Gen Z, when it is perceived that new technologies represent social status or identity, the quicker Gen Z will adopt them. Similarly, in a study by Doğan et al. (2023), a correlational screening model was used to survey 234 students from the Department of Sports Science at Karabuk University. Their findings were that the students surveyed displayed a general positive view toward these AI-based technologies, and that students who had knowledge of AI showed a stronger positive view than those who did not know anything about AI. Also, studies have found that students have a strong desire for using AI tools in many areas including creative writing, visual development, and foreign language learning (Doğan et al., 2023).

Students' "general" attitudes toward artificial intelligence were studied by Kum (2023). Students' "general" attitudes toward artificial intelligence demonstrated predominantly positive views of artificial intelligence while simultaneously demonstrating a moderate number of negative views toward artificial intelligence. No differences in students' attitudes toward artificial intelligence were found based on demographic factors. As such, it is suggested that educationally relevant materials should be revised to reflect current developments in the field of artificial intelligence. Studies have been done regarding generative AI (e.g., ChatGPT). Chan and Hu (2023) conducted a study with 399 university student participants in China in which students demonstrated an overall positive view of tools like ChatGPT. These students identified the benefits of using tools such as ChatGPT as being able to provide them with customized learning experiences and assistive functions for creative writing. However, the students also expressed concerns related to the accuracy of the information provided by tools such as ChatGPT, and privacy and ethical issues related to the use of tools such as ChatGPT. Yadrovskaia et al. (2023) conducted a study to examine how well the application of artificial intelligence can enhance societal progress and how well the integration of artificial intelligence into human experience will develop. The results of the study indicated that students who participated in this study viewed the application of artificial intelligence as having a positive impact on society. Students also believed that there would be limited loss of jobs due to the slow rate of dissemination of artificial intelligence technology at the time of the study. However, students believed that additional preparation needs to occur for both the business sector and society to appropriately prepare for the emergence of new technologies such as artificial intelligence.

The sample for the Yılmaz and Yılmaz (2024) study consisted of 318 university students surveyed using a survey technique, with the survey administered through a convenience sampling methodology. According to the Yılmaz and Yılmaz study, there existed a moderate level of concern pertaining to AI among university students. There was an identifiable statistically significant difference in the degree of concern toward AI among university students, as a function of class, academic achievement, work experience, and ownership of digital technology. The purpose of Mart and Kaya's (2024) study was to investigate the relationship between the attitudes toward AI of preschool teacher candidates and the AI literacy of those same candidates. As a result of the Mart and Kaya study, the utilization of AI tools is shown to be contingent upon the individual needs of the candidate, and further demonstrates the existence of significant correlations between variations in both attitudes toward AI and literacy levels, and demographic characteristics. In her 2024 study, Başer investigated the knowledge base and perception of AI and ChatGPT among students studying health-related fields, including perceptions toward the use of artificial intelligence, technostress levels relative to AI technologies, and other relevant factors. The results of the study showed that students displayed a moderate level of technostress relative to AI technologies; however, the majority expressed an interest in utilizing AI in the domain of health, as well as obtaining education/training in AI. Accordingly, the study suggests that the inclusion of artificial intelligence-related course content within the health services curriculum could reduce the level of anxiety experienced by students, while promoting technological adaptability.

Ülkü›s study from 2024 has investigated the impact of AI-related anxiety on students› innovative behaviors at Tokat Gaziosmanpasa University in Turkey, defining this type of anxiety as an aspect of future anxiety. This study also examines how younger people are influenced by advancements in AI and how those same advancements will impact the innovative behaviors in the potential workforce. The results indicate that AI-anxiety can positively affect students' innovative behavior, and that the future anxiety is used to act as a mediator for this relationship. A very similar study was completed in Slovenia using a survey of 422 students regarding their use of and perceptions of AI-based tool usage. Fosner's (2024) study identified that students believe that AI increases the efficiency of learning and the educational experience; however, they are concerned with the detrimental impacts of AI on the quality of education and the academic honesty of the student body.

Studies conducted concurrently produced similar research findings on a larger scale. As evidence, a large-scale study using a sample of 702 medical students in Pakistan reported 80 percent of the students responded positively about AI and nearly 90 percent believed AI is effective (60.8%) and trustworthy (58.4%) for the purpose of learning (Sami et al., 2025). Another large-scale international study using a sample of 2240 students from various Arab countries reported that approximately 47 percent of students had knowledge of ChatGPT and that 53 percent had used it before (Abdaljaleel et al., 2024). Students reported using AI for reasons including: ease of use; usefulness; general positive views toward technology; and low perceptions of risk. Sun and Zhou (2024) conducted a study that examined the attitudes of college students toward generative AI-based on gender, department, and experience with generative AI. The data collected in the study suggested that female students and students with experience using generative AI had more positive attitudes toward generative AI compared to their male counterparts and students without experience using generative AI. Additionally, students majoring in education reported greater success using generative AI than students from other majors. These results emphasize the need for all students to have access to educational experiences that involve generative AI; however, these experiences should take into consideration the students' gender, prior experience, and academic discipline when designing AI education.

A face-to-face survey study completed with 254 students from Marmara University, by Yakut et al. (2025), identified three different types of student profiles. According to the results of the study, 83.9 percent of students received some type of support from artificial intelligence; 96 percent of students did not believe the use of AI was ethical or reliable; and 63 percent of students feared the effects of AI (Giray Yakut et al., 2025). Using a large-scale study with a sample size of 400 students, Eti (2025) also reported that most students expressed a positive or slightly positive view of artificial intelligence. The results of this study reported that most students expressed positive views toward artificial intelligence (Eti, 2025). Muradi (2025) discovered a relationship existed between e-health literacy and positive views toward artificial intelligence among nursing students. Additionally, Muradi (2025) found a weak positive relationship existed between these two variables. A study using a sample of 448 students from Konya Selçuk University reported that students who used AI applications such as ChatGPT reported more positive views toward AI. Based on the findings of this study, there appears to be a need to include AI in the nursing curriculum and to educate nursing students regarding AI.

In a study conducted by Elmaoğlu and Güleç (2025) with 318 students, the relationship between nursing students' attitudes toward AI and their readiness for medical AI was examined. The study found a moderate positive relationship between the two. The findings indicate that as students cultivate favorable attitudes toward AI technologies, their aptitude for medical AI concomitantly enhances. Akman and Akman explored the association between candidate teacher's views on education, and their views toward artificial intelligence in their 2025 study. Their results found that progressivism was the most powerful predictor of candidate teachers' views toward artificial intelligence. A study using a sample of 508 students from Süleyman Demirel University reported that candidate teachers' views toward AI were moderate and differed according to the types of views that candidate teachers held toward education. Results indicated that candidate teachers' progressive, perennialist, and essentialist views significantly predicted candidate teachers' views toward artificial intelligence. As a result, the present body of literature concerning Turkey indicates that university students have generally positive views toward artificial intelligence, and these views are associated with knowledge level and demographic factors. However, existing research has identified several potential concerns, including ethical, security, and misinformation issues (e.g., inequalities in education, risk of information accuracy) (Eti, 2025).

Abdulmumin and Abdulrahman (2025) conducted a study of how Nigerian University Students utilized the AI-based conversational tool ChatGPT. This study explored the students' perception and attitudes toward the utilization of this conversational tool and drew upon data collected from a sample of Nigerian University Students. Similar to many studies involving the utilization of AI-based tools to assist students in completing school assignments or gaining conceptual clarity during the learning process, most students stated they utilized ChatGPT for similar reasons as well. Both gender and the type of institution of higher education positively impacted the students' attitudes and perceptions toward utilizing ChatGPT. Therefore, it is critical for institutions of higher education to establish programs and policy to educate students on the capabilities and limitations of AI-based tools. Additionally, institutions of higher education should establish guidelines regarding the ethical usage of these tools and ensure that students utilize them responsibly.

AI in Educational Contexts

Integrating AI into educational settings is becoming increasingly prevalent and influencing how learning occurs. ITS (Intelligent Learning Systems), for example, can provide students with customized learning experiences by adjusting the type of material and pace of learning to meet each student's unique needs. ITSs analyze students' progress in real-time and offer additional assistance when a student demonstrates weaknesses, while guiding them to more challenging material when they demonstrate strengths (Ünsal and Karaoğlan Yılmaz, 2024). AI-based assessment tools allow teachers to focus less on grading work while allowing students to receive immediate feedback, which enables a faster learning cycle. AI-based virtual assistants and chatbots using NLP (Natural Language Processing) allow students to ask questions anytime and anywhere, which allows students to continue learning continuously without interruption. Analyzing educational materials and using learning analytics allow teachers to have a better understanding of how students perform in class and to determine where they need to intervene. A number of studies have shown that the design of AI-supported educational environments can lead to increased student engagement and improved academic outcomes, while enabling students to take greater control over their learning experience (Temur, 2024).

Xu et al. (2024) identified that both faculty attitudes and school district infrastructure played a large role in students' ability to adapt to new technology. A common theme in the existing literature is that in order to successfully implement and utilize automation technologies like artificial intelligence, students must assess their future professional identity and whether they perceive technology as a risk or an opportunity to those identities. Factors such as unequal access to technology, students' level of digital literacy, and their perceived sense of technological competence also contribute to the differences in students' adaptation to AI technology (Xu et al., 2024). Similarly, a study examining the literacy levels and attitudes of 701 students majoring in religious studies (theology) at Necmettin Erbakan and Selçuk Universities was carried out by Karacan and Çiçek (2024). Findings indicated that the students demonstrated high literacy levels and generally favorable attitudes toward AI, and therefore, literacy appears to positively correlate with attitudes (Karacan & Çiçek, 2024). An experiment used AI-based chatbots (such as ChatGPT) as a teaching/learning tool. Following the experiment, a survey was administered to determine whether the students believed that AI-based tools would benefit them, and if they found them to be user-friendly; students reported that they expected benefits and believed they could easily use the tools (Uçar & Sözer, 2024). In their study, Yılmaz et al. (2024) assessed the awareness and opinions of students at the School of Health Sciences regarding AI and its application in healthcare. Results indicated that although most students had a positive view of AI, many demonstrated knowledge gaps and concern about AI applications; thus, the authors suggested the inclusion of AI-based topics in health education curricula.

The vast majority of students (domestic and foreign) view artificial intelligence positively, based upon their fields of study, technology literacy, and gender. Both foreign and domestic literature also discuss the benefits to students from artificial intelligence (i.e., customized learning assistance), but there are many other issues that have been discussed about artificial intelligence as well (e.g., ethical, security, and information accuracy). For example, Turkish students and international participants stated the advantages of artificial intelligence, but emphasized that there is a need for careful consideration of the potential risks of artificial intelligence (e.g., misinformation, loss of personal data/privacy). While there is a prevailing view that AI is an inevitable tool for transformation in education, the importance of policy and education for managing this transformation effectively and ethically is also emphasized.

Method

Research Model and Design

The research was conducted using the descriptive survey model among the survey models. The descriptive survey model was selected to reveal the attitudes of students studying in eight different programs at the Sakarya University of Applied Sciences (SUBU) School of Information Technologies toward AI (Büyüköztürk et al., 2017). The research was conducted using the descriptive survey model, one of the quantitative research methods. For this research project, this model was considered the most suitable because it makes it possible to gather a large amount of quantitative information on a sample size that allows for the description of a particular phenomenon in its current condition. In this case, the phenomenon in question was university students' attitudes toward AI. The primary objective was not to establish causal relationships, which would require an experimental design, but rather to identify the prevalence of these attitudes and explore their relationships with various demographic and experiential variables. Thus, the descriptive survey model is methodologically aligned with the study's aim of portraying the existing situation and examining relationships between variables.

Sample

The population of this study includes each and every one of the students enrolled in the SUBU School of Information Technologies during the 2024–2025 school year. Convenience sampling was used to determine the sample size for this study, which is a type of non-probabilistic sampling methodology. A primary reason for selecting this method was due to the accessibility of the student population at hand; this allowed for an efficient collection of data from the 351 students who volunteered to participate in this research study. The demographic characteristics of the 351 participants include: the total number of participants included 330 students, of which 116 (33.05%) indicated they are females, and 235 (66.95%) indicated they are males. Students participating in the study were enrolled in the following academic programs: Computer Programming (n = 189); Multidimensional Modeling and Animation (n = 58); Artificial Intelligence Operations (n = 23); Front-End Software Development (n = 19); Back-End Software Development (n = 21); Cloud Computing Operations (n = 21); Big Data Analytics (n = 20). As for the technical background of the participants, it was reported that 304 students (86.61%) had prior knowledge of programming. In addition, the study was carried out in compliance with the ethics committee approval according to the decision made by the SUBU Scientific Research and Publication Ethics Committee at the meeting held on May 7, 2025, and under protocol number 56, in accordance with Article 35. All data collected as part of the study were collected on a voluntary basis, and confidentiality of participant identity was maintained throughout the study.

Data Collection Instrument

Turgut and Kunuroğlu's (2025) "University Students' Attitudes Scale Toward Artificial Intelligence (SATAI)" measures students' attitudes toward artificial intelligence. The primary goal of this scale is to measure students' attitudes toward artificial intelligence. The scope of this study includes students' attitudes, both cognitive, affective, and behavioral, toward technology and artificial intelligence. This scale uses a 5-point Likert scale with three sub-dimensions, namely, positive attitude, negative attitude, and trust in technology. To adapt the SATAI scale to the Turkish language a careful process of forward translation followed by backward translation was used. Confirmatory factor analysis was conducted on the three-factor structure of the scale to establish the reliability and validity of the scale. The scale provided evidence of structural validity in that it produced meaningful associations.

Data Collection and Analysis

The Statistical Package for the Social Sciences (SPSS) 26.0 software was used for the analysis of the data collected during this study. A normality test was completed prior to any other statistical tests in order to verify the distribution of the data. Cronbach's Alpha Coefficient was also calculated to assess the reliability of the data.

To assess the credibility of the measurement instrument used in the current research, an assessment of the psychometric properties of the SATAI scale was repeated using data collected from the participants in this study. First, the internal consistency reliability of the SATAI scale was evaluated. As indicated in Table 4, the Cronbach's alpha coefficient was found to be .945 which indicates that the SATAI scale is reliable, according to George and Mallery (2003). Second, the construct validity of the SATAI scale was reassessed. High values on the Kaiser-Meyer-Olkin (KMO) statistic (.947) and a statistically significant Bartlett's test of sphericity ($p < 0.001$), as indicated in Table 5, were both used to confirm that the data are suitable for factor analysis. A subsequent factor analysis (Table 6) revealed a three-factor solution that accounted for approximately 59.74% of the total variability of the data, thus providing strong evidence for the robust construct validity of the SATAI scale in this study.

- Descriptive Statistics: Descriptive statistics, including frequency, percent, mean, and standard deviation, were determined for all participant demographic information and scale scores.
- t-test for Independent Groups: An independent-samples t-test was conducted to evaluate differences across the groups based on the categorical variables of gender and class status.
- One-Way Analysis of Variance (ANOVA): A one-way ANOVA was conducted to assess differences in attitudes toward AI by category of department, age group, and programming experience.

The purpose of this section is to provide additional information regarding the study's methodology, which includes a description of the study's design, population, sample, instruments used to collect data, and statistical methods used to analyze the collected data. The results of the study will be discussed and explained in detail in the next section based on the data that was collected through these methodologies.

Findings

A comprehensive evaluation of the data set revealed the absence of missing values. All variables were included in the analyses without any omissions.

Table 1
Valid and Missing Data Frequency Values

Status	n	Percentage (%)
Valid	351	100.0
Missing	0	0.0

As illustrated in Table 1, the scale total scores are not missing from the data. The analysis was conducted using data collected from 351 participants. This is a favorable circumstance with regard to the integrity of the data set and lends credence to the reliability of the results.

Table 2
Artificial Intelligence Attitude Scale Basic Descriptive Statistical Findings

Statistical Value	Result
Mean	104.22
Median	107
Standard Deviation	16.24
Minimum – Maximum	51 – 130
Skewness	-0.904
Kurtosis	0.747

An assessment of the key statistical data collected from a survey instrument used to measure students' perceptions about AI as an emerging technology revealed that there was a significant majority of students who have very favorable views of AI. The mean score for student perception of AI is 104.22, while the median score is 107; therefore, it can be inferred that the majority of respondents have scored their perceptions above the mean. The standard deviation of 16.24 represents a moderate degree of variability with respect to the responses provided by the students. The lowest possible response on the instrument was 51, and the highest possible response was 130; thus, the range of student responses was represented across all levels of perceived attitude toward AI. The skewness value of -0.904 suggests that the data set is negatively skewed or that students with positive perceptions toward AI responded at a greater frequency than those with negative perceptions toward AI. Additionally, the kurtosis value of 0.747 represents that the distribution of data is slightly less peaked than that which would represent a normally distributed population; therefore, the number of outliers (extreme responses) within the data set is somewhat limited. Overall, these results indicate that the majority of students perceive artificial intelligence positively and with considerable strength.

Table 3

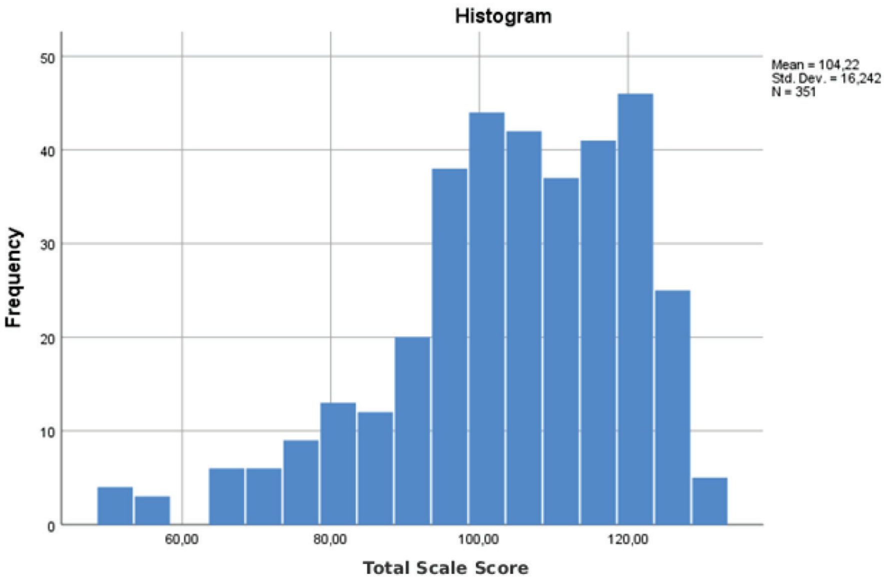
Artificial Intelligence Attitude Scale Basic Descriptive Statistical Findings

Test	Statistic	df	Sig. (p)
Kolmogorov-Smirnov	0.072	351	< .001
Shapiro-Wilk	0.943	351	< .001

The overall average of the total scores from the survey tool (104.22) shows that students have a generally favorable disposition toward AI, as shown in Table 3. As presented in Table 2, the median score of 107 is higher than the average, and the skewness of -0.904 indicated that there is a left-skewed distribution, showing that most participants rated the items very highly. Kurtosis for the distribution showed it has some peaks, with a measure of 0.747. The p-value for both the Kolmogorov-Smirnov test, as well as the Shapiro-Wilk test, in Table 3 was < .001. Nevertheless, because the skewness and kurtosis measures are each less than ±2, as indicated by Tabachnick and Fidell (2013), the data are considered normally distributed and thus parametric tests were used throughout the study.

Figure 2

Histogram Distribution of the Total Scale Score



The data in Figure 2 has a clearly negatively skewed distribution. A large number of participants have an average score of 100–120. Scores of 100–120 appear to be the modal or most common scores. Lower scores between 60 and 80 tend to occur at much smaller frequencies.

This result is consistent with the findings from the previous statistical test for skewness (-0.904), which provided evidence supporting the view that participants have positive attitudes toward artificial intelligence. Additionally, even though both Kolmogorov-Smirnov and Shapiro-Wilk normality tests provided p values less than $p < .001$, this may provide some indication that there is a lack of symmetry in the distribution; however, since the skewness and kurtosis coefficients fall within the ±2 bounds, Tabachnick and Fidell (2013) suggest that it is acceptable to conclude that the shape of the data distribution is very similar to that of a normal distribution in the social sciences.

Table 4

Internal Consistency Statistical Findings of the Artificial Intelligence Attitude Scale

Statistic	Value
Cronbach's Alpha	.915
Cronbach's Alpha (Standardized Items)	.945
Number of Items (N of Items)	26

A high Cronbach's Alpha coefficient (a measure of internal consistency) of .945 was obtained as an indicator of internal consistency from a thorough assessment of the internal consistency of the SATAI scale (Table 4). This indicates that the items of the scale are very consistent with one another and that the scale has a strong structural reliability. Alpha coefficients at .90 or greater indicate "excellent" reliability (George & Mallery, 2003); therefore, the .945 Alpha coefficient obtained after standardizing the items indicates that the internal consistency of the scale is further enhanced by using a standardized scoring system. Therefore, it may be stated that this 26-item scale is internally consistent and does provide a reliable measure of attitudes toward AI (George & Mallery, 2003).

Table 5

KMO and Bartlett's Sphericity Test Statistical Findings

Test	Value
KMO (Kaiser-Meyer-Olkin)	.947
Bartlett's Test	$\chi^2 = 6143.418$, $df = 325$, $p < .001$

The Kaiser-Meyer-Olkin (KMO) score was .947 as indicated by Table 5, which indicates high sample adequacy. Data sets are considered to have high suitability for factor analysis when their KMO scores are .90 or greater (Kaiser, 1974). Bartlett's test of sphericity generated a statistically significant result ($\chi^2(325) = 6143.418$, $p < .001$), demonstrating considerable intercorrelation among the items and supporting the appropriateness of factor analysis.

Table 6

Confirmatory Factor Analysis Statistical Findings

Factor	Eigenvalue	Explained Variance (%)	Cumulative (%)
1	12.288	47.260	47.260
2	1.993	7.666	54.926
3	1.253	4.819	59.744

In addition to what is shown in Table 6, the variation in the scale can be explained by a combination of three factors, which collectively explain 59.74% of the observed variation. Factor one accounts for 47.26% of the variation; factor two explains 7.67%; and factor three explains 4.82%. In total, the three factors combined explained 59.74% of the total variation in the scale. According to Hair et al. (2014), an explanation of 50% or greater of the total variation is generally accepted as sufficient. Therefore, based on the results of the factor analysis, the factor structure of the scale is considered acceptable.

The results of the factor analysis indicated that the KMO measure of sampling adequacy for the current study was .947, which indicates that the sample has an "excellent" degree of sampling adequacy. The Bartlett Sphericity Test was also found to have produced a statistically significant result ($p < .001$), which further supports that the data collected for the current study were appropriate for factor analysis. Overall, the total amount of variance explained in the study was 59.74%, which is generally accepted as sufficient for studies in the social science disciplines. The analysis resulted in three factors, and it was determined that there were significant correlations among the three factors. The results provided strong evidence of the robust construct validity of the scale.

Table 7

Exploratory Analysis Findings According to the Gender

Gender	n	Mean	Standard Deviation	Standard Error of the Mean
Male	235	104.9532	15.55	1.01447
Female	116	102.7328	17.53	1.62792

Table 8

Independent Samples t-test Analysis by Gender

Subscale	t	df	p (2-tailed)	Mean Diff.	F	p (ANOVA)
Total	1.206	349	0.229	2.220	3.171	0.076
Cognitive	-0.43	349	0.661	-0.152	< .001	0.992
Emotional	0.990	349	0.323	0.723	0.107	0.740
Behavioral	1.642	349	0.102	1.649	10.557	0.001

Table 7 provides an overview of the results from the analysis. The analysis examined the attitudes held by university students regarding AI, distinguishing between male and female students.

As indicated by the results of the t-test for independent samples in Table 8, the mean total attitude score for male students ($\bar{X}$ = 104.95) was higher than that for female students ($\bar{X}$= 102.73). However, this discrepancy did not reach statistical significance (t (349) = 1.206, p = 0.229). Analyses conducted at the sub-dimension level also revealed no significant difference between genders in terms of cognitive (p = 0.661), affective (p = 0.323), and behavioral (p = 0.102) attitude scores.

However, a one-way analysis of variance (ANOVA) revealed a significant discrepancy in the behavioral attitude sub-dimension, with a statistical significance of F = 10.557 and a p-value of 0.001. The results of the one-way analysis of variance (ANOVA) indicate that gender may be an effective factor in behavioral attitudes. No statistically significant differences were identified in the other subdimensions or total attitude scores (p > 0.05).

Table 9

Findings of Descriptive Analysis According to the of Learning With Artificial Intelligence

AI Learning	n	Mean	Std. Deviation	Std. Error Mean
Yes	96	103.10	17.32	1.768
No	255	104.64	15.83	0.991

Table 10

Findings of the Independent Samples t-test Analysis Based on Learning With Artificial Intelligence

Subscale	t	df	p (2-tailed)	Mean Difference	F	p (ANOVA)
Total	-0.789	349	0.431	-1.54	0.639	0.424
Cognitive	-2.036	349	0.430	-0.75	2,048	0.153
Emotional	-1.482	349	0.139	-1.14	0.034	0.855
Behavioral	0.329	349	0.742	0.35	0.960	0.328

The study presents the results of explanatory statistical analyses in Table 9, which address the question of whether students have taken a course on artificial intelligence. Additionally, Table 10 provides an examination of the existence of a significant difference in AI attitude scores. The t-test results for independent samples indicated that the mean total attitude score of students who had taken the AI course (X = 103.10) was lower than that of students who had not taken the course (X = 104.64). However, this discrepancy did not reach statistical significance (t(349) = 0.7888, p = 0.431).

Subsequent analysis at the sub-dimension level revealed no significant differences in cognitive (p = 0.430), affective (p = 0.139), and behavioral (p = 0.742) attitude scores. Despite the finding that students who had completed the course demonstrated lower scores on the cognitive and affective subscales, these disparities were not statistically significant.

The results of the one-way analysis of variance (ANOVA) further corroborate this finding. In contrast, the analysis of variance (ANOVA) revealed that there was no statistically significant difference in total attitude scores (p = 0.424), as well as in scores on the cognitive (p = 0.153), affective (p = 0.854), and behavioral (p = 0.327) subscales, based on the participants' course enrollment status.

Table 11

Descriptive Analysis Findings According to the Programming Knowledge

Programming Knowledge	n	Mean	Std. Deviation	Standard Error (SE)
Yes	304	105.05	15.69	0.89996
No	47	98.87	18.75	2.73508

Table 11 examines students' attitudes toward AI based on whether or not they possess programming knowledge.

Table 12

Findings of the Independent Samples t-test Analysis Based on the Programming Knowledge

Subscale	t	df	p (2-tailed)	Mean Difference	Std. Error	F	p (ANOVA)
Total	2.442	349	0.015	6.173	2.527	3.290	0.071
Cognitive	2.247	349	0.025	1.075	0.478	0.393	0.530
Emotional	2.256	349	0.025	2.264	1.003	3.394	0.066
Behavioral	2.046	349	0.041	2.834	1.385	3.208	0.074

The results from the independent-samples t-tests are shown in Table 12. It has been shown by the t-test results, as indicated in the table, that the mean total-attitude score for students with prior knowledge of programming ($\bar{X}$ = 105.05) is significantly greater than for students without such a background ($\bar{X}$ = 98.87) (t(349) = 2.442, p = 0.015). In addition to the overall attitudes of students, analogous findings have also emerged with respect to their attitudes toward each of the three sub-dimensions of attitudes (cognitive, affective, and behavioral). The mean total-attitude scores for students with prior knowledge of programming were significantly different (at the 0.05 level) from those of students without programming experience on all three sub-dimensions of attitudes. These results reflect a difference of 1.08, 2.26, and 2.83 points between the mean attitude scores of the two groups of students on the three respective sub-dimensions of attitudes. On the other hand, when an ANOVA was performed for both the total-attitude measure and the three subscale measures, the F-values associated with the total-attitude measure and the subscale measures approached but did not exceed the typical alpha-level for determining statistical significance (p = 0.071). However, further analysis of the results showed that the t-test results were the only ones to be statistically significant. As previously mentioned, there are several possible explanations for why the t-test results were the only statistically significant results. One explanation is that there was an unequal number of participants in each group, resulting in an imbalanced sample. Another possible explanation is that the variables used to develop the total-attitude measure and the three subscale measures exhibited variability that resulted in non-normal distributions of the data.

Table 13

Descriptive Analysis Findings According to Awareness of Artificial Intelligence Tools

Awareness of AI Tools	n	Mean	Standard Deviation	Standard Error (SE)
Yes	314	104.97	15.43	0.87055
No	37	97.81	21.18	3.48158

As illustrated in Table 13, a comparative analysis of attitude scores concerning artificial intelligence is presented, with the data categorized based on the extent of awareness regarding AI tools among the student population. As indicated by the results of the descriptive statistics, the mean total attitude score of students who are aware ($\bar{X}$ = 104.97) was found to be significantly higher than that of students who are not aware ($\bar{X}$ = 97.81).

Table 14

Findings of the Independent Samples t-test Analysis Based on the Awareness of Artificial Intelligence Tools

Dimension	t	df	p (2-tailed)	Mean Difference	Std. Error	F	p (ANOVA)
Total	1.996	349	0.053	7.16	3.59	6.124	**0.014**
Cognitive	2.434	349	0.010	1.285	0.766	18.524	**< .001**
Emotional	2.249	349	0.092	2.503	1.113	4.402	**0.037**
Behavioral	2.196	349	0.029	3.370	1.734	1.363	0.244

In the independent sample t-test in Table 14, while there was a statistically insignificant result between the groups with regard to the total attitude score ($t(349) = 1.996$, $p = 0.053$), a statistically significant result was found in the behavioral attitude subscale ($t(349) = 2.196$, $p = 0.029$). Statistically non-significant results were found regarding the attitudinal aspects of the cognitive ($p = 0.10$) and affective ($p = 0.092$) subscales. Statistical non-significance was found for these two subscales, however. Significant effects were found from the ANOVA with regard to the total attitude ($F = 6.124$, $p = 0.014$) and both attitudinal aspects of the cognitive ($F = 18.524$, $p < 0.001$) and affective ($F = 4.402$, $p = 0.037$) attitudes; however, the ANOVA indicated that there were no significant effects among the groups with regard to the attitudinal aspect of the behavioral attitude ($F = 1.363$, $p = 0.244$).

Students familiar with AI tools displayed a greater positive inclination toward AI compared to those unaware of them. These results suggest that practical experience with AI tools fosters attitudes grounded in application and active engagement.

Table 15

Explanatory Analysis Findings According to the Professional Future Anxiety Status

Professional Future Anxiety	n	Mean	Std. Deviation	Standard Error (SE)
Yes (Positive effects)	288	104.30	16.38	0.965
No (Does not have a positive effect)	63	103.84	15.71	1.979
Average difference		→ 0.46 points		

Table 16
Findings of the Independent Samples t-test Analysis According to the Professional Future Anxiety

Subscale	t	df	p (2-tailed)	Mean Difference	Standard Error	F	p (ANOVA)
Total	0.204	349	0.839	0.461	2.262	0.010	0.921
Cognitive	-0.041	349	0.968	-0.017	0.427	0.692	0.406
Emotional	-0.189	349	0.851	-0.169	0.897	0.047	0.828
Behavioral	0.524	349	0.601	-0.647	1.236	0.242	0.623

Table 15 presents a comparison of students' attitudes toward AI-based on their beliefs concerning its potential positive impact on their professional futures. According to the findings of descriptive statistics, the mean total attitude score for students who expressed a favorable opinion ($\bar{X}$ = 104.30) was approximately 0.46 points higher than for those who expressed a negative opinion ($\bar{X}$ = 103.84). However, this discrepancy was not found to be statistically significant.

As demonstrated in Table 16 above, the total score and subdimensions (cognitive, emotional, behavioral) of university students' attitudes toward AI were evaluated using an independent samples t-test and one-way analysis of variance (ANOVA) in terms of the professional future anxiety variable.

The results of the study indicate that no statistically significant differences were found in any subdimensions or total score. In all subdimensions, both t-test and ANOVA results have p-values well above .05. The findings indicate that the professional future anxiety variable does not exert a substantial influence on university students' attitudes toward artificial intelligence.

As indicated by the findings presented in Table 17, variance analyses (ANOVA) demonstrate that there are substantial variations in the attitudes of university students toward AI across certain subdimensions. Statistically significant differences were identified between groups in the total scale score ($F = 3.313$; $p = 0.004$), the emotional sub-dimension ($F = 2.715$; $p = 0.015$), and the behavioral sub-dimension ($F = 3.938$; $p = 0.002$). The investigation revealed no statistically significant disparities in the cognitive sub-dimension ($F = 1.051$; $p = 0.392$). The findings suggest that, at the cognitive level, students' attitudes toward AI are comparable across various groups. However, disparities emerge in their emotional and behavioral attitudes.

Table 17
Analysis of Variance Between Groups by Department and Significant Pairwise Comparisons in the Subdimensions of University Students' Attitudes Toward Artificial Intelligence

Subscale	F	p	p < .05	Significant Pairwise Comparisons*
Total Scale	3.313	0.004	✓	Computer Programming – Multidimensional Modeling: -8.33 (p = 0.030, GA = [-16.17;-0.48]) Front-End Dev. – Multidimensional Mode: -14.71 (p < .001, GA = [-24.22;-5.20])
Cognitive	1.051	0.392	✗	-
Emotional	2.715	0.015	✓	Computer Programming – Multidimensional Modeling: -3.15 (p = 0.042, GA = [-6.23;-0.06]) Front-End Dev. – Multidimensional Model: -5.36 (p < .001, GA = [-8.85; -1.87])
Behavioral	3.938	0.002	✓	Computer Programming – Multidimensional Modeling: -4.29 (p = 0.035, GA = [-8.40; -0.18]) Front-End Dev. – Multidimensional Mode: -7.91 (p = 0.001, GA = [-13.30; -2.53])

A subsequent examination of meaningful pairwise comparisons reveals that the "Multidimensional Modeling" group, in particular, demonstrated lower total scale and sub-dimension scores in comparison to the "Computer Programming" and "Front-End Development" groups. For instance, a statistically significant difference of -8.33 points ($p = 0.030$) was observed between the "Computer Programming" categories and the other categories. The "Multidimensional Modeling" exhibited a statistically significant difference of -14.71 points ($p < .001$) compared to the "Front-End Dev." variable. The "Multidimensional Modeling" variables were found to be significant for the total scale. Conversely, the scores of the "Multidimensional Modeling" group were found to be significantly lower than those of the other two groups in the emotional and behavioral sub-dimensions.

Students' attitude toward AI showed differences in both behaviorally and emotionally based upon domain or use (i.e., info-prog, front-end, etc.) and also that students who worked with multidimensional models had a significantly lower emotional and behavioral predisposition toward AI compared to others. Research results indicated that varying student attitudes are largely due to the nature of the applications; therefore, differing methods, and needs exist for AI educational purposes. Students' behaviors and attitudes toward artificial intelligence change depending on their experience with different applications of AI.

Table 18
Between-Groups Analysis of Variance and Significant Pairwise Comparisons Regarding How Often University Students Use AI Attitude Subdimensions

Subscale	F	p	p < .05	Significant Group Comparisons (I - J) Mean Difference (GA) p
Total Scale	6.095	< .001	✓	Every day – Every 2-3 days: Mean Diff = 21.10 (p < .001, GA = [7.37; 34.82]) Every day – Several times a week: Mean Diff = 17.76 (p < .001, GA = [6.32; 29.20]) Every day – Once a month: Mean Diff = 15.29 (p < .001, GA = [4.87; 25.71]) Every day – Never: Mean Diff = 13.63 (p = 0.003, GA = [3.09; 24.16])
Cognitive	1.995	0.096	✗	-
Emotional	4,502	0.002	✓	Every day – Every 2-3 days: Mean Diff = 7.62 (p = 0.001, GA = [2.13; 13.11]) Every day – Several times a week: Mean Diff = 5.50 (p = 0.008, GA = [0.93; 10.07]) Every day – Once a month: Mean Diff = 5.60 (p = 0.002, GA = [1.43; 9.76]) Every day – Never: Mean Diff = 5.10 (p = 0.007, GA = [0.89; 9.32])
Behavioral	6.471	< .001	✓	Every day – Every 2-3 days: Mean Diff = 11.19 (p < .001, GA = [3.70; 18.68]) Every day – Several times a week: Mean Diff =10.31 (p = 0.001, GA = [4.07; 16.55])

The findings in Table 18 demonstrate that university students' attitudes toward AI vary considerably based on frequency of use. A statistically significant discrepancy was identified between the groups with regard to the total scale score ($F = 6.095$; $p < .001$), the emotional sub-dimension ($F = 4.502$; $p = 0.002$), and the behavioral sub-dimension ($F = 6.471$; $p < .001$). Conversely, no substantial discrepancy was observed in the cognitive sub-dimension ($F = 1.995$; $p = 0.096$). The findings indicate that while there was no substantial change in students' cognitive attitudes according to frequency of use, significant differences were observed at the emotional and behavioral levels.

Students who utilized AI 'every day' scored significantly higher across each dimension of the total scale compared to other groups, based on the frequency of their AI usage. This is evident when compared to students who utilized the technology 'every 2–3 days', 'several times a week', 'once a month', or 'never'. The comparison between the groups of students that utilized AI tools 'every day' and 'every 2–3 days' resulted in a 21.10-point difference ($p < .001$); similarly, the comparison between the groups of students utilizing the technology 'every day' and 'several times a week' resulted in a 17.76-point difference ($p < .001$). The comparison between students who utilized AI 'every day' and those who utilized it 'once a month' resulted in a statistically significant difference, with a mean difference of 29 points (p = .000), indicating a highly significant difference between the two groups. Similarly, the comparison between the group that utilized AI tools 'every day' and the group that 'never' utilized them revealed a statistically significant difference, with a 13.63-point difference (p = .003). Further examination of the Emotional and Behavioral subdimensions indicated that students utilizing AI tools on a daily basis reported more favorable attitudes compared to other groups.

Table 19

Variance Analysis and Significant Pairwise Comparisons Between Groups in Sub-Dimensions Regarding the Purpose of Using Artificial Intelligence Tools

Subscale	F	p	p < .05	Significant Group Comparisons (I - J, Mean Difference [GA], p)
Total Scale	3.215	0.013	✓	None (Closest: Education–Curiosity, p = 0.054, not significant)
Cognitive Attitude	2.437	0.048	✓	None (Closest: Education–Curiosity, p = 0.119, not significant)
Emotional Attitude	2.066	0.086	✗	-
Behavioral Attitude	3,260	0.013	✓	Education–Curiosity: 7.04 0.30;13.780.30; 13.78 (p = 0.034) ✓

The goal of Table 19 is to investigate if the student's attitude toward AI differs in each of its sub-dimensions depending on how often the student uses an AI tool. As indicated by the F-statistic (F = 3.215; p = 0.013), statistically significant differences existed between the two groups in terms of the total scale (general attitude), cognitive attitude (F = 2.437; p = 0.048), and behavioral attitude (F = 3.260; p = 0.013) dimensions of attitudes toward AI. On the other hand, no statistically significant variation was noted between the two groups in terms of the emotional attitude dimension (F = 2.066; p = 0.086). Thus, it appears that students' emotional attitudes toward AI did not differ based upon the reasons they used AI tools. Nonetheless, several significant differences were found across the three general attitude (total scale), cognitive, and behavioral dimensions.

Additionally, an analysis of the pairwise comparisons showed the closest group difference was evident within both the total scale and cognitive attitude dimensions and specifically between AI usage for "education" and "curiosity." Nonetheless, these differences were not statistically significant (p > 0.05). Furthermore, in the behavioral attitude dimension, a statistically significant difference of 13.78 points (p = 0.034) was evident between students who used AI for educational purposes and those who used AI for curiosity purposes. The results from this research indicate that students using

AI tools for education have significantly higher behavioral attitude scores than those students using AI tools for personal interest.

Table 20

Most frequently used AI tool

Subscale	F	p	p < .05	Meaningful Group Comparisons (I - J, Mean Difference [GA], p)
Total Scale	1.861	0.077	✗	-
Cognitive Attitude	1.931	0.067	✗	-
Emotional Attitude	2.382	0.026	✓	ChatGPT–Copilot: 6.07 [0.12;12.01] (p = 0.046) Google Gemini–Other: 9.21 [0.21;18.20] (p = 0.042) Grok–Le Chat: 4.50 [0.42;8.58] (p = 0.031)
Behavioral Attitude	1.123	0.344	✗	-

The objective of this study is to examine whether there is a significant difference in the subdimensions of attitudes toward AI according to the AI tool most frequently used by university students. The results of this examination are presented in Table 20. The findings revealed no statistically significant differences between the groups in terms of the total scale ($F = 1.861$; $p = 0.077$), cognitive attitude ($F = 1.931$; $p = 0.067$), and behavioral attitude ($F = 1.123$; $p = 0.344$) dimensions. However, a substantial discrepancy was identified between the groups in the emotional attitude dimension ($F = 2.382$; $p = 0.026$).

A difference in emotional attitude was found for the most frequently utilized AI tool in comparing pairs of groups. In particular, the results indicated a statistically significant difference of 6.07 points ($p = 0.046$), 9.21 points ($p = 0.042$) and 4.50 points ($p = 0.031$) respectively when comparing the usage of ChatGPT vs. Copilot, Google Gemini vs. all other tools and Grok vs. Le Chat. These statistics suggest that students who regularly use specific AI tools demonstrate marked variations in their emotional predisposition.

Discussion and Conclusion

This current research investigated students' views toward artificial intelligence (AI) with reference to their experiences and demographics; i.e., gender, programming experience, experience with AI tools, reasons for using AI and how often they use AI. The results indicate that most students are developing a favorable view toward AI, but the degree of favorable attitudes toward AI varies according to the students' experiences.

For example, students who were familiar with programming, demonstrated the highest overall positive AI attitudes and the highest positive cognitive, affective and behavioral attitudes toward AI. This is indicative of the fact that having both technical skills and technology infrastructure will promote students' deliberation and positive attitudes toward AI technologies. Furthermore, the degree of familiarity with AI tools appears to directly influence students' attitudes toward AI, particularly their cognitive and affective attitudes, since students familiar with AI tools exhibited greater cognitive and affective attitudes toward AI than did students without such familiarity.

The findings of this research indicate that the frequency at which AI tools are used by students along with the purpose they were used for has a major influence on the student's attitudinal response toward technology. The comparative data indicated that students that used the AI tools daily had much more positive attitudes than any of the other groups that were analyzed; as evidenced by the total attitude scores and sub-scores being significantly higher than the other groups. In addition to being a marker of how much students have been exposed to technology; these results indicate that how often students use AI tools is also a marker of how much the students have internalized their experiences and developed positive experiences using the technology. Students that used AI tools for educational purposes showed much higher total and behavioral attitude scores than students that used them because they were curious about the tools. These results indicate that the use of AI tools for educational purposes develops greater involvement in learning and positively influences behavioral tendencies toward technology. In the comparative data, the most commonly used AI tools indicated that the users of ChatGPT, Google Gemini and Grok showed significantly higher affective attitude scores than the users of all the other AI tools. This difference is important since it shows that user-friendly AI tools that are widely accepted will result in a greater positive affective response in students.

The data in this research indicates that a student's degree of understanding of AI, as well as the amount of experience the student has using AI, influences the student's attitudes toward AI. More specifically, the results of this research found that programming knowledge, how often a student uses AI, and the reasons why they are using AI were all variables that significantly impacted the differences in attitude scores for students. These findings emphasize the need for educators to include practical, hands-on, and cognitively rich curriculum in education about AI, which will lead to the creation of more positive, thoughtful, and long-term attitudes by students toward AI. Thus, it is suggested that universities create more comprehensive courses in AI than currently exist, and that there be developed formalized strategies to help students become effective users of AI technology in their daily, academic, and professional lives.

The study found that students with coding experience have a better disposition to AI. Furthermore, users of AI daily have an average attitude score much larger than those who do not. The study found the same as many other studies from the literature referenced here. For example, Süleymanoğulları et al. (2024) found that there is a relationship that is positive between the AI Literacy and Attitudes toward AI. In addition, KPMG and the University of Melbourne (2025) found a similar trend globally. This trend shows that people who use AI tools more frequently develop a more positive disposition toward AI. The findings also support the validity of the study at both the local and the global level.

Student use of AI for academic purposes resulted in significantly greater behavioral attitudes than student use of AI for personal interests. The study also found that students who preferring tools like ChatGPT, Google Gemini, and Grok had higher affective attitudes toward the tools used than did students using different tools. This is in line with previous research on this topic. Pitts et al. (2025), for example, found that when students employed AI to enhance their ability to learn and access information, they were more likely to have favorable attitudes toward it; however, the study's distinction between the uses and preferences of specific tools provides a new contribution to the prior research.

The cognitive, affective, and behavioral aspects of attitudes toward AI were also studied separately as part of the scale sub-factor dimensions. In other words, while there were large differences in both the affective and behavioral domains of the scales; they were less distinct in the cognitive domain. This methodology has been used similarly in a number of prior studies in the extant literature. For example, İlhan and Önal (2025) tested the three factor model (Cognitive, Affective, and Behavioral) of the attitude scale toward AI and related those factors. However, this current study provides a comprehensive view of the prior research by thoroughly examining the differences among the various dimensions and relating each of those to specific variables.

The results of the study are consistent with the findings of previous research; however, they also offer original contributions, particularly in the detailed examination of the relationships between the purpose of use, tool preference, and attitude components. This contributes to the enhancement of the study's value from both theoretical and practical standpoints.

Quantitative data were used for measuring attitudes in this research. Following studies will provide greater insight when researchers utilize qualitative methods for examining the personal values, emotions, and experiences that individuals associate with Artificial Intelligence. This could occur with the use of student interviews, focus groups or open-ended written descriptions. Longitudinal research design in future studies would allow researchers to more accurately assess changes in students' attitudes toward AI over time and the factors that contribute to those changes. Large differences in attitudes were also seen between students attending different academic departments; therefore, the inclusion of field-based AI integration into curricula is an important consideration for future research. For example, comparative studies could investigate AI knowledge and familiarity levels, and attitudes in different fields (i.e., engineering, healthcare, social sciences, arts). The results from this study demonstrate how certain tools increase positive attitudes toward AI. However, the psychological effects of variables such as interface design, language support, usability, and dependability of the tools studied in this research are still unknown. Therefore, future studies could explore the effects of these tool characteristics and user experience on attitudes toward AI utilizing psychometric models.

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Universiteto studentų nuostatų į dirbtinį intelektą veiksniai: tyrimas apie demografinius kintamuosius, naudojimo įpročius ir lygmenis

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Santrauka

Šiame tyrime nagrinėjamos universiteto studentų nuostatos į dirbtinį intelektą (toliau – DI) ir kaip šios nuostatos formuojasi priklausomai nuo įvairių demografinių ir patirtinių kintamųjų. Tyrime dalyvavo 351 studentas, šiuo metu studijuojantis Sakarijos taikomųjų mokslų universiteto Informacinių technologijų mokykloje. Duomenys buvo renkami naudojant Universiteto studentų nuostatų į dirbtinį intelektą skalę (angl. *University Students' Attitude Towards Artificial Intelligence Scale*, SATAI), o vertinami taikant aprašomąją statistiką, nepriklausomų imčių *t* kriterijų, vienkryptę dispersinę analizę (angl. *Analysis of Variance*, ANOVA) ir koreliacijos analizę. Tyrimo rezultatai parodė, kad studentai paprastai formuoja teigiamas nuostatas į DI. Studentai, turintys programavimo patirties ir gerai išmanantys DI įrankius, pasižymėjo žymiai aukštesniais bendrais nuostatų bei atskirų jų dimensijų įverčiais. Buvo nustatytas reikšmingas teigiamas ryšys tarp DI naudojimo dažnumo ir tyrime dalyvavusių studentų nuostatų. Taip pat tyrimo rezultatai atskleidė, jog naudojant DI įrankius švietimo srityje buvo daugiausia teigiamų rezultatų, ypač susijusių su elgesiu. Tyrimo rezultatai parodė, kad praktinė patirtis naudojant DI įrankius skatina teigiamas studentų nuostatas į šią technologiją. Todėl rekomenduojama universitetų lygmeniu skatinti su DI susijusias švietimo iniciatyvas, taip siekiant didinti studentų technologinį sąmoningumą.

Esminiai žodžiai: *nuostatos į dirbtinį intelektą, universiteto studentai, dirbtinis intelektas švietime, technologinis sąmoningumas.*

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