The Impact of Task-Technology Fit on the Intention to Use Artificial Intelligence in the Education of Information Technology Students in Universities: The Role of Self-Efficacy

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ABSTRACT
This study aims to examine university students' intentions to use artificial intelligence (AI) applications in their educational processes within the context of job characteristics (JC), technology characteristics (TC), task-technology fit (TTF), and self-efficacy (SE). The research was conducted with 965 students enrolled in Information Technology programs at four foundation universities in Istanbul. Data were collected through a structured questionnaire and analyzed using SPSS 24. Linear regression analysis was employed to interpret the relationships among the variables. According to the findings, both job characteristics ($\beta = 0.609$, $p<0.01$) and technology characteristics ($\beta = 0.883$, $p<0.01$) were found to have a positive and significant effect on TTF. Furthermore, TTF was identified as a significant predictor of AI usage intention ($\beta = 0.644$, $p<0.01$). Also, the self-efficacy variable moderate significantly the relationship between TTF and AI usage intention ($\beta = 0.115$, $p <0.01$). The independent variables in the research model explained 18% of the variance in task-technology fit and 64% of the variance in AI usage intention. The findings suggest that enhancing students' technological self-efficacy and developing user-friendly AI solutions may encourage the adoption of AI technologies in educational settings. One of the limitations of this study is that the sample was restricted to students from four foundation universities in Istanbul. Therefore, future research is recommended to include larger and more diverse samples from different regions and disciplines to improve the generalizability of the results.
Keywords: Artificial Intelligence Technologies, Task Technology Fit Model, Self-Efficacy, Artificial Intelligence, Information Technologies.

Introduction
Artificial Intelligence (AI) is defined as the ability of computer systems to mimic human-like cognitive processes (Russell, 2016). Encompassing capabilities such as learning, problem-solving, decision-making, and language comprehension, AI has been driving transformative changes across various domains, including healthcare, finance, transportation, education, and industry (McAfee, 2017). In particular, advancements in deep learning algorithms have significantly enhanced AI's capacity to analyze complex datasets and generate outputs that closely resemble human intelligence (LeCun, 2015). In this context, the integration of AI into the field of education enables the emergence of new paradigms in teaching and learning processes (Halverson, 2019).

The potential of AI in education can be summarized as offering personalized learning experiences to students, reducing teachers' workload, optimizing assessment processes, and creating new opportunities in education overall (Halverson, 2019). The use of AI in education dates back to the 1980s and has evolved through applications such as expert systems, personalized instructional software, and intelligent tutoring systems (Brusilovsky, 2001). Since the 2000s, progress in machine learning and deep learning has further strengthened the application of AI in educational settings (Siemens, 2013). Today, AI is employed in various areas including predicting student performance, identifying learning difficulties, personalizing educational content, analyzing student feedback, and assisting teachers in managing instructional processes (Siemens, 2013). These developments demonstrate the transformative potential of AI within educational systems. However, realizing this potential requires careful consideration of issues such as ethical use of AI, data privacy, equity, and accessibility (Watkins, 2018).

In Turkey, the integration of Artificial Intelligence (AI) into the field of education has also gained momentum in recent years (Aydın, 2021). Current studies focus on the potential of AI to personalize learning experiences, support teachers, and optimize educational management processes (Ercan, 2020). Particularly, AI applications in online learning platforms, educational software, and intelligent tutoring systems have become increasingly prevalent (Akın, 2019; Gökçe, 2018). Examples of such applications include platforms that analyze student performance to offer personalized learning recommendations, tools that provide customized educational content based on students' interests and learning styles, and intelligent assistants that support teachers in lesson planning (Gökçe, 2018). However, the integration of AI in the Turkish education system is still in its early stages, and there is a need for more research, practical implementations, and policy development in this area (Yıldız, 2022).
In this context, the Technology Acceptance Model (TAM) (Davis, 1989) and Task-Technology Fit (TTF) model (Goodhue & Thompson, 1995), which aim to explain individuals' behaviors regarding the adoption and use of new technologies, have gained importance. TAM explains technology acceptance through the constructs of perceived usefulness and perceived ease of use (Venkatesh, 2000). The TTF model, on the other hand, reflects individuals' beliefs regarding the integration of a given technology into their tasks and the extent to which the technology enhances task performance (Bandura, 1997).

This study investigates the Task-Technology Fit (TTF) levels and usage intentions regarding the use of AI in education among students at foundation (non-profit private) universities in Istanbul, while also examining the moderating role of self-efficacy perceptions in this relationship.

The primary aim of this study is to determine the TTF levels, usage intentions, and self-efficacy perceptions of students from foundation universities in Istanbul in the context of AI use in education, and to reveal the moderating role of self-efficacy in the relationship between TTF and usage intention.

Literature Review

In the era of rapid digital transformation, the integration of Artificial Intelligence (AI)-based applications into educational systems is becoming increasingly widespread. This development has heightened the need for comprehensive and empirically validated theoretical models to understand individuals' acceptance processes toward such innovative technologies. In this context, the Technology Acceptance Model (TAM) and the Task-Technology Fit (TTF) model are widely recognized and frequently utilized theoretical frameworks in the academic literature for explaining users' technology adoption behaviors.

Technology Acceptance Model (TAM)

Developed by Davis (1989), the Technology Acceptance Model explains individuals' intentions and behaviors regarding the adoption of new technologies through two fundamental cognitive beliefs: perceived usefulness and perceived ease of use. According to the core proposition of the model, a user's intention to use a technology is primarily influenced by these two determinants. Over time, the model has been revised and expanded—first as TAM2 by Venkatesh and Davis (2000), and later as TAM3—to incorporate additional factors such as social influence, cognitive instrumental processes, and individual differences.

Post-2020 Applications of TAM

TAM has been extensively applied to analyze the acceptance of e-learning platforms, AI-supported educational systems, mobile learning applications, and cloud-based solutions. For instance, Al-Emran and Shaalan (2021) analyzed university students' acceptance levels of AI-supported learning systems within the TAM framework, empirically demonstrating the decisive effect of perceived usefulness on usage intention. Similarly, Chatterjee et al. (2022) employed the TAM and Extended TAM (ETAM) models to examine students' adaptation to digital systems in post-pandemic hybrid learning environments.

Task-Technology Fit (TTF) Model

Developed by Goodhue and Thompson (1995), the Task-Technology Fit (TTF) model posits that the effective use of a technology depends on the alignment between the capabilities of the technology and the requirements of the user's tasks. In other words, if the features of a technological tool enhance the user's ability to perform their tasks, both the intention to use the technology and its actual usage are expected to increase. The TTF model is particularly evaluated in terms of its impact on individual performance and is frequently applied in educational contexts to assess the alignment between digital applications and the needs of students and instructors. At its core, the model emphasizes the principle of mutual compatibility among technology, task, and individual.

Post-2020 Applications of TTF

In the post-2020 literature, the TTF model is often integrated with the Technology Acceptance Model (TAM) to enable more holistic analyses. For example, Misra and Pandey (2021) combined TAM and TTF to examine the fit between university students in India and e-learning systems, analyzing the relationship between learning outcomes and technology fit. Their findings indicated that task-technology fit had an indirect yet significant effect on learning performance. Similarly, Yousafzai et al. (2023) investigated the acceptance of AI-based learning systems within the combined frameworks of TAM and TTF, and statistically demonstrated the indirect effects of TTF constructs on students' academic performance.

These studies illustrate that the joint application of TAM and TTF provides a valuable approach to analyzing technology acceptance processes more comprehensively. While TAM focuses on individual perceptions and attitudes, TTF assesses the degree of technical fit within the context of the user's tasks. The post-2020 literature encourages the integration of these two models, offering more valid and comprehensive explanations for the adoption processes of AI-based systems in education. Empirical studies conducted within this framework underscore the theoretical and practical contributions of using TAM and TTF together to better understand the acceptance of educational technologies.

Future research is recommended to test the validity of this integrated approach across various educational levels, cultural contexts, and technology types. Furthermore, the effects of cultural, demographic, and institutional differences on technology acceptance processes can be examined in greater detail within this framework.

Methodology

This study was conducted using a quantitative research method based on the descriptive survey model. Quantitative research designs are systematic approaches grounded in objective data analysis, aiming to measure and interpret causal relationships between phenomena through numerical data (Creswell, 2014). In this context, data were collected using structured scales to statistically determine the relationships among variables that influence the adoption of AI-based educational technologies—the main objective of the study.

A five-point Likert-type scale was employed as the data collection instrument. This scale allowed participants to express their attitudes and perceptions toward specific statements on a continuum ranging from "Strongly Disagree" to "Strongly Agree." Likert-type scales are widely recognized as reliable and valid tools for measuring attitudes (Likert, 1932). The scale used in this study was adapted from previously validated instruments to ensure content validity and reliability (Jarada, 2021; Güleren, 2017; Torun, 2019).

During the data collection process, the scale was administered both online and in printed form. Participation was based on the principle of voluntariness. The collected data were analyzed using the SPSS 24 statistical analysis software.

Purpose of the Study

The primary aim of this study is to examine the intention of students studying in the field of Information Technologies at foundation universities in Istanbul to use Artificial Intelligence (AI) technologies in educational processes. The analysis is conducted within the framework of the variables: task characteristics (TC), technology characteristics (TEC), task-technology fit (TTF), and self-efficacy (SE).

Research Model and Hypotheses

The conceptual framework of this research focuses on investigating the factors that influence students' adoption and intention to use Artificial Intelligence (AI) applications. The core variables included in the research model, presented in Figure 1, along with their conceptual definitions, are described below:

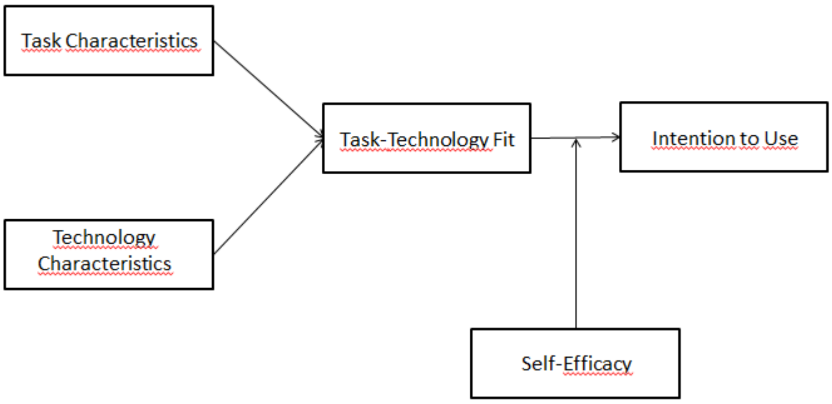

Figure 1. Research Model

Task Characteristics
This variable refers to students' perceptions regarding the potential benefits of AI applications in the context of their academic tasks. It encompasses students' beliefs about the capacity of AI to facilitate their academic work, enhance productivity, support academic success, and contribute positively to the overall learning process (Halverson, 2019). In this context, task characteristics represent the perceived advantages that students may gain from using AI technologies for educational purposes.

Technology Characteristics
This variable reflects students' perceptions of the technical attributes of AI applications. It includes key factors such as ease of use, reliability, security, accessibility, and other technical features that shape the overall user experience (Siemens, 2013). Students' views on the practical usability and functionality of AI systems are assessed under this construct.

Task-Technology Fit (TTF)
TTF refers to students' perceptions of how well AI applications align with their academic workflows and their ability to benefit from the potential advantages these technologies offer (Venkatesh, 2000). This construct captures students' beliefs regarding the extent to which AI is suitable for their learning processes, assignments, research activities, and overall academic goals. A high level of TTF indicates a strong belief that using AI for educational purposes is compatible with their individual needs and preferred working styles.

Intention to Use
This variable reflects students' tendencies and willingness to use AI applications in the future (Taylor, 1995). It measures the strength of their intention to actively engage with AI technologies in their educational activities and to benefit from such tools. A high level of intention to use indicates that students are likely to view AI as an integral part of their learning processes and are inclined to adopt it regularly.

Self-Efficacy
Self-efficacy refers to students' beliefs in their own abilities to successfully use, learn, and manage AI applications (Bandura, 1977). This construct represents their confidence in interacting with AI technologies, overcoming technical difficulties, and utilizing AI tools effectively. High self-efficacy suggests that students feel competent in their ability to engage with AI and believe they can successfully learn and apply these technologies.

In this study, the relationships among the variables described above are examined to gain a more comprehensive understanding of students' adoption and use of AI for educational purposes. In particular, the moderating role of self-efficacy in the effects of task characteristics and technology characteristics on task-technology fit and intention to use is explored.

Research Hypotheses
H1: The task characteristics of artificial intelligence perceived by university students have a positive effect on task-technology fit.

H2: The technology characteristics of artificial intelligence perceived by university students have a positive effect on task-technology fit.
H3: The task-technology fit of artificial intelligence perceived by university students has a positive effect on their intention to use AI.
H4: Self-efficacy moderates the relationship between task-technology fit and the intention to use artificial intelligence among university students.

Population and Sample Selection
The target population of this study consists of students enrolled at foundation universities located in Istanbul. The sample comprises university students studying in information technology–oriented programs at İstinye University, Istanbul Topkapı University, Istanbul Esenyurt University, and Istanbul Gelişim University. A purposive sampling method was employed for the selection of participants. Purposive sampling is a non-probability sampling technique in which participants are deliberately selected based on specific characteristics that align with the research questions and objectives (Patton, 2015). Rather than relying on random selection, this method emphasizes the researcher's knowledge and judgment in identifying appropriate participants. Purposive sampling is particularly common in qualitative research aiming to gain in-depth understanding of a specific phenomenon, benefit from expert opinions, or focus on a particular subgroup (Creswell, 2014).

Data Collection Method and Instrument
In this study, a survey method was employed. Questionnaires were administered in both online and printed formats. The survey, consisting of items formatted on a five-point Likert scale, was completed by students on a voluntary basis in order to address the research problem.

Likert Scale: This is one of the most widely used scaling methods. It asks participants to indicate the degree to which they agree or disagree with a given statement on a scale ranging from "Strongly Agree" to "Strongly Disagree" (Likert, 1932).

During the validity and reliability testing of the scale, one item from the "task characteristics" variable was found to have low item-total correlation and reduced the reliability of the scale; therefore, it was removed from the study. The final analysis proceeded with three items representing the task characteristics construct. The third item under task characteristics was a reverse-coded item, and as such, it was recoded accordingly prior to analysis.

Findings
For the data analysis process, SPSS version 24—widely used in the social sciences and recognized for its robust statistical computing capabilities—was utilized. To ensure the validity and reliability of the scales, comprehensive evaluation criteria recommended in the literature were followed, drawing upon the methods proposed by Jarada (2021), Güleren (2017), and Torun (2019). During the analysis, Cronbach's Alpha coefficient (Cronbach, 1951) and Composite Reliability (Field, 2018) values were calculated to demonstrate the measurement reliability of the scales. These analyses provided scientific evidence regarding the repeatability, consistency, and internal reliability of the measurement instruments.

As presented in Table 2, the demographic characteristics of the participants were analyzed in detail. In terms of age distribution, a significant majority (68.0%) of respondents were in the 17–20 age range, followed by 24.7% in the 21–24 age range, and 7.4% aged 25 and above. This indicates that the study sample predominantly consisted of younger individuals. Regarding education level, 93.2% of participants were enrolled in associate degree programs, while only 6.8% were pursuing undergraduate (bachelor's) studies. This finding reveals that the study primarily focuses on students engaged in vocational and technical education.

In terms of gender distribution, 71.9% of the respondents were male, and 28.1% were female. This indicates a male-dominated sample, which should be considered when interpreting the findings. In summary, the majority of participants were young, enrolled at the associate degree level, and predominantly male. These demographic characteristics are key factors in shaping both the structure of the sample and the framework for interpreting the results obtained in this study.

Table 2. Descriptive Statistics

Variable	Category	Frequency (n)	Percentage (%)
Age	17–20	656	68.0%
	21–24	238	24.7%

Variable	Category	Frequency (n)	Percentage (%)
	25 and above	71	7.4%
	Total	965	100.0%
Education Level	Associate Degree	899	93.2%
	Bachelor's Degree	66	6.8%
	Total	965	100.0%
Gender	Male	694	71.9%
	Female	271	28.1%
	Total	965	100.0%

Reliability Analysis Results

As shown in Table 3, the validity and structural integrity of the measurement scales used in this study were ensured by applying evaluation methods recommended in the literature, particularly those proposed by Jarada (2021), Güleren (2017), and Torun (2019). To assess the reliability of the study, the repeatability and internal consistency of the scales were evaluated using Cronbach's Alpha coefficient (Cronbach, 1951) and Composite Reliability values (Field, 2018), which are commonly employed in social science research.

These analyses provided scientific evidence that the data collection instruments yielded reliable and replicable results, free from significant measurement errors. As a result, the data quality of the study was strengthened, supporting the accuracy and validity of the findings obtained.

One item under the "Task Characteristics" construct was excluded from the analysis due to its negative impact on the validity and reliability of the scale. Consequently, the analyses proceeded with the remaining three items.

Table 3. Reliability Analysis Results

Construct	Number of Items	Cronbach's Alpha (α)
Task Characteristics	3	0.739
Technology Characteristics	3	0.843
Task-Technology Fit	4	0.875
Self-Efficacy	3	0.715
Intention to Use	4	0.885

Hypothesis Testing

To evaluate whether the data conformed to a normal distribution, skewness and kurtosis values were analyzed. According to Tabachnick and Fidell (2013), skewness and kurtosis values within the ±1.5 range indicate that the assumption of normality is largely satisfied. As shown in Table 4, the skewness and kurtosis values for all variables fall within this acceptable range. Based on these results, it can be concluded that the dataset meets the assumption of normality, and the use of parametric tests is appropriate for subsequent analyses.

Table 4. Skewness and Kurtosis Values

Construct	vness	Error (Skewness)	Kurtosis	Std. Error (Kurtosis)
Intention to Use	–0.941	0.110	1.454	0.220
Self-Efficacy	–0.913	0.110	1.393	0.220
Task Characteristics	–0.675	0.110	1.468	0.220
Technology Characteristics	–0.706	0.110	1.493	0.220
Task-Technology Fit	–0.645	0.110	1.012	0.220

The skewness and kurtosis values presented in Table 4 were analyzed to assess the normality of the distributions for the variables included in the study. The results indicate that all skewness values are negative and fall within acceptable limits. Specifically, the skewness values for Intention to Use (–0.941), Self-Efficacy (–0.913), Task Characteristics (–0.675), Technology Characteristics (–0.706), and Task-Technology Fit (–0.645) suggest a slight left-skew in the data distribution; however, these values do not indicate substantial deviation from normality and can be considered acceptable.

Regarding kurtosis, the values for Intention to Use (1.454), Self-Efficacy (1.393), Task Characteristics (1.468), Technology Characteristics (1.493), and Task-Technology Fit (1.012) range between 1.012 and 1.493. These results suggest that all variables exhibit slightly platykurtic distributions, yet remain close to normal. Furthermore, the fact that all skewness and kurtosis values fall within the ±2 range supports the conclusion that the data do not contain significant distortions, thereby justifying the use of parametric statistical analyses (George & Mallery, 2010; Kline, 2011).

Overall, these findings confirm that the dataset satisfies the fundamental assumptions required for statistical testing and is suitable for parametric techniques such as linear regression.

Table 5. Correlation Coefficients

Relationship	r	p-value
Task Characteristics and Task-Technology Fit	0.424	0.000
Technology Characteristics and Task-Technology Fit	0.805	0.000
Task-Technology Fit and Intention to Use	0.583	0.000

$p < 0.01$

Based on the correlation analysis results presented in Table 5, a positive and significant relationship was found between Task Characteristics and Task-Technology Fit ($r = 0.424$, $p < 0.01$). This finding suggests that the structural features of academic tasks play a supportive role in aligning users with AI systems. Similarly, a very strong and positive correlation was observed between Technology Characteristics and Task-Technology Fit ($r = 0.805$, $p < 0.01$). This indicates that attributes of technological systems—such as ease of use, perceived usefulness, and user-friendly interfaces—positively influence their integration into task-related processes.

Moreover, there was a strong and significant relationship between Task-Technology Fit and Intention to Use ($r = 0.583$, $p < 0.01$). This suggests that users' perceptions of alignment between their tasks and technological systems significantly affect their willingness and tendency to adopt AI technologies in educational contexts.

According to the regression coefficients presented in Table 6, Task Characteristics have a positive and significant effect on Task-Technology Fit ($\beta = 0.609$, $p < 0.01$). This result indicates that the structure and nature of academic tasks facilitate users' integration with AI-based systems and contribute to the adaptation of such technologies into their workflows.

Likewise, Technology Characteristics were also found to have a highly positive and significant impact on Task-Technology Fit ($\beta = 0.883$, $p < 0.01$). This highlights that technical features—such as usability, accessibility, and functional performance—strengthen individuals' perceptions of task-technology alignment.

In terms of explanatory power, Task Characteristics account for 18% of the variance in Task-Technology Fit ($R^2 = 0.180$), while Technology Characteristics explain 64.7% of the variance in Task-Technology Fit ($R^2 = 0.647$). Furthermore, Task-Technology Fit explains 34% of the variance in Intention to Use AI ($R^2 = 0.340$).

Additionally, the moderating effect of Self-Efficacy in the relationship between Task-Technology Fit and Intention to Use was found to be statistically significant ($B = 0.115$; $R^2 = 0.452$; $F = 794.512$; $p < 0.001$). These findings suggest that the development of user-friendly AI solutions and enhancement of students' technological self-efficacy may significantly encourage the adoption of AI applications in educational environments.

Table 6. Regression Coefficients Indicating the Effects in the Regression Models

Model	R^2	F	p-value	β (Standardized)	VIF	Hypothesis Decision
Effect of Task Characteristics on Task-Technology Fit	0.180	211.148	0.000	0.609	1.000	Accepted
Effect of Technology Characteristics on Task-Technology Fit	0.647	1768.699	0.000	0.883	1.000	Accepted
Effect of Task-Technology Fit on Intention to Use	0.340	495.070	0.000	0.644	1.000	Accepted
Moderating Role of Self-Efficacy in the Effect of Task-Technology Fit on	0.452	794.512	0.000	0.115	1.000	Accepted

Model	R^2	F	p-value	β (Standardized)	VIF	Hypothesis Decision
Intention to Use (Interaction: TTF × SE)						

As proposed by Baron et al. (1986), a moderator variable is defined as a factor that can alter both the direction and the strength of the relationship between an independent and a dependent variable. The empirical testing of such moderating effects follows the methodology outlined by Sharma et al. (1981), which involves creating an interaction term representing the product of the independent variable and the potential moderator. This interaction term is then included as a predictor in the regression model. A statistically significant effect of the interaction term on the dependent variable is interpreted as evidence of a moderating relationship.

In the context of the present study, the potential moderating role of self-efficacy is examined. Accordingly, an interaction term was computed to capture the interaction between task-technology fit (independent variable) and self-efficacy (moderator). This interaction term was subsequently included in a simple linear regression model as an additional predictor.

The results for this interaction term are presented in Table 6. Through this analysis, the study aims to determine whether self-efficacy serves to strengthen or weaken the existing relationship between task-technology fit and intention to use (dependent variable).

Research Delimitations

This study is limited to students enrolled in Information Technology programs at four foundation universities located in Istanbul. As such, the generalizability of the findings to student populations in other geographic regions, public universities, or different academic disciplines is constrained. Future research could enhance the scope and generalizability of the results by including samples from public universities, institutions in various cities, and students from a broader range of academic fields.

Conclusion and Recommendations

The linear regression analyses conducted within the scope of this study confirmed that all proposed relationships were statistically significant, and the hypotheses were supported. The effect of Task Characteristics on Task-Technology Fit was found to be significant ($B = 0.609$; $R^2 = 0.180$; $F = 211.148$; $p < 0.01$), indicating a positive and substantial relationship between the nature of work processes and technological alignment. This finding suggests that technological solutions designed in accordance with task requirements contribute significantly to users' ability to integrate with the technology.

Similarly, the effect of Technology Characteristics on Task-Technology Fit was found to be highly significant and strong ($B = 0.883$; $R^2 = 0.647$; $F = 1768.699$; $p < 0.01$). This result indicates that users' positive perceptions of technological features greatly enhance the integration of such technologies into work processes. The user-friendliness and functional accessibility of technological infrastructure emerge as critical factors that strengthen task-technology fit.

The study also found a significant and positive effect of Task-Technology Fit on Intention to Use ($B = 0.644$; $R^2 = 0.340$; $F = 495.070$; $p < 0.01$). This suggests that when a technology is perceived as compatible with users' workflows, it increases their intention to actively use that technology. However, the moderate effect size implies that task-technology fit alone is not a sufficient determinant; other influencing factors should also be considered. One of the most influential among these appears to be users' self-efficacy—their belief in their own abilities to effectively use AI technologies. Individuals with high self-efficacy are more likely to adopt and efficiently use new technologies.

Lastly, the moderating effect of self-efficacy on the relationship between task-technology fit and intention to use was found to be statistically significant ($B = 0.115$; $R^2 = 0.452$; $F = 794.512$; $p < 0.01$). This indicates that self-efficacy positively moderates this relationship. Individuals with higher self-efficacy are more motivated to use technologies that are aligned with their tasks.

In this regard, promoting the adoption of AI applications in educational environments requires enhancing users' self-efficacy and improving the accessibility and user-friendliness of technological systems. Educational institutions should develop supportive strategies to empower users in technology adoption, which would, in turn, increase both the acceptance and usage rates of AI-based solutions in learning environments.

Discussion
The findings of this study are largely consistent with the existing literature. In particular, the significant impact of self-efficacy on intention to use aligns well with previous research. For example, Korkmaz et al. (2024), in their study titled *"The Impact of Attitude, Ease of Use, Sophistication, and Trust in Artificial Intelligence on Purchase Intention,"* concluded that individuals who use AI technologies tend to be satisfied with them and are inclined to continue using them in the future. Similarly, in the present study, university students' positive attitudes toward AI and their high levels of self-efficacy emerged as strong predictors of their intention to use AI in educational contexts.

The effect of task-technology fit on usage intention also mirrors findings reported in the literature. In a study by İşler et al. (2021), titled *"The Use and Development of Artificial Intelligence in Education,"* the authors emphasized the increasing role of AI applications in educational settings and their supportive role in learning processes. These findings support the current study's result that alignment between work processes and technological infrastructures positively influences users' attitudes toward such technologies.

Additionally, a study by Bayraktar et al. (2023) found that teachers working in schools affiliated with the Turkish Ministry of National Education generally held favorable attitudes toward the use of AI technologies in education. This is in line with the positive attitudes displayed by university students in the present study and highlights a growing trend of acceptance and interest in AI technologies across different age and professional groups within the education sector.

Comparable results are also found in the international literature. Zawacki-Richter et al. (2019) drew attention to the rising role of AI applications in education, particularly emphasizing the effectiveness of algorithms that support student-centered learning processes in enhancing learning motivation. Moreover, Lee (2021) emphasized that increasing students' self-efficacy significantly boosts their trust in and engagement with AI-based learning systems. These findings corroborate the moderating role of self-efficacy found in our study.

In conclusion, the findings of this study underscore the critical role of variables such as self-efficacy, technology characteristics, and task-technology fit in the adoption of AI technologies in educational settings. Based on the results, it is recommended that programs aiming to enhance users' technological competence be implemented, and that greater efforts be made to ensure that AI systems are accessible and user-friendly in order to support their effective use in education.

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Conflict of Interest
The authors declare that there are no personal or financial conflicts of interest related to this study.

Author Contributions
The authors contributed equally to the planning, execution, and writing of this study.

References
Akın, Ö., & Çakır, O. (2019). The effects of artificial intelligence on the education system: The case of Turkey. *Journal of Information Society and Technology*, *9*(1), 5–17.
Aydın, N., & Kaya, R. (2021). AI-supported education: The current state and future expectations in Turkey. *Education and Science*, *46*(210), 322–336.
Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215.
Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173–1182.
Bayraktar, A., Yıldız, M., & Demir, S. (2023). Teachers' views on the use of artificial intelligence technologies in education. *Journal of Educational Technology Research*, *5*(2), 45–62.
Bayraktar, B., Gülderen, S., Akça, S., & Serin, E. (2023). Teachers' views on the use of artificial intelligence technologies in education. *National Journal of Education*, *3*(11), 2012–2030. https://www.uleder.com/index.php/uleder/article/view/380

Brusilovsky, P. (2001). Adaptive hypermedia. *User Modeling and User-Adapted Interaction, 11*(1–2), 87–110.
Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). Sage.
Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika, 16*(3), 297–334.
Çakır, O., & Akın, Ö. (2021). The use of artificial intelligence in the field of health in Turkey. *Journal of Health Technologies*, *10*(2), 65–82.
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.
Ercan, T., & Güneş, S. (2020). The use of artificial intelligence in education: Opportunities and challenges in Turkey. *Journal of Educational Sciences and Practices*, *15*(1), 45–58.
Field, A. (2018). *Discovering statistics using IBM SPSS* (5th ed.). Sage.
Gefen, D., & Straub, D. W. (2000). A practical guide to factorial validity using confirmatory factor analysis. *Communications of the Association for Information Systems, 4*(1), 71–105.
George, D., & Mallery, P. (2010). *SPSS for Windows step by step: A simple guide and reference* (10th ed.). Pearson.
Gökçe, D., & Oğuz, A. (2018). The use of artificial intelligence in education: A literature review. *Journal of Technology and Education*, *2*(1), 11–24.
Güleren, G. (2017). An investigation of students' attitudes toward mobile learning technologies within the framework of the Technology Acceptance Model (TAM). *Journal of Education and Technology*, *7*(1), 25–38.
Halverson, R., & Hochman, M. (2019). Artificial intelligence in education. In *Handbook of research on educational communications and technology* (pp. 1067–1089). Routledge.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.
İşler, B., & Kılıç, M. (2021). The use and development of artificial intelligence in education. *New Media Electronic Journal*, *5*(1), 1–11.
İşler, H., Yılmaz, E., & Karaca, N. (2021). The use and development of artificial intelligence in education. *Journal of Educational Sciences*, *15*(1), 23–39.
Jarada, M. (2021). Technology acceptance and learning analytics in higher education. *Educational Technology Journal, 34*(2), 115–130.
Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). The Guilford Press.
Korkmaz, İ. (2024). The effect of attitude, ease of use, advancement, and trust toward artificial intelligence on purchase intention. *Afyon Kocatepe University Journal of Economics and Administrative Sciences*, *26*(2), 318–339. https://doi.org/10.33707/akuiibfd.1522892
Korkmaz, K., & Öztürk, M. (2023). The future of artificial intelligence: Turkey's place in the changing world of technology. *Journal of Technology and Society*, *20*(1), 32–51.
Korkmaz, R., Yücel, T., & Şahin, M. (2024). The effect of attitude, ease of use, advancement, and trust toward artificial intelligence on purchase intention. *Journal of Marketing and Consumer Research*, *8*(1), 12–30.
LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444.
Lee, J. (2021). The role of self-efficacy in students' adoption of AI-based learning systems. *Computers & Education, 166*, 104154. https://doi.org/10.1016/j.compedu.2021.104154
Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 140*(1), 1–55.
McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future*. W. W. Norton.
Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). Sage.
Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Pearson.
Schunk, D. H. (1985). Self-efficacy and achievement behavior. *Educational Psychology Review, 1*(1), 1–39.
Sharma, S., Durand, R. M., & Gurarie, O. (1981). Identification and analysis of moderator variables. *Journal of Marketing Research, 18*(3), 291–300.
Siemens, G. (2013). Learning analytics: Towards a data-driven understanding and improvement of educational practices. *International Journal of Educational Technology in Higher Education, 10*(1), 1–14.
Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Pearson.
Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(2), 144–176.
Torun, F. (2019). Teachers' views on the use of cloud computing technologies in education. *Theory and Practice in Education, 15*(2), 101–120.
TÜBİTAK. (2022). *Artificial intelligence strategy*. TÜBİTAK.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.
Watkins, C., & Holley, H. (2018). Artificial intelligence in education: A critical review. *British Journal of Educational Technology, 49*(3), 369–381.
Yıldız, M., & Başaran, B. (2022). Artificial intelligence and education: Ethics, privacy, and access. *Journal of Information Technologies and Society, 18*(1), 18–35.
Yılmaz, M., & Arslan, A. (2020). The impact of artificial intelligence on the Turkish economy. *Journal of Economic Policies, 17*(2), 102–120.
Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0
Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology, 25*(1), 82–91.