Exploring Education Sciences Students' Intentions to Use Artificial Intelligence for Academic Use

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Abstract: This study advances the understanding of Artificial Intelligence (AI) adoption in higher education by introducing an extended Technology Acceptance Model (TAM) that integrates Social Influence, Trustworthiness, and Ethics. Partial Least Squares and SEM (PLS-SEM) analysis was conducted. Based on data collected from 131 Greek Education Sciences students at the National and Kapodistrian University of Athens, the model demonstrates substantial explanatory power, accounting for 64% of the variance in behavioral intention. While the core TAM constructs (Perceived Usefulness, Perceived Ease of Use, and Attitude) remain fundamental, the research highlights a notable "Ethics-Intention Gap," as ethical considerations were found to have no significant direct effect on behavioral intention. Instead, users appear to prioritize functional reliability, while social influence contributes to adoption through its effects on core TAM constructs. Furthermore, the results indicate that social circles play a significant role in shaping perceived ease of use of AI tools, functioning as informal support structures that facilitate engagement with emerging technologies. These findings offer important insights for stakeholders and developers, suggesting that fostering trust and leveraging social influence may represent more influential drivers of AI integration than an exclusive focus on ethical frameworks. By identifying these nuanced behavioral drivers, this research provides a robust empirical foundation for future strategies in AI-enhanced educational environments.

Keywords: Artificial Intelligence, Technology Acceptance Model, Social Influence, Trustworthiness, Ethics-Intention Gap, Higher Education

1. Introduction

The rapid emergence of Artificial Intelligence (AI) has initiated a paradigm shift in higher education, offering unprecedented opportunities for personalized learning, automated feedback, and cognitive scaffolding (Kasneci et al., 2023; Lim et al., 2023). Recent developments in generative AI, particularly ChatGPT, have further expanded these possibilities by enabling adaptive learning experiences, supporting instructional processes, and facilitating student engagement through real-time interaction and feedback (Baidoo-Anu & Ansah, 2023). For students in Education Sciences, who represent the next generation of educators, developing AI-related competencies and understanding the pedagogical use of AI tools such as ChatGPT is becoming increasingly important for future classroom practice (Crompton & Burke, 2023; Grassini, 2023; Cukurova & Miao, 2024; Nyaaba, 2024). Despite its evident potential, the integration of AI into educational practices remains a complex process shaped by a range of cognitive, social, and technological factors (Dwivedi et al., 2021). Students' willingness to adopt AI tools is determined not only by their functional capabilities but also by broader perceptions, beliefs, and contextual influences.

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), remains one of the most influential frameworks for explaining user acceptance of technology. Within this model, perceived usefulness and perceived ease of use are identified as key determinants of technology acceptance. Recent studies have successfully applied TAM to AI-related contexts, confirming its explanatory power while also emphasizing the need for extensions when examining advanced intelligent systems (Chatterjee & Bhattacharjee, 2020; Scherer et al., 2019).

In educational contexts, AI adoption is further influenced by pedagogical, institutional, and ethical considerations. For instance, AI literacy has been identified as a critical factor shaping how learners understand, evaluate, and use AI systems. Beyond technical competence, AI literacy encompasses awareness of ethical issues such as algorithmic bias, transparency, accountability, and responsible use of AI technologies (Long & Magerko, 2020; Mustofa et al., 2025). Moreover, contemporary research suggests that the educational use of AI extends beyond its role as a technological tool, as its implementation is closely intertwined with pedagogical practices, human judgment, and instructional decision-making processes (Holmes et al., 2023; Kasneci et al., 2023; Zawacki-Richter et al., 2019).

A crucial dimension of AI adoption concerns the role of trust. Due to the opaque nature of AI systems, users often rely on perceptions of reliability, transparency, and accuracy when deciding whether to adopt such technologies (Shin, 2021; Glikson & Woolley, 2020). At the same time, ethical concerns such as data privacy,

algorithmic bias, and academic integrity have become central to discussions on AI use in higher education (Crompton & Burke, 2023; Floridi et al., 2018; Kasneci et al., 2023; Lim et al., 2023).

Although previous research has examined AI adoption across diverse populations, limited attention has been given to pre-service teachers within specific cultural contexts. There is a lack of empirical evidence exploring how functional, social, and ethical factors interact to shape AI adoption among Greek students in Education Sciences.

Therefore, this study aims to investigate the determinants of students' intention to use AI for academic purposes by extending the Technology Acceptance Model. By incorporating Social Influence, Trustworthiness, and Ethics into the model, the study seeks to provide a more comprehensive understanding of how future educators balance the practical benefits and ethical challenges associated with AI technologies.

2. Conceptual Model and Hypotheses Development

The conceptual framework of this study (Figure 1) is based on an extended version of the Technology Acceptance Model (TAM) (Davis, 1989). The model illustrates the key constructs and the hypothesized relationships among them.

While the original TAM emphasizes cognitive and instrumental processes, AI adoption is increasingly recognized as a socio-technical phenomenon shaped by social, trust-related, and ethical considerations. Therefore, the inclusion of Social Influence, Trustworthiness, and Ethics enables a more comprehensive understanding of AI acceptance in educational contexts (Fjeld et al., 2020; Floridi et al., 2018; Shin, 2021; Venkatesh et al., 2003).

2.1 Core TAM Constructs: PU, PEOU, and ATT

At the core of the model are Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the extent to which a student believes that using AI will enhance academic performance, whereas PEOU refers to the degree to which using AI is perceived as effortless (Davis, 1989).

In AI-enabled educational environments, user-friendly systems reduce cognitive load and enhance usability, thereby strengthening perceptions of usefulness (Chatterjee & Bhattacharjee, 2020). According to TAM, PEOU is expected to have a direct effect on PU (H1). In addition, both PU and PEOU are key determinants of students' Attitude (ATT) toward technology use (Scherer et al., 2019).

A positive attitude toward AI, together with perceived usefulness, is expected to influence Behavioral Intention (BI) to adopt AI for academic purposes (Strzelecki, 2024).

H1: PEOU has a direct positive effect on PU.

H2: PEOU has a direct positive effect on ATT.

H3: PU has a direct positive effect on ATT.

H4: PU has a direct positive effect on BI.

H5: ATT has a direct positive effect on BI.

2.2 Social Influence (SI)

Social Influence reflects the perceived expectations and opinions of significant others in an individual's social environment regarding technology use (Venkatesh et al., 2003). In educational settings, the social context plays a critical role in shaping students' perceptions and behavioural intentions. When AI tools are endorsed by instructors or widely adopted by peers, students are more likely to perceive them as useful and to develop favourable attitudes toward their use (Strzelecki, 2024). Moreover, social interaction and peer support may reduce uncertainty and facilitate engagement with AI technologies, thereby enhancing perceived ease of use (Venkatesh et al., 2003; Mustofa et al., 2025).

H6: SI has a direct positive effect on PU.

H7: SI has a direct positive effect on ATT.

H8: SI has a direct positive effect on PEOU.

2.3 Trustworthiness (TR)

Trustworthiness (TR) is a pivotal construct in AI adoption research, defined as users' confidence in the reliability, integrity, and objectivity of AI-generated outputs (Mustofa et al., 2025; Shin, 2021). Unlike traditional software systems, AI often operates with a degree of opacity ("black box" characteristics), making trust a critical prerequisite for adoption (Shin, 2021). For future educators, trust is particularly important, as they must feel confident that AI systems generate reliable information and can support educational practices effectively (Kelly et al., 2023). Therefore, trustworthiness is hypothesized to have a direct positive effect on behavioural intention to use AI (Mustofa et al., 2025).

H9: TR has a direct positive effect on BI.

2.4 Ethics (ET)

The inclusion of Ethics (ET) addresses the moral dimensions of AI, including data privacy, algorithmic bias, and academic integrity (Floridi et al., 2018; Fjeld et al., 2020). Ethical considerations play an important role in AI acceptance, as they shape user concerns, foster trust, and ensure alignment with societal values and professional norms (Floridi et al., 2018). In educational contexts, students who are more aware of ethical issues may exhibit increased scrutiny toward AI adoption. Recent studies have suggested that ethical perceptions may influence behavioural intention, as users are more likely to adopt AI tools when their use is perceived as ethically acceptable and aligned with academic standards (Mustofa et al., 2025).

H10: ET has a direct positive effect on BI.

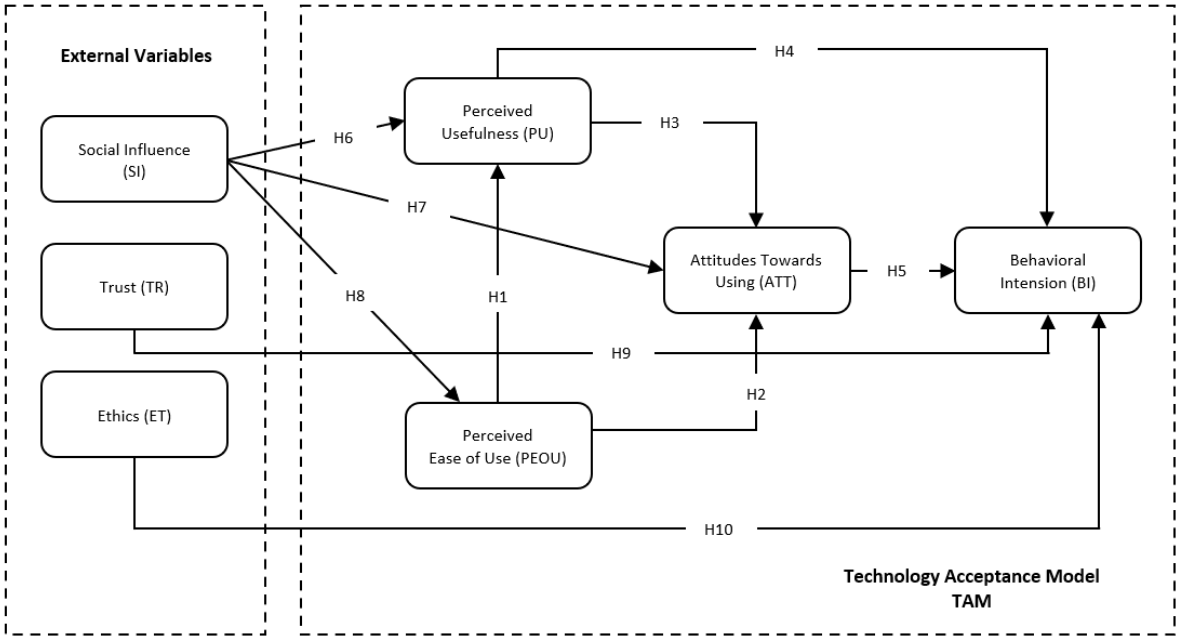

Figure 1. The conceptual model

Note: H1 to H10 are hypotheses regarding the direct effect among the constructs

3. Research Objectives

The goal of this study is to explore the multifaceted determinants that influence the willingness of Education Sciences students in Greece to adopt AI during their studies and future professional practice. Rather than relying solely on the classic TAM, this research extends the framework to encompass a broader socio-technical perspective. Specifically, the study evaluates how three critical external dimensions-Social Influence, Trustworthiness, and Ethics-interact with the core TAM constructs to shape students' behavioral intentions. By examining these variables, we aim to provide a nuanced understanding of how Greek pre-service teachers balance the functional advantages of AI with the social pressures and moral considerations inherent in intelligent classroom technologies.

4. Methodology

4.1 Research Procedure

To address the research questions, a quantitative, cross-sectional survey design was employed. Data collection took place during November 2025. The survey was administered electronically via Google Forms, ensuring participant anonymity and voluntary involvement. To mitigate potential bias and ensure data integrity, the research design adhered to the methodological considerations outlined by Lavidas et al. (2022) regarding the reliability of students' self-reports. Specifically, the questionnaire was designed to be completed in approximately 8 to 10 minutes; this duration was strategically chosen to reduce the effect of social desirability bias and survey fatigue, ensuring that participants provided authentic rather than "idealized" responses. By maintaining a brief and focused completion time, the study aimed to minimize the cognitive burden on students, thereby enhancing the objectivity and impartiality of the collected data concerning their perceptions of AI.

4.2 Research Instrument

The measurement instrument was divided into two distinct sections. The first section was designed to collect demographic data, including gender, year of study, and experience with AI, to establish the profile of the participating pre-service teachers. The second section comprised 21 items specifically adapted to evaluate the constructs of the proposed conceptual model within the context of Artificial Intelligence. All items were assessed using a five-point Likert-type scale, with response options ranging from strongly disagree (1) to strongly agree (5). To ensure the validity and reliability of the scales, the items were drawn from established academic literature on AI adoption, as mentioned in section 2.

4.3 Data Analysis Strategy

The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM), implemented within the R software environment via the 'plspm' package (Sanchez, 2013). A two-step analytical procedure was adopted. First, the measurement model was assessed to establish internal consistency reliability, convergent validity, and discriminant validity. Second, the structural model was evaluated by examining the hypothesized relationships among the latent constructs through path coefficients, their statistical significance, and the explained variance (R^2) of the endogenous variables.

4.4 Participants

A convenience sample of 131 undergraduate students from the Department of Early Childhood Education and the Department of Pedagogy and Primary Education at the National and Kapodistrian University of Athens was used. Regarding gender distribution, the sample consisted of 97 females (74%) and 34 males (26%). In terms of year of study, the participants were categorized as follows: first 12,2%, second 22,1%, third 44,3%, fourth 19,8%, and fourth+ 1,5%. Regarding prior experience with AI, 25,2% had never used AI before, 26% for 1 year, 22,1% for 2 years, and 26,7% over 2 years.

5. Results

The results section starts with the evaluation of the measurement model, focusing on the reliability and validity of the research instrument. It then proceeds with the analysis of the structural model to test the proposed hypotheses.

Table 1 presents the reliability and convergent validity indices of the measurement model. For all constructs, Composite Reliability exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency reliability (Hair & Alamer, 2022; Raykov, 1997). Cronbach's Alpha values were also above 0.70 for all constructs except Ethics (α = .654). Although the Cronbach's Alpha of the Ethics construct was slightly below the recommended threshold, both Composite Reliability (.752) and Average Variance Extracted (AVE = .504) exceeded the acceptable levels, indicating adequate reliability and convergent validity for exploratory research. Furthermore, all indicators exhibited loadings above 0.70, apart from two items within the Ethics construct. The Average Variance Extracted (AVE) values exceeded the recommended threshold of 0.50 for all constructs, supporting satisfactory convergent validity (Hair & Alamer, 2022; Sanchez, 2013).

Table 1: Descriptive statistics, reliability, and validity indices for the constructs of the TAM model.

	Mean (SD)	*λ*	*a*	*CR*	AVE
Behavioral Intention (BI)	3.30 (.99)		.896	.935	.829
B1. I intend to continue utilizing artificial intelligence applications in my studies.		.895			
B2. I intend to use Artificial Intelligence applications in my studies as often as possible.		.892			
B3 I intend to consistently use Artificial Intelligence applications in my studies.		.943			
Attitude Towards Using (ATT)	3.29 (.97)		.805	.842	.639
ATT1. I like to use Artificial Intelligence applications in my studies		.830			
ATT2. I think it is worthwhile to use Artificial Intelligence applications in my studies		.811			
ATT3. In my opinion, it is very desirable to use Artificial Intelligence applications in my studies		.755			
Perceived Usefulness (PU)	3.62 (.98)		.844	.863	.677
PU1. Artificial Intelligence makes it easier for me to complete my lecture assignments faster		.855			
PU2. Currently, almost all of my lecture activities are assisted by Artificial Intelligence		.838			
PU3. Artificial Intelligence is beneficial in my studies		.774			
Perceived Ease of Use (PEOU)	4.13 (.76)		.783	.809	.587
PEOU1. Artificial Intelligence is easy to use		.858			
PEOU2. Artificial Intelligence does not require any special skills to work with		.732			
PEOU3. I can quickly learn the features of Artificial Intelligence when needed		.700			
Social Influence (SI)	2.86 (.91)		.833	.875	.700
SI1. Those close to me, including friends and family, think I should use Artificial Intelligence in my studies.		.831			
S2. People who influence me believe I should use Artificial Intelligence in my studies		.842			
S3. Those whose opinions matter to me would like me to use Artificial Intelligence in my studies as well		.836			
Trustworthiness (TW)	3.09 (.82)		.779	.818	.604
TW1. I trust the results provided by Artificial Intelligence recommendations		.770			
TW2. I can rely on Artificial Intelligence to answer and complete my assignments		.784			
TW3. Artificial Intelligence may help me address different academic difficulties		.778			
Ethics (ET)	2.87 (.77)		.654	.752	.504
ET1. I do not believe that using Artificial Intelligence violates academic ethics		.779			

	Mean (SD)	*λ*	*a*	*CR*	AVE
ET2. I believe it is necessary to consult with lecturers before using Artificial Intelligence		.698			
ET3. I have included references to the use of Artificial Intelligence in my assignments		.647			

λ=Factor loadings, a=Cronbach's Alpha, CR=Composite reliability, and AVE=average variance extracted.

Table 2: Evaluation of inter-construct correlations and discriminant validity through the Fornell-Larcker criterion for the TAM constructs.

Component	BI	ATT	PU	PEoU	SI	TW	ET
BI	(.910)						
ATT	.750**	(.799)					
PU	.722**	.730**	(.823)				
PEoU	.520**	.439**	.532**	(.766)			
SI	.502**	.517**	.473**	.338**	(.837)		
TW	.620**	.600**	.652**	.417**	.329**	(.777)	
ET	.246*	.154*	.141*	.148*	.287*	.145*	(.710)

Moreover, Pearson's linear correlation coefficients among the constructs are statistically significant (see Table 2). Furthermore, the Fornell-Larcker criterion (1981) confirmed satisfactory discriminant validity as the square root of each construct's AVE (presented in the diagonal cells) exceeds all inter-construct correlations.

Diagonal values (in parentheses) indicate the square root of the AVE for each construct. Off-diagonal values show Pearson correlations among the constructs. BI: Behavioral Intention, ATT: Attitude Toward Using, PU: Perceived Usefulness, PEoU: Perceived Ease of Use, SI: Social Influence, TW: Trustworthiness, ET: Ethics.

Correlation is significant at the **. 0.01 level, *. 0.05 (two-tailed).

Table 3 shows the path coefficients among constructs and their estimation by robust 95%-confidence intervals (Sanchez, 2013). Considering the confidence intervals, 9 out of 10 hypotheses that are presented in the conceptual model (Figure 1) were supported. Moreover, as a footnote in the table, is shown the R^2 (the coefficient of determination), that is the explained variance for each endogenous variable in the model.

Table 3: Structural model: Path coefficients and 95% confidence intervals with bootstrapping (2000 samples)

	Path Coeff.	95% CI	Results
H1: PEOU -> PU	.319	.178 - .465	Supported
H2: PEOU -> ATT	.251	.155 -.331	Supported
H3: PU -> ATT	.401	.246 - .528	Supported
H4: PU -> BI	.415	.257 - .548	Supported
H5: ATT -> BI	.427	.263 - .564	Supported
H6: SI -> PU	.255	.156 - .336	Supported
H7: SI -> ATT	.279	.171 - .368	Supported
H8: SI -> PEOU	.149	.094 - .198	Supported
H9: TW -> BI	.359	.224 - .475	Supported
H10: ET -> BI	-.067	-.133 - .096	Not Supported

Explained variance for each endogenous variable in the model: R^2(BI)=64%, R^2(ATT)=58%, R^2(PU)=38%, R^2(PEOU)=11,4%.

6. In Conclusion

This study employed an extended Technology Acceptance Model (TAM) to investigate the determinants of Greek students' behavioral intention (BI) to adopt Artificial Intelligence (AI) for academic purposes. Specifically, the model examined the influence of three external factors: Social Influence (SI), Trustworthiness (TW), and Ethics (ET). The findings provide empirical support for the proposed extended TAM and demonstrate its substantial explanatory capability. In particular, the model accounted for 64% of the variance in Behavioral Intention, indicating that the combination of the core TAM constructs and the external variables effectively explain students' intentions to adopt AI technologies. Furthermore, the model explained a considerable proportion of the variance in Attitude (58%) and Perceived Usefulness (38%), further supporting its robustness in predicting technology adoption behavior.

The core hypotheses of the original TAM (H1-H5) were all supported with high statistical significance, consistent with the foundational work of Davis (1989) and subsequent research confirming the model's validity across diverse technological contexts (King & He, 2006). In the present study, Perceived Usefulness (PU) and Attitude (ATT) emerged as the strongest predictors of Behavioral Intention (BI), with path coefficients of 0.415 and 0.427, respectively. These findings reinforce the central assumption of TAM that perceptions of usefulness and favorable attitudes play a decisive role in shaping users' intentions to adopt new technologies. The significant effect of Perceived Ease of Use (PEOU) on both PU and ATT further indicates that ease of use constitutes a fundamental prerequisite for the development of positive perceptions toward AI technologies. This finding is consistent with previous research suggesting that technical accessibility facilitates users' recognition of the potential benefits associated with AI systems (Chatterjee & Bhattacharjee, 2020; Davis, 1989; Scherer et al., 2019).

One notable finding of this study concerns the broad influence of Social Influence (SI). The results indicate that SI significantly affects not only Perceived Usefulness and Attitude but also Perceived Ease of Use. This finding suggests that social environments may serve as informal support networks that help reduce the perceived complexity of AI tools and facilitate their adoption. Although SI explained a relatively modest proportion of the variance in PEOU (11.4%), its significant effect highlights the importance of social context in shaping technology acceptance. These results are consistent with previous research highlighting the importance of social influence in technology and AI adoption (Mustofa et al., 2025; Strzelecki, 2024; Venkatesh et al., 2003). The findings further suggest that, among Education Sciences students, social influence may contribute indirectly to behavioural intention by shaping perceptions of usefulness, attitude, and ease of use.

The findings also reveal a clear distinction between the roles of trust-related and ethical considerations in AI adoption. Trustworthiness emerged as a significant predictor of Behavioural Intention, supporting previous research that identifies trust as a critical prerequisite for the acceptance of AI technologies (Glikson & Woolley, 2020; Shin, 2021). In contrast, the relationship between Ethics and Behavioural Intention was not statistically significant. This finding may indicate that ethical concerns, although important at a conceptual level, are less influential than trust-related perceptions in shaping students' intentions to use AI. Consequently, the results suggest that students' intentions to use AI are influenced more strongly by perceptions of reliability, accuracy, and trustworthiness than by broader ethical considerations. This interpretation is partially consistent with previous studies suggesting that users often prioritize the practical benefits and perceived effectiveness of AI systems when deciding whether to adopt them (Strzelecki, 2024), while differing from research that identified ethics as a significant predictor of AI adoption intentions (Mustofa et al., 2025).

From a practical perspective, the findings suggest that initiatives aimed at strengthening perceptions of trustworthiness and fostering positive social support may contribute to greater acceptance of AI technologies in higher education. Educational institutions should therefore focus on promoting transparent and reliable AI systems while simultaneously encouraging collaborative learning environments in which students can exchange experiences and develop confidence in using AI tools.

Several limitations should be acknowledged. First, the study relied on self-reported data, which may be subject to response bias and social desirability effects. As noted by Lavidas et al. (2022), students' responses may vary across different educational contexts, potentially affecting the accuracy of self-reported measures. Second, the study was conducted with a relatively limited sample drawn from a single academic field and institution, which may restrict the generalizability of the findings. Future research should therefore examine more diverse samples across different universities, disciplines, and cultural contexts. Additionally, the incorporation of objective measures of AI usage could provide further insights into the relationship between behavioral intentions and actual adoption behavior.

Ethics Declaration

This study involved an anonymous and voluntary survey and did not collect any sensitive personal data. Participation was voluntary, and informed consent was obtained from all participants before their involvement in the study.

AI Declaration

The authors did not use an AI tool in the development of their paper.

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