Research Article

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Investigating the Factors Influencing Teachers' Intention to Use Chatbots in Primary Education in Greece

https://doi.org/10.1515/edu-2025-0104
received July 01, 2025; accepted September 12, 2025

Abstract: The usage of artificial intelligence (AI) in education is quickly growing, with chatbots gaining popularity as potential tools for supporting teaching and learning. This study looks into the elements that influence teachers' willingness to use chatbots in their teaching techniques. Drawing on the Unified Theory of Acceptance and Use of Technology, the research focuses on performance expectancy (PE), effort expectancy (EE), and social influence (SI). In addition, it incorporates personal innovativeness (PI), perceived risk (PR), and personal experience with AI (PEAI) as supplementary variables. A quantitative approach was followed, using a questionnaire administered to 241 primary education school teachers in Greece. The proposed model was tested through partial least squares structural equation modeling. Findings reveal that PE is the strongest predictor of behavioral intention. PEAI positively affects both performance and EE and also has a direct impact on intention. EE and SI are also significant positive predictors, whereas PR negatively affects intention. Although PI does not directly influence intention, it contributes indirectly by enhancing perceived usefulness and ease of use and by lowering PR.

Keywords: chatbots, primary education, Unified Theory of Acceptance and Use of Technology (UTAUT), perceived risk, personal innovativeness, personal experience with AI, Greece

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1 Introduction

In recent years, artificial intelligence (AI) has emerged as a key driver of technological transformation, often associated with the fourth industrial revolution. This shift is fueled by rapid advancements in digital technologies and the increasing interconnectivity of societies across the globe. These developments, commonly referred to as "megatrends," are reshaping multiple dimensions of modern life, from economic systems to environmental challenges (Bruun & Duka, 2018; Haluza & Jungwirth, 2023). The proliferation of mobile internet access and the exponential growth of data availability are critical factors accelerating AI, while deep learning marked a breakthrough in capabilities such as image and speech recognition (Sheikh, Prins, & Schrijvers, 2023; Zhang & Lu, 2021).

The integration of AI into education offers significant potential for changing teaching and learning methods (Farahani & Ghasmi, 2024). Examples include chatbots and virtual assistants, intelligent educational systems, automated grading, simulations, virtual reality, and even robotics (Auerbach, Concordel, Kornatowski, & Floreano, 2018; Higgins & Heilman, 2014; Hsu, 2022; Ijaz, Bogdanovych, & Trescak, 2017; Nabiyev, Çakiroğlu, Karal, Erümit, & Çebi, 2016; Smutny & Schreiberova, 2020; Zipitria, Arruarte, & Elorriaga, 2011).

AI in education presents considerable advantages, transforming both the learning experience for students and the instructional approach of educators (Lameras & Arnab, 2021). It enables personalized access to content and adapts to diverse learning paces and needs with intelligent systems providing tailored instruction in real time (Ayeni, Al Hamad, Chisom, Osawaru, & Adewusi, 2024; Zaman, 2024).

At the same time, concerns remain about algorithmic bias, privacy and surveillance, and the impact of automation on teacher and student autonomy (Akgun & Greenhow, 2022; Hrastinski et al., 2019; Regan & Jesse, 2019; Zhai et al., 2021).

Among AI applications, chatbots have gained momentum because they use natural language processing to interact with users, deliver immediate feedback, and potentially foster self-regulation and metacognition (Al-Abdullatif, Al-Dokhny, & Drwish, 2023; Feine, Gnewuch, Morana, & Maedche, 2019; Mohd Rahim, Iahad, Yusof, & Al-Sharafi, 2022; Palasundram, Sharef, Nasharuddin, Kasmiran, & Azman, 2019; Wilson, Daugherty, & Morini-Bianzino, 2018). The emergence of ChatGPT has further amplified interest, showcasing classroom applications for personalized support, content generation, and feedback (Adiguzel, Kaya, & Cansu, 2023; Baidoo-Anu & Ansah, 2023; García-Peñalvo, Llorens-Largo, & Vidal, 2024; Lo, 2023; Sharma & Yadav, 2022).

Educator acceptance is pivotal for meaningful integration of these tools in classrooms (Ghimire & Edwards, 2024). Without teachers' willingness and readiness, the potential of AI technologies may remain underused.

In Greece, although there have been notable state investments in educational technologies, persistent barriers exist in terms of infrastructure and professional training. Many teachers still report feeling underprepared to exploit AI tools effectively (Foutsitzi & Caridakis, 2021; Lazaridou, Dimou, Korkakaki & Nousia, 2010). This underscores the importance of studying Greek educators' views on AI and chatbots in particular.

2 Related Research

Recent academic research has shed light on Greek educators' views on the implementation of AI in teaching and learning. Perceived usefulness has been identified as the most significant factor influencing teachers' intentions to adopt educational AI tools (Velli & Zafiropoulos, 2024). Also, foreign language teachers in Greece are more generally positive toward the adoption of AI in their work (Rapti & Panagiotidis, 2024). Nevertheless, many of the educators feel insufficiently prepared due to a lack of knowledge and training on how to use AI effectively (Varsamidou, 2024). Such concerns mirror previous research on ICT integration. Limited time, poor infrastructure, and a lack of technical support were highlighted as major obstacles (Kokkinaki, 2010). Overall, according to these findings, the need for comprehensive training and institutional support to ensure effective AI integration in Greek educational settings is underscored.

In the current educational landscape, the way teachers perceive chatbots is of particular importance. These personal views influence whether such tools will be used at all, as well as how they will be applied in everyday teaching. If educators believe that chatbots can genuinely support student learning, they tend to experiment with them and gradually integrate them into their teaching practice (Van Katwijk, Jansen, & Van Veen, 2023). Educators who prefer student-centered and exploratory pedagogical approaches are more likely to see AI in education as useful and reliable (Velli & Zafiropoulos, 2024).

Recent studies examine educators' attitudes toward AI as well as the use of chatbots (Al Darayseh, 2023; Bii, Too, & Mukwa, 2018; Chocarro, Cortiñas, & Marcos-Matás, 2023; Chuah & Kabilan, 2021; Ghimire & Edwards, 2024; Lucas, Zhang, Bem-haja, & Vicente, 2024; Uygun, 2024; Velli & Zafiropoulos, 2024). There are also studies examining students' views (Al-Abdullatif, 2023; Ragheb, Tantawi, Farouk, & Hatata, 2022; Tiwari, Bhat, Khan, Subramaniam, & Khan, 2024; Zou & Huang, 2023).

Most educators view chatbots positively and find them user-friendly and beneficial, recognizing the variety of benefits offering AI to their teaching practices, such as enhancing content creation and facilitating various educational tasks (Bii et al., 2018; Chuah & Kabilan, 2021; Uygun, 2024). Still, only about a quarter of the participants had actually used AI tools in their teaching, despite the fact that many appeared open to the idea of incorporating such technologies into education This indicates a gap between acceptance and actual application. The intention to adopt AI appears to be a significant predictor of its integration into educational practice (Tram, 2024). General perceptions of AI applications play a key role in determining whether such practices are adopted in teaching (Al Darayseh, 2023). Positive attitudes are associated with a higher likelihood of integrating AI tools into the classroom. On the contrary, some educators express hesitation about using chatbots due to concerns about time consumption of their profession. They also highlight the importance of careful planning in incorporating chatbots into existing teaching curricula (Bii et al., 2018). Moreover, several researchers highlight the need for practical, hands-on applications to ensure that chatbots are used effectively within real classroom settings (Diep & Dang, 2025).

3 Theoretical Framework: The Unified Theory of Acceptance and Use of Technology (UTAUT) Model and Its Extensions

The UTAUT is a leading framework for explaining individual and organizational technology adoption. Developed by Venkatesh, Morris, Davis, and Davis (2003), it integrates constructs from eight earlier models, including TAM, TRA, and TPB (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017; Menon & Shilpa, 2023; Venkatesh et al., 2003).

UTAUT identifies four key determinants of technology adoption: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions. Their effects are moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003; Xue, Rashid, & Sha, 2024).

The model has been applied across education, healthcare, banking, and other domains, confirming its generalizability (Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016; Venkatesh, Thong, & Xu, 2012). UTAUT2 extended the framework to consumer contexts by adding hedonic motivation, price value, and habit, thereby enhancing explanatory power (Venkatesh et al., 2012). However, criticism concerns its complexity, context-specific adaptations, and limited theoretical advancement, which may restrict generalizability (Blut, Chong, Tsigna, & Venkatesh, 2022; Chatterjee, Rana, Khorana, Mikalef, & Sharma, 2021; Dwivedi et al., 2017).

The UTAUT model has been applied and expanded to examine technology acceptance and usage intention across different settings. Researchers' interest in understanding the acceptance of chatbots, such as ChatGPT and AI in education through the UTAUT framework has grown considerably in recent years (Diep & Dang, 2025; Foroughi et al., 2023; Menon & Shilpa, 2023; Polyportis & Pahos, 2024; Ragheb et al., 2022; Strzelecki, 2023; Terblanche & Kidd, 2022; Tian, Ge, Zhao & Zheng, 2024; Tram, 2024; Widyaningrum, Wulandari, Zainudin, Athiyallah, & Rizqa, 2024).

It is evident that UTAUT has been successfully employed in a variety of technologies and contexts, including chatbots and may be regarded as a valid and reliable theory for measuring and understanding the impact of technology on users' intention to use. It is common practice in quantitative research to extend this particular model in order to explore the complexity of influencing factors on usage intention. Perceived risk (PR), personal innovativeness (PI), and personal experience are some of the variables that can enrich such models of technology acceptance and use (Al-Abdullatif, 2023; Alkawsi, Ali, & Baashar, 2021; Chang, Hajiyev, & Su, 2017; Lai, Cheung, Chan, & Law, 2024; Twum, Ofori, Keney, & Korang-Yeboah, 2022; Zou & Huang, 2023).

The application of UTAUT in AI/chatbot research is particularly relevant in education given its ability to identify and explain the main determinants of technology acceptance among students and educators. The framework systematically highlights factors such as PE, EE, SI, and facilitating conditions, which have consistently been shown to influence the intention and actual use of AI chatbots in educational contexts (Bilquise, Ibrahim, & Salhieh, 2023; Tao, Yang, & Qu, 2024; Wijaya, Su, Cao, Weinhandl, & Houghton, 2024). Beyond these core constructs, UTAUT is characterized by flexibility and extensibility. It can incorporate additional variables such as PI, PR, or user satisfaction, allowing it to capture the specificities of AI-driven tools and their role in education (Tao et al., 2024).

Another strength of UTAUT is its strong empirical foundation. Evidence from multiple studies in diverse educational settings confirms the model's explanatory reliability, demonstrating that it effectively captures both motivational drivers (e.g., SI, PI) and barriers (e.g., PR) to chatbot adoption (Bilquise et al., 2023; Tian et al., 2024; Wijaya et al., 2024). This body of evidence underscores the robustness of the framework across different cultural and institutional contexts. Finally, UTAUT offers clear practical value. By identifying the mechanisms that shape acceptance and use, it provides educators and policymakers with actionable guidance for designing targeted interventions that can facilitate the integration of AI chatbots into teaching and learning practices (Bilquise et al., 2023; Tao et al., 2024; Wijaya et al., 2024).

Expectations surrounding the role of AI in education are particularly high, often emphasizing its transformative potential. Key anticipated benefits include personalization and enhanced learning, as AI promises individualized support, real-time feedback, and increased learner autonomy, performance, creativity, and innovation (Chan & Hu, 2023; Chen, Chen, & Lin, 2020; García-Martínez, Fernández-Batanero, Fernández-Cerero, & León, 2023; Wang & Li, 2024). Moreover, AI is associated with greater student motivation and emotional well-being, since positive affect, digital confidence, and satisfaction are considered crucial for sustaining autonomous learning (Almufarreh, 2024; Wang & Li, 2024). A further expectation concerns the improvement of administrative and teaching processes, as AI can automate assessment, adapt instructional content, and optimize learning management (Chen et al., 2020; García-Martínez et al., 2023).

However, research also highlights several critical challenges and limitations that temper these optimistic claims. One major concern is the prevalence of overestimated expectations and techno-optimism, where assumptions about AI's transformative role are based on misinterpretations of technical capacities and the neglect of inherent constraints (Holmes & Tuomi, 2022; Williamson, 2024). Equally important is the lack of robust empirical evidence: despite numerous pilot projects and case studies, large-scale and long-term data confirming AI's transformative effects in education remain scarce (García-Martínez et al., 2023; Holmes & Tuomi, 2022; Williamson, 2023).

Other limitations stem from issues of accuracy, ethics, and privacy, including concerns about the reliability of AI outcomes, the protection of personal data, algorithmic opacity, and broader ethical implications (Chan & Hu, 2023; Wu, Zhang, Li, & Liu, 2022; Zhang et al., 2023). In addition, scholars warn of social and value-related challenges, as AI risks exacerbating inequalities, disrupting student–teacher relationships, generating anxieties around job displacement, and undermining educational values (Chan & Hu, 2023; Williamson, 2023; Zhang et al., 2023). Finally, important research gaps persist, with much of the literature focusing on technological capabilities while overlooking the deeper social, pedagogical, and psychological consequences of AI integration (Holmes & Tuomi, 2022; Xu & Fan, 2021).

4 Application of the Model to the Present Study

According to recent literature, the integration of AI into education is considered highly innovative and continues to draw interest from the academic community (Al-Amri & Al-Abdullatif, 2024; Diep & Dang, 2025). However, there are significant research gaps that warrant further investigation despite the increasing amount of research on AI in education. While the UTAUT model is commonly used to explain individuals' intention to use technology, relatively few studies have focused specifically on the use of chatbots in primary education.

Moreover, this research focuses on a population that has not been extensively studied, Greek educators, aiming to explore their attitudes toward the use of AI tools and chatbots. The conduct of this study is valuable, aiming to shed light on key aspects necessary to decode Greek educators' perceptions regarding the integration of chatbots in education, taking into account the prevailing patterns of acceptance and usage within the teaching community.

The research builds upon central elements of the UTAUT model. Specifically, the key constructs are PE, EE, and SI. Additionally, PI, PR, and personal experience with AI (PEAI) are included as additional factors.

The data collection tool was developed through the synthesis of variables from four validated questionnaires. Specifically, the final questionnaire of the present study was constructed by integrating elements from the following research instruments: Al-Abdullatif (2023), Galindo-Domínguez, Sainz de la Maza, Campo, and Losada (2024), Mohd Rahim et al. (2022), and Strzelecki (2023).

5 Hypothesis Formulation

While the UTAUT remains one of the most widely used models in technology adoption research (Williams, Rana, & Dwivedi, 2015), it is worth noting that more than 75% of its applications include extra factors to better reflect the unique features of their specific research (Dwivedi et al., 2017). Recent research has increasingly focused on understanding the factors that influence individuals' intention to adopt AI tools (Chatterjee & Bhattacharjee, 2020) as well as the use of ChatGPT (Menon & Shilpa, 2023; Ragheb et al., 2022) has concluded that PE, EE, and SI play a significant role in technology adoption. Research consistently shows that PE, EE, and SI are significant direct predictors of individuals' intention to use chatbots and AI tools (Budhathoki, Zirar, Njoya, & Timsina, 2024; Strzelecki, 2023; Terblanche & Kidd, 2022).

Based on these findings, the following hypotheses are proposed:

H1: PE has a significant positive effect on behavioral intention (BI).

H2: EE has a significant positive effect on behavioral intention.

H3: SI has a significant positive effect on behavioral intention.

Studies have shown that SI not only directly encourages the actual use of AI tools but also enhances users' PE. Recent research has emphasized that social support strengthens perceived usefulness, thereby motivating students' continued intention to engage in e-learning (He, Jiang, Zhu, & Hu, 2023). Furthermore, when individuals observe peers or colleagues successfully using AI or chatbots, they are more likely to perceive these tools as effective and beneficial, which in turn raises their own expectations of improved performance (Gursoy, Chi, Lu, & Nunkoo, 2019). Hence, the following hypothesis is proposed:

H4: SI has a significant positive effect on PE.

PR refers to individuals' general belief that they may experience some form of loss when pursuing a particular outcome (Warkentin, Gefen, Pavlou, & Rose, 2002). PR tends to be present in uncertain situations, where outcomes are potentially negative due to poor or incorrect decisions. Data privacy and security raise concerns, which play a key role in the intention to adopt a new technology. Previous studies have shown that such concerns can reduce user satisfaction and as a result, negatively affect their intention to use the technology (Cheng & Jiang, 2020; Ikkatai, Hartwig, Takanashi, & Yokoyama, 2022). In the case of ChatGPT, specific concerns have been raised regarding its reliability. Recent findings about chatbots and ChatGPT identify PR as the second significant factor discouraging students from using these tools (Lai et al., 2024). Based on these findings, the following hypothesis is proposed:

H5: PR has a significant negative effect on BI.

The concept of PI is defined as individual's willingness to take risks and explore new technologies. As it influences both the antecedents and consequences of these perceptions, according to Agarwal & Prasad (1998), PI plays a crucial role in shaping an individual's view of technology. In the context of AI and chatbots, PI has been found to reduce PR. Studies have shown that individuals with higher levels of innovativeness are less negatively affected by the risks associated with using such technologies (Yu, Lee, Ha, & Zo, 2017). Lower resistance to adopting AI tools seems to have teachers who are more open to trying out innovative tools, as they feel more motivated and confident in their ability to use them effectively (Hidayat-ur-Rehman & Ibrahim, 2024). These individuals are also more willing to experiment, perceive greater control over technology use, and consequently experience lower levels of PR. Furthermore, according to recent studies, PI has been found to have a statistically significant effect on both PE and EE (Alkawsi et al., 2021; Mazman Akar, 2019; Twum et al., 2022). More specifically, educators who are more open to new experiences and inclined to explore innovative solutions are more likely to perceive AI-based educational tools as both useful and easy to use. As a result, the study proposes the following hypotheses:

H6: PI has a significant positive effect on behavioral intention.

H7: PI has a significant positive effect on PE.

H8: PI has a significant positive effect on EE.

In the case of AI and chatbots, research shows that PI reduces PR and fosters willingness to experiment (Hidayat-ur-Rehman & Ibrahim, 2024; Yu et al., 2017). People are generally more willing to explore and experiment, feel a greater sense of control over the technology, and therefore perceive it as less risky. As a result, the following hypothesis is proposed:

H9: PI has a significant negative effect on PR.

PEAI can be understood as individuals' personal and professional interactions with AI technologies. This dimension examines both the extent and the nature of direct or indirect experiences people have had with AI, which shape their perceptions, beliefs, and behaviors toward this technology (Galindo-Domínguez et al., 2024; Venkatesh et al., 2003). The intention to use a given technology has been shown that it is influenced by prior experience. For instance, according to Galindo-Domínguez et al. (2024), there is a relationship between teachers' PEAI and their willingness to adopt it. Similarly, Zou and Huang (2023) demonstrated that students were more likely to perceive ChatGPT as useful and easy to use in academic writing tasks if they had prior experience using it. Their findings further suggest that as students gain more experience with ChatGPT, their perceptions of its ease of use and usefulness tend to improve (Zou & Huang, 2023). This pattern aligns with similar findings on technology acceptance that also emphasizes the influence of prior experience on both PE and EE (Izkair & Lakulu, 2021; Purnomo & Lee, 2013; Yang & Wang, 2019). For example, Chang et al. (2017) found that students with greater experience using computers were more likely to perceive e-learning platforms as both more useful and easier to use. In line with these findings, it seems likely that having personal experience with generative AI tools such as ChatGPT can boost confidence, reduce uncertainty, and positively affect their technology adoption decisions. Consequently, the hypotheses developed are as follows (Figure 1):

H10: PEAI has a significant positive effect on behavioral intention.

H11: PEAI has a significant positive effect on PE.

H12: PEAI has a significant positive effect on EE.

6 Materials and Methods

The present study involved primary education teachers working in schools across Greece, including both primary education schools and kindergartens. A total of 241 teachers voluntarily participated in the research. This study aims to explore the factors that influence teachers' intention to use chatbots in their work and teaching practices. It focuses on collecting and analyzing data from Greek primary school teachers to better understand their perspectives on this new technology.

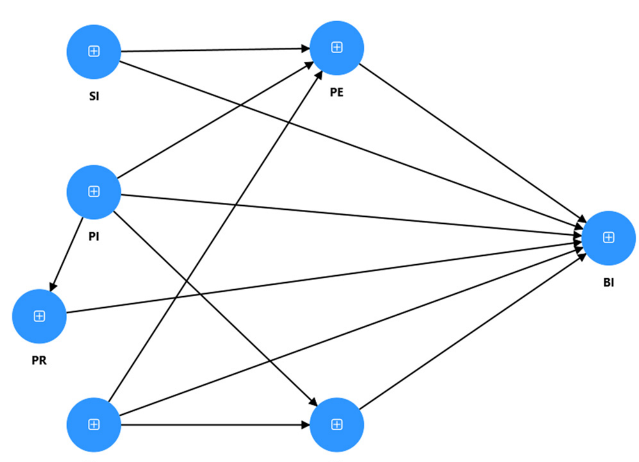

Figure 1: Path coefficients of the research model and direct effects results.

The descriptive analysis of the sample focuses on gender, age, and academic qualifications. A significant majority of the participants (79.7%) identified as female, while male participants accounted for 19.5% of the sample, with two participants preferring to withhold their gender. Regarding age, the largest proportion of participants were between 21 and 30 years old (73%), followed by the 31–40 age group (13.3%), over 50 years old (8.7%), and finally the 41–50 age group (5%). In terms of academic qualifications, 64.7% held only a bachelor's degree, while 34% also held a master's degree. Only three of the participants had a doctoral degree or were currently pursuing doctoral studies.

6.1 Instrument of This Study

The questionnaire was distributed to participants via email, through group chat applications used by educators, social media groups, as well as through direct correspondence with various primary schools and kindergartens across the country. The demographic factors of gender, age, and academic qualifications are being investigated in this research.

The questionnaire consisted of closed-ended questions, including items on participants' demographic characteristics. Regarding the measurement of quantitative variables, a five-point Likert scale was used (ranging from "strongly agree" to "strongly disagree"), while the three demographic questions included a single-choice answer option. In total, the questionnaire comprised 29 items and were translated from English into Greek with appropriate linguistic adaptations. The questionnaire items were translated and linguistically adapted into Greek. However, no pilot study or pre-test was conducted to formally assess translation validity and cultural adaptation. This constitutes a limitation of the present study, as minor nuances in language or cultural interpretation may have influenced participants' responses.

The research tool was accompanied by an introductory consent form, which outlined the purpose of the study, emphasized the voluntary and anonymous nature of participation, assured the protection of personal data, and clarified that there would be no associated risks, costs, or rewards. To ensure that the research adhered to current ethical standards and legislation, the researchers submitted a request to the university's research ethics committee (REC), which granted approval (No. 22/17.1.2024). The questionnaire was designed to require approximately 10 min to complete. Data collection took place between November 2024 and January 2025.

The data collection instrument was developed by synthesizing selected variables from the questionnaires used in four previous studies: Mohd Rahim et al. (2022), Strzelecki (2023), Al-Abdullatif (2023), and Galindo-Domínguez et al. (2024). The questionnaire consists of seven sections, comprising a total of 29 items designed to assess teachers' perceptions regarding PE, EE, SI, PR, PI, PEAI, and BI. Specifically, 18 items were adapted from the study by Mohd Rahim et al. (2022), 4 items from Strzelecki (2023), 3 items from Al-Abdullatif (2023), and 4 items from Galindo-Domínguez et al. (2024). In the latter, the term "academic" was replaced with the term "educational" and the term "daily campus life" was replaced with "daily work as an educator" (Table 1).

7 Statistical Analysis

Partial least squares-structural equation modeling (PLS-SEM) in this study was the preferred modeling tool due to the emphasis on prediction. PLS is particularly suitable when the research focuses on identifying key driver constructs, the model is complex, and when sample size may be relatively modest. Also, PLS-SEM does not rely on strict assumptions of multivariate normality, but instead it uses Bootstrapping algorithms (Table 2).

The final sample consisted of 239 primary education teachers. The majority were female (80.3%). Most participants were young educators aged 21–30 (73.0%), with the remaining 27.0% aged over 31. Regarding educational background, 64.7% held a bachelor's degree, while 35.3% had completed postgraduate studies.

7.1 Measurement Model Assessment

The internal consistency of each latent construct was assessed using Cronbach's alpha, rho_A, and composite reliability (rho_C). All values exceeded the recommended threshold of 0.70, indicating strong internal consistency for all constructs. Convergent validity was assessed through the average variance extracted (AVE). All constructs reported AVE values above the recommended cutoff of 0.50 (Table 3).

The Fornell–Larcker criterion was used to assess discriminant validity. Correlations between latent variables are smaller than square roots of AVE (Table 4).

The heterotrait–monotrait ratio of correlations (HTMT) is used in PLS-SEM analysis for discriminant

Table 1: Measurement scales

Construct	Item no.	Item	Reference
PE	PE1	I find chatbots useful in my daily work as an educator	Mohd Rahim et al. (2022)
	PE2	Using a chatbot increases my chances of achieving education-related information that is important to me	
	PE3	Using a chatbot helps me accomplish my problems in managing educational matters more quickly	
	PE4	Using a chatbot increases my productivity	
	PE5	Overall, I would find a chatbot to be advantageous for my work as an educator	
EE	EE1	Learning how to use chatbots is easy and practical	Mohd Rahim et al. (2022)
	EE2	The instructions and communication with the chatbot are clear and understandable	
	EE3	I find chatbots easy to use	
	EE4	It is easy for me to become skillful at using chatbot problems in managing educational matters	
	EE5	I find it easy to get the information as per my expectations while using a chatbot	
SI	SI1	People who are important to me think that I should use a chatbot	Mohd Rahim et al. (2022)
	SI2	People who influence my behavior think that I should use a chatbot	
	SI3	People whose opinions I value prefer that I use a chatbot	
	SI4	A friend's suggestion and recommendation will affect my decision to use a chatbot	
	SI5	I would use a chatbot because a proportion of my friends use a chatbot	
PR	PR1	I feel unsafe when using a chatbot	Al-Abdullatif (2023)
	PR2	I am worried that personal information would be leaked when using a chatbot	
	PR3	I am worried about personal information suffering from unauthorized use when using a chatbot	
PI	PI1	I like experimenting with new information technologies	Strzelecki (2023)
	PI2	If I heard about a new information technology, I would look for ways to experiment with it	
	PI3	Among my family/friends, I am usually the first to try out new information technologies	
	PI4	In general, I do not hesitate to try out new information technologies	
PEAI	PEAI1	I have never interacted with AI in an educational or general context	Galindo-Domínguez et al. (2024)
	PEAI2	I have had positive experiences with the use of AI in education	
	PEAI3	I can share my knowledge and skills about AI with other teachers	
	PEAI4	I have had some experiences with the use of AI in education	
BI	BI1	BI1: I will use a chatbot in solving problems related to my academic query	Mohd Rahim et al. (2022)
	BI2	BI2: I plan to use the chatbot frequently	
	BI3	BI3: I will recommend others to use a chatbot for academic matters	

validity assessment. According to a previous study, HTMT values should typically be below 0.85 (conservative criterion) or at least below 0.90 (liberal threshold) to confirm discriminant validity. All values in the model are below 0.85 (Table 5).

Cross-loadings are used to verify that each indicator loads most on the construct it is meant to measure. This is indeed true for our case (Table 6).

Table 2: Descriptive analysis of the sample

	Counts	% of total
Gender		
Female	192	80.3%
Male	47	19.7%
Age		
21–30	176	73.0%
>31	65	27.0%
Educational level		
Bachelors	156	64.7%
Postgraduate degree	85	35.3%

Table 3: Construct reliability and validity

Construct	Cronbach's alpha	rho_A	rho_C	AVE
BI	0.918	0.928	0.948	0.859
EE	0.907	0.910	0.931	0.729
PE	0.909	0.913	0.932	0.734
PEAI (PEx)	0.853	0.860	0.911	0.773
PI	0.873	0.882	0.913	0.725
PR	0.717	0.909	0.835	0.652
SI	0.871	0.890	0.907	0.662

Table 4: Discriminant validity of the measurement model based on the Fornell–Larcker criterion

	BI	EE	PE	PEx	PI	PR	SI
BI	0.927						
EE	0.564	0.854					
PE	0.652	0.547	0.857				
PEx	0.628	0.512	0.549	0.879			
PI	0.443	0.463	0.404	0.509	0.852		
PR	−0.326	−0.287	−0.144	−0.221	−0.186	0.808	
SI	0.475	0.337	0.531	0.314	0.247	−0.224	0.814

8 Findings

Each endogenous variable's R^2 are presented in Table 7. The model explains 59.1% of the variance in teachers' intention to use chatbots (BI), a strong result in educational technology studies. EE and PE are explained moderately well by the model (R^2 = 0.318 and 0.454 respectively). The variance explained for PR is extremely low (R^2 = 0.035) and statistically non-significant (p = 0.219). This suggests that the included predictors do not substantially account for how teachers assess the risks of using AI/chatbots.

Table 8 presents the direct, total indirect, and total effects along with their significance level p. PE is the strongest predictor of BI (β = 0.307, p < 0.001). Personal Experience (PEx) significantly predicts PE (β = 0.365) and EE (β = 0.371) and directly affects BI (β = 0.292), p < 0.001. Familiarity with AI boosts positive attitudes. EE also predicts BI (β = 0.140, p = 0.031). SI significantly affects both PE (β = 0.386) and BI (β = 0.131). PR negatively affects BI (β = −0.138, p = 0.007), confirming H5. Risk acts as a barrier. PI significantly predicts EE (β = 0.277) and PE (β = 0.123).

Additionally, it negatively predicts PR (β = −0.187), which supports the idea that more innovative individuals tend to perceive lower risk. H6 (PI → BI) is not supported (β = 0.049, p = 0.389). PI does not directly impact intention. PE and personal experience play an important role, especially with regard to AI-specific tools like chatbots. Although H6 is not supported at the direct level, the significant indirect effects (β = 0.102, p = 0.001) reveal a meaningful mediating mechanism through performance and EE.

There is an indirect influence of PI through mediators like EE and perceived experience. On the contrary, risk perception, while important for intention, is not integrated into performance beliefs. Social norms shape both perceived usefulness and intention, especially in collaborative school environments (Figure 2).

Table 5: Heterotrait–monotrait ratio

	Heterotrait–monotrait ratio
EE ↔ BI	0.610
PE ↔ BI	0.707
PE ↔ EE	0.600
PEx ↔ BI	0.701
PEx ↔ EE	0.577
PEx ↔ PE	0.618
PI ↔ BI	0.489
PI ↔ EE	0.514
PI ↔ PE	0.450
PI ↔ PEx	0.584
PR ↔ BI	0.366
PR ↔ EE	0.341
PR ↔ PE	0.168
PR ↔ PEx	0.265
PR ↔ PI	0.217
SI ↔ BI	0.523
SI ↔ EE	0.376
SI ↔ PE	0.586
SI ↔ PEx	0.357
SI ↔ PI	0.278
SI ↔ PR	0.264

Table 6: Cross-loadings matrix

	BI	EE	PE	PEx	PI	PR	SI
BI1	0.934	0.617	0.658	0.654	0.426	−0.326	0.475
BI2	0.932	0.486	0.543	0.520	0.417	−0.273	0.423
BI3	0.914	0.449	0.601	0.559	0.386	−0.301	0.417
EE1	0.439	0.822	0.445	0.362	0.342	−0.202	0.265
EE2	0.474	0.873	0.434	0.427	0.366	−0.213	0.246
EE3	0.492	0.894	0.492	0.467	0.401	−0.222	0.229
EE4	0.502	0.849	0.468	0.475	0.465	−0.272	0.328
EE5	0.492	0.828	0.491	0.440	0.392	−0.310	0.366
PE1	0.569	0.483	0.879	0.505	0.406	−0.105	0.467
PE2	0.525	0.443	0.840	0.404	0.286	−0.167	0.406
PE3	0.535	0.453	0.853	0.473	0.331	−0.094	0.441
PE4	0.519	0.424	0.812	0.461	0.360	−0.067	0.467
PE5	0.636	0.532	0.898	0.500	0.340	−0.181	0.488
PEx2	0.550	0.432	0.526	0.863	0.437	−0.238	0.298
PEx3	0.598	0.480	0.495	0.905	0.516	−0.185	0.288
PEx4	0.501	0.435	0.419	0.869	0.377	−0.156	0.237
PI1	0.395	0.454	0.376	0.440	0.885	−0.158	0.187
PI2	0.368	0.355	0.390	0.475	0.870	−0.112	0.257
PI3	0.290	0.318	0.295	0.388	0.778	−0.142	0.235
PI4	0.441	0.438	0.309	0.427	0.869	−0.218	0.172
PR1	−0.085	−0.118	−0.036	−0.080	−0.041	0.406	−0.067
PR2	−0.319	−0.275	−0.129	−0.179	−0.169	0.943	−0.218
PR3	−0.310	−0.269	−0.149	−0.241	−0.192	0.950	−0.212
SI1	0.413	0.271	0.473	0.273	0.198	−0.234	0.878
SI2	0.408	0.307	0.507	0.285	0.262	−0.158	0.889
SI3	0.458	0.302	0.467	0.287	0.241	−0.236	0.857
SI4	0.311	0.257	0.369	0.226	0.165	−0.087	0.688
SI5	0.318	0.227	0.305	0.186	0.108	−0.181	0.736

Table 7: R^2 values of the model's endogenous variables

Endogenous variable	R^2	T	p
BI	0.591	15.152	0.000
EE	0.318	5.675	0.000
PE	0.454	9.068	0.000
PR	0.035	1.234	0.217

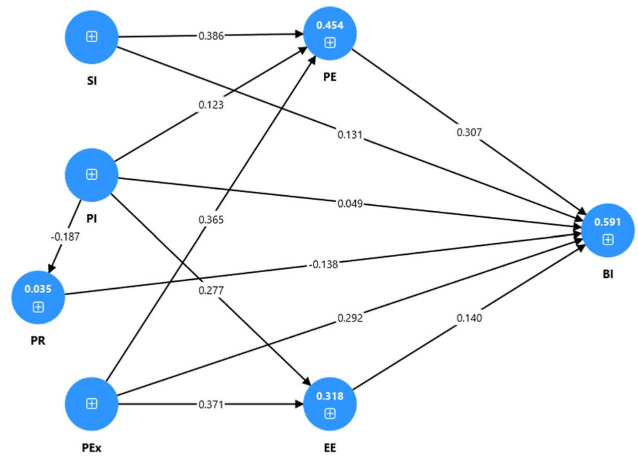

Figure 2: Path coefficients of the research model (direct effects).

9 Discussion

The purpose of this study was to investigate the factors influencing Greek primary education teachers' intention to use chatbots in the classroom, applying SEM analysis through PLS. The research model is distinct in that it combines constructs from established technology acceptance frameworks, including constructs such as PE and EE, along with constructs such as PI, PR, SI, and PEAI. The analysis confirmed high reliability of the measurement scales and satisfactory convergent and discriminant validity, supporting the robustness of the framework.

Regarding the first hypothesis, PE was the strongest direct predictor of BI, although PEAI exhibited the highest total effect when both direct and mediated effects are considered. Similarly, Ragheb et al. (2022) reported a statistically significant impact of PE on BI toward chatbots. These findings are supported by Terblanche and Kidd (2022) and Tian et al. (2024). Strzelecki (2023) also identified PE as the second most important predictor of students' BI toward ChatGPT. Likewise, Menon and Shilpa (2023), through semi-structured interviews with users in India, concluded that PE plays a key role in the adoption of this technology.

Concerning the second hypothesis, EE was also found to have a statistically significant effect on BI. This is consistent with Chatterjee and Bhattacharjee (2020), who observed a positive relationship between EE and BI in the context of AI adoption. Similar results were reported by Ragheb et al. (2022), Strzelecki (2023), and Menon and Shilpa (2023). In Malaysia, Foroughi et al. (2023) also confirmed the role of EE in influencing users' intentions. On the contrary, in the literature no significant effect of EE on BI related to ChatGPT for educational purposes was found. They suggested that students' high digital literacy may reduce perceived effort, thereby weakening the influence of EE.

As for the third hypothesis, SI proved to be a meaningful factor in predicting BI toward chatbots. Strzelecki (2023) emphasized SI as a significant component influencing intention to use ChatGPT. Similarly, Ragheb et al. (2022) confirmed SI as an important factor among 385 university students in Egypt regarding their intention to adopt chatbots.

The fourth hypothesis was confirmed, indicating that SI significantly enhances PE. When educators observe

Table 8: Direct, indirect, and total effects of the research model

	Direct effects	p	Total indirect effects	p	Total effects	p
EE → BI	0.140	0.031			0.140	0.031
PE → BI	0.307	0.000			0.307	0.000
PEx → BI	0.292	0.000	0.164	0.000	0.456	0.000
PEx → EE	0.371	0.000			0.371	0.000
PEx → PE	0.365	0.000			0.365	0.000
PI → BI	0.049	0.389	0.102	0.001	0.152	0.011
PI → EE	0.277	0.000			0.277	0.000
PI → PE	0.123	0.043			0.123	0.043
PI → PR	−0.187	0.008			−0.187	0.008
PR → BI	−0.138	0.007			−0.138	0.007
SI → BI	0.131	0.016	0.118	0.000	0.249	0.000
SI → PE	0.386	0.000			0.386	0.000

peers effectively integrating AI tools like chatbots, they are more likely to believe in the potential of such technologies to improve their own teaching outcomes (Gursoy et al., 2019). This is consistent with findings showing that social support positively affects perceived usefulness and encourages continued use of educational technologies (He et al., 2023).

Regarding the fifth hypothesis, PR was found to significantly affect BI among Greek primary school teachers. In a study by Chatterjee and Bhattacharjee (2020), PR was shown to negatively impact the intention to use AI. Similarly, Lai et al. (2024) identified PR as the second most significant barrier to students' use of ChatGPT, citing concerns over privacy, plagiarism, and possible sanctions.

Furthermore, concerning the sixth hypothesis, PI did not emerge as a statistically significant predictor of BI. While Strzelecki (2023) reported PI as a weak positive influence, Tian et al. (2024) found it to be the second most influential factor. Similarly, Velli and Zafiropoulos (2024) reported a significant relationship between PI and BI regarding AI tools among Greek educators.

The seventh and eighth hypotheses explored the impact of PI on both PE and EE. The results showed statistically significant relationships in both cases. These findings are consistent with Alkawsi et al. (2021), who identified PI as a predictor of both PE and EE. Twum et al. (2022) also confirmed the influence of PI on PE.

When compared with international findings, the Greek case appears broadly consistent but also contextually distinctive. Similar to studies conducted in Egypt (Ragheb et al., 2022), India (Menon & Shilpa, 2023), and Malaysia (Foroughi et al., 2023), PE emerged as the strongest predictor of intention to use chatbots. Likewise, EE and SI were significant but comparatively weaker factors, as also reported in China (Tian et al., 2024) and across European contexts (Strzelecki, 2023). What differentiates Greece, however, is the particularly strong role of PEAI, which exerted both direct and indirect effects on intention. This finding likely reflects the early adoption stage of AI in Greek primary schools, where hands-on exposure may be a prerequisite for building confidence. Furthermore, the relatively modest impact of SI in Greece may mirror the limited diffusion of AI culture within schools, contrasting with more mature ecosystems in other countries where peer and institutional norms play a stronger role. These comparisons suggest that while Greek educators follow global patterns of valuing usefulness and ease of use, the path to adoption is more contingent on individual experience than on institutional or social factors.

Supporting H9, the findings indicate that PI affects in an indirect PR, lowering PR. Individuals who are more open to trying new technologies tend to feel less concerned about potential risks related to AI tools such as chatbots (Yu et al., 2017). In educational contexts, teachers with higher levels of innovativeness show reduced resistance to adopting AI, as they feel more empowered and motivated to use these tools effectively (Hidayat-ur-Rehman & Ibrahim, 2024). This highlights the importance of encouraging PI to overcome risk-related barriers to AI adoption.

With regard to the tenth hypothesis, PEAI appeared as the second most significant factor influencing BI. Zou and Huang (2023) showed that students with more experience using ChatGPT were more willing to adopt it. Likewise, Galindo-Dominguez et al. (2024) found that teachers with personal AI experience were more likely to integrate such tools into their teaching practice.

Finally, the 11th and 12th hypotheses were supported, confirming that PEAI positively influences both PE and EE. This aligns with previous research showing that users with greater exposure to digital technologies are more likely to perceive them as useful and easier to use (Purnomo & Lee, 2013; Yang & Wang, 2019). Zou and Huang (2023) specifically found that students who had prior experience with ChatGPT expressed greater confidence and perceived it as more effective for academic writing tasks. Similarly, other studies have shown that familiarity with AI tools reduces uncertainty and builds trust in their functionality (Chang et al., 2017; Izkair & Lakulu, 2021). These findings highlight the importance of hands-on experience in shaping positive attitudes toward the adoption of AI-driven educational technologies.

While most hypotheses were supported, some effects such as the influence of social norms on BI remained weak in magnitude. This may reflect the limited diffusion of AI culture in primary schools, or the early adoption phase of chatbot tools in Greece. Similarly, the low explanatory power of the PR construct (R^2 = 0.035) despite significant paths suggests that risk perceptions may be shaped by unmeasured contextual variables.

Results suggest that teachers who have PEAI are more willing to use chatbots in their teaching. If training programs are to be implemented, they should include practical activities that provide teachers with opportunities to try out chatbot tools in safe environments and also provide examples of how they can help with daily teaching tasks, such as giving feedback, managing information, or helping students work independently.

Teachers who are more innovative tend to feel less reluctant to use AI. Creating a culture in schools where trying new things is encouraged, and offering time, resources, and support for experimentation could help.

SI had a small effect. In that sense seeing successful examples in real classrooms may be more helpful than general encouragement. Schools could organize small projects or communities of practice where teachers share ideas and results from using chatbots.

Regarding research, the study confirms that PE and EE are important factors. It also supports that other personal factors, such as innovativeness, experience, and feeling safe, also matter. PI didn’t directly affect intention, but it affected it indirectly by shaping how teachers saw the usefulness and ease of the chatbot. This means that future research should not only look at what teachers think of a tool, but also who the teachers are and what kind of learners they are themselves.

PR had a clear effect on intention, but since no more explanatory variables were included in the model, further research should consider cultural and institutional factors, such as trust in technology or support from leadership, to provide a more comprehensive understanding.

Policy actions should focus on building confidence and experience. Training such as pilot projects, classroom demonstrations, and success stories from real-life experiences can help advance teachers’ and school leaders’ understanding and acceptance.

Training programs should focus not just on how to use a tool, but also on understanding AI, dealing with ethical concerns, and connecting AI with teaching goals.

10 Limitations and Future Research

A key limitation of this study is the sample size and composition, as convenience sampling and a predominance of women (79.7%) under 30 years old (73%) limit the generalizability of the results. The exclusive use of quantitative questionnaires may also introduce subjectivity and lack qualitative insights from educators’ experiences, which could deepen understanding. Moreover, no observations of actual chatbot use in classrooms were conducted, reducing the connection between theory and practice. Limited familiarity with chatbots among participants likely affected response quality. Important demographic factors like teaching experience or training were not considered.

On the basis of these limitations, future research should use larger, more diverse samples and combine quantitative with qualitative methods, such as interviews, to better explore educators’ attitudes and motivations regarding chatbot use. Future studies should examine their impact across different subjects, document the challenges and limitations faced by teachers, and explore factors influencing their attitudes toward using these tools. Additionally, investigating demographic factors such as teachers’ experience could provide deeper insight into what affects their intention to use chatbots. Finally, capturing the perceptions and experiences of both educators and students regarding chatbots is essential, as understanding these aspects can guide the development of tools better tailored to the Greek educational context.

Beyond methodological considerations, the findings also carry implications for educational design and practice. A clearer roadmap for operationalizing these results involves translating them into guidelines for different stakeholders. For instance, tool developers could prioritize user-friendly interfaces and features that enhance perceived usefulness, while also addressing concerns about reliability and data security. Curriculum designers might explore how chatbots can be embedded in lesson planning to support differentiated instruction and provide real-time feedback, while policy makers could invest in professional development programs that give teachers safe spaces to experiment with AI tools.

The study highlights the need for a deeper engagement with the ethical challenges of educational chatbots. Issues such as algorithmic bias, transparency of chatbot responses, student data protection, and the potential erosion of teacher and student autonomy warrant careful consideration. Future research should investigate how these ethical concerns influence not only teachers’ intentions but also actual classroom practices. Longitudinal studies and participatory research with educators could help design AI tools that are both pedagogically valuable and ethically responsible.

11 Conclusion

In conclusion, this study sheds light on the key factors influencing Greek primary education teachers’ intention to adopt chatbots in the classroom, highlighting the pivotal roles of PE, EE, SI, PR and PEAI. While PI did not directly predict BI, its significant indirect effects underscore its importance in shaping perceptions and reducing risk. The validated research model and robust findings offer valuable insights for policymakers, educators, and developers aiming to enhance AI integration in education. However, further research with more diverse samples and mixed methods is essential to deepen understanding and bridge the gap between theoretical intention and actual classroom use.

Beyond summarizing the main findings, this study also makes an important theoretical contribution by extending the UTAUT with three additional constructs: PI, PR, and PEAI. Incorporating these factors provides a more comprehensive understanding of technology acceptance in educational contexts, highlighting indirect pathways of influence that traditional UTAUT models often overlook. At the same time, the study offers a novel empirical contribution by focusing specifically on primary education in Greece, a setting where AI adoption remains in its early stages and has received little scholarly attention. By doing so, it enriches the international literature with evidence from a context that differs in infrastructure, policy environment, and teacher preparedness from many of the better-studied educational systems. Together, these contributions emphasize that the value of this research lies not only in its practical implications for teacher training and policy but also in advancing theoretical models of technology adoption in education.

Funding information: The authors state no funding involved.

Author contributions: Conceptualization, V.P. and K.Z.; Methodology, V.P. and K.Z.; Investigation, V.P.; Data curation, V.P. and K.Z.; Writing—original draft preparation, V.P.; Writing—review and editing, K.Z.; Visualization, V.P. and K.Z. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors state no conflict of interest.

Data availability statement: The data supporting this study are not publicly available due to restrictions imposed by the Ethics Committee of the University of Macedonia.

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