Computers and Education Open 10 (2026) 100359

Contents lists available at ScienceDirect

Computers and Education Open

journal homepage: www.sciencedirect.com/journal/computers-and-education-open

Talking mathematics with AI: Understanding teachers' motivation for utilizing chatbots

Robert Weinhandl [a,*], Branko Andic [b], Tommy Tanu Wijaya [c], Valentina Bleckenwegner [a], Viktoria Riegler [a], Selina Baldinger [a], Jonas Mayrhofer [a], Christoph Helm [d]

[a] *Center for Open Digital Education, Department of Mathematics Education, Johannes Kepler University, Linz, Austria*
[b] *Linz School of Education, Johannes Kepler University, Linz, Austria*
[c] *School of Mathematical Sciences, Beijing Normal University, Beijing, China*
[d] *Department of Education and Educational Psychology, Johannes Kepler University, 4040 Linz, Austria*

ARTICLE INFO

Keywords:
AI chatbots
Mathematics teachers
Unified theory of acceptance and use of technology
Structural equation modelling
Technology-enhanced teaching

ABSTRACT

How About A Nice Game of Chess? A conversation like this with a computer agent was long the preserve of science fiction films. However, the rapid technological development of recent years suggests that chatbots can be used to engage in serious conversations on complex topics. Chatbots are also increasingly being used in educational contexts, which led us to investigate what might motivate mathematics teachers to use chatbots for teaching purposes. To determine the source of motivation for mathematics teachers using chatbots for teaching purposes, we conducted a digital questionnaire study involving 448 teachers. With the collected data, we conducted a structural equation modelling analysis. The results of our study show that Performance Expectancy, Effort Expectancy, and Social Influence affect mathematics teachers' Behavioral Intentions concerning chatbot use and that Behavioral Intentions and Facilitating Conditions influence mathematics teachers' actual use of chatbots for teaching purposes.

Introduction

Are we right to assume that you are analytical, research-oriented, have sound methodological expertise, and are interested in evidence-based results? ChatGPT states that if you read our article, you should fit this description. In December 2024, ChatGPT recorded 3.7 billion total visits[1], and the launch of the new AI chatbot software DeepSeek caused the share prices of several tech giants to tumble by hundreds of billions of US dollars. These figures illustrate that AI chatbots have fully arrived at the center of our societies and economies. The fact that chatbots have already entered the field of education is evident from the large number of systematic reviews on the topic of chatbots, education, and schools (e.g. [1–4]). There are also systematic reviews of AI in the teaching and learning of mathematics (e.g. [5,6]) and chatbots such as ChatGPT [7].

Although the use of AI chatbots in education, including mathematics teaching, is steadily increasing and numerous literature reviews exist (e.g. [1,2]), research that quantitatively examines which factors motivate mathematics teachers to adopt these tools in their teaching, particularly within a European context, remains scarce. Most previous studies focus on technical aspects or on isolated implementation cases [8,9], while a systematic understanding of teachers' motivation within a theoretical framework such as the UTAUT model remains largely absent. This gap is particularly significant because, as Drijvers [10] highlights, mathematics teachers play a crucial role in integrating digital technologies into mathematics teaching. Understanding the factors that shape their attitudes and intentions could help educational institutions to develop targeted support and professional development strategies, potentially accelerating and improving the integration of these technologies into teaching practices. For this reason, our research aims to identify the factors that motivate secondary mathematics teachers to use chatbots for teaching.

To achieve this, we conducted a questionnaire study among Austrian mathematics teachers in line with the Unified Theory of Acceptance and Use of Technology [11]. We analyzed the results of our data collection using structural equation modelling.

* Corresponding author.
E-mail address: robert.weinhandl@jku.at (R. Weinhandl).

[1] https://www.similarweb.com/website/chatgpt.com/ [31.01.2025]

https://doi.org/10.1016/j.caeo.2026.100359
Received 30 April 2025; Received in revised form 10 April 2026; Accepted 11 April 2026
Available online 12 April 2026

Literature review

Teaching-Related activities of mathematics teachers with chatbots

Mathematics teachers use chatbots for various instructional purposes. A study by Lee and Yeo [12] describes the development of a chatbot that serves as a virtual student to support trainee teachers in practicing responsive teaching in fractions. This application allows teachers to target student misconceptions and formulate adaptive explanations. According to Birenbaum [9], teachers can ask chatbots about common mistakes in specific mathematical topics. They can then use the explanations to understand the calculations of students who made mistakes and how they should have calculated instead. Furthermore, teachers utilize chatbots for lesson planning. A study by Beyer et al. [8] shows that the perceived usefulness of an intent-based chatbot plays a central role in its use during planning. The chatbot was used, in particular, for brainstorming, structuring, and overcoming planning uncertainties. During the planning phase, the chatbot also helped reduce unpleasant emotions such as uncertainty and improved conceptual understanding. Mathematics teachers, in particular, can use chatbots to learn effective methods for explaining complex mathematical topics [13]. In addition to lesson planning and explanation suggestions, chatbots can also be used by teachers to create a variety of teaching materials, quizzes, and tests [9].

Birenbaum [9] further found that mathematics teachers use chatbots to plan lessons and conduct various teaching activities directly in the classroom. The author also claims that chatbots can be used as tools to promote problem-solving skills and help teachers stimulate students' curiosity and independent and critical thinking. To support critical thinking skills and promote learning, Birenbaum [9] suggests various tasks: Teachers can set tasks in which their students have to evaluate answers from a chatbot or creatively present the information learned through chatting with the chatbot differently, for example, in the form of a comic or a poem.

In their systematic literature review, Labadze et al. [2] identified several benefits of AI-powered chatbots for mathematics lessons for both teachers and students. These benefits include automating administrative tasks such as scheduling or grading. Furthermore, chatbots can facilitate the delivery of personalized educational content and its adaptation to different learning styles. With the help of chatbots, educators can develop learning materials tailored to students' levels and interests, enabling differentiated instruction. For example, through alternative explanations or customized questions from chatbots, teachers can reach students with different learning styles [2].

As a further aspect, Egara and Mosimege [13] point out that mathematics teachers can specifically use chatbots to obtain personalized suggestions for professional development materials tailored to their interests in order to develop and improve themselves personally. By using chatbots, math teachers can improve their skills, among other benefits, leading to more effective teaching experiences.

Attitudes of mathematics teachers towards chatbots

Their attitude towards the technology significantly influences mathematics teachers' acceptance of chatbots. Chocarro et al. [14] found that the perceived ease of use of chatbots is a decisive factor in teachers' use of AI chatbots for work purposes. Teachers are more willing to use chatbots for their work if they perceive them to be easy to understand and use. Chocarro et al. [14] also highlight perceived usefulness as a significant factor in chatbot acceptance. Teachers are more likely to accept chatbots if they find them useful for their work, for example, because they perceive an improvement in work performance. According to Chocarro et al. [14], the two factors of perceived ease of use and usefulness, based on the Technology Acceptance Model (TAM; [15]), have a positive impact on the acceptance of chatbots by teachers. In terms of conversational design, a formal language style in chatbots increases teachers' willingness to use them.

Limna et al. [16] also showed that teachers rate chatbots positively, as they take over routine tasks, allowing teachers to focus on more complex tasks and thus reduce their workload. Chocarro et al. [14] emphasize that catbots can take over routine tasks, such as certain questions about homework, leaving more instructional time, which in turn enables students' personalized learning even in the absence of teachers.

However, there are concerns about the accuracy of the information provided by a chatbot and the potential loss of personal interactions in classrooms. Similarly, in a study by Limna et al. [16], some teachers expressed concerns about the accuracy and reliability of the information provided by chatbots and worried about incorrect or incomplete information. Furthermore, teachers emphasized the need for strong data protection measures and clear communication about data privacy to ensure their and their students' personal information.

Enabling and hindering factors for the use of chatbots

Several factors could influence whether mathematics teachers integrate chatbots into their teaching. From Chocarro et al. [14], we already know that the perceived simplicity and usefulness of chatbots, in addition to their formal language characteristics, lead to greater acceptance and a higher intention to use them by teachers. Accordingly, the results of the study by Beyer et al. [8] show that perceived usefulness was a significant predictor of chatbot use. Perceived usefulness was the most frequently cited category and the main reason for using chatbots in planning tasks. Ease of use was not a major issue for most participants, but it did influence their use of chatbots.

According to Bii et al. [17], the use of chatbots by teachers is also facilitated by a positive attitude toward chatbots and their integration into the curriculum. Teachers tend to use chatbots when time is provided in schools or explicitly in the curriculum for appropriate technology use. Teachers consider it important that chatbots can provide information beyond the school curriculum so that they and their students have access to additional knowledge [17].

In contrast to the aspects that promote the use of chatbots in the classroom, Bii et al. [17] describe a lack of time or loss of time as potential obstacles. In their study, some teachers see the need to cover the curriculum and prepare students for final exams as an obstacle to the use of chatbots in the classroom.

In Beyer et al. [8], technical problems and problems with the user interface are frequently cited as obstacles to chatbot use. According to Beyer et al. [8], the teachers in their study who used a chatbot also had difficulties with human-machine interaction, suggesting that the chatbot did not always respond as expected or that communication between humans and the system was not intuitive. In addition, there was a need for additional guidance. Teachers were unsure how to use the chatbot effectively and wanted a clearer structure or assistance.

Some studies that examine the influence of gender (e.g. [18–20]), age (e.g. [21,22]), and teaching experience (e.g. [23,24]) on the acceptance and use of technology by mathematics teachers investigate different influencing factors and reveal contradictions. Based on the UTAUT model by Venkatesh et al. [25], its further development by Wijaya et al. [26], and the relevant literature on the use of digital technologies by mathematics teachers, we assume that gender, age, and teaching experience influence the acceptance and use of technology by mathematics teachers. Although age and teaching experience are very similar constructs, we believe that a certain decoupling of age and teaching experience could take place as more and more lateral entrants enter the mathematics teaching profession. In line with this potential decoupling of age and teaching experience, we use both constructs in the moderation analyses in our research.

Theoretical considerations and hypothesis development

Various theoretical models have been used to analyze the acceptance and utilization of technology in the educational context. In this regard, Šumak and Šorgo [27] highlight the "Unified Theory of the Acceptance and Use of Technology" (UTAUT) model as one of the most promising approaches. Furthermore, several recent studies (e.g. [28–30]) have demonstrated that the UTAUT is also suitable for examining the acceptance of artificial intelligence and intelligent systems.

The UTAUT model was developed by Venkatesh et al. [25] and is based on a variety of established theories that offer significant insights into the factors influencing technology acceptance. These theories examine attitudes toward technology, explain relationships between perceived usefulness, ease of use, and behavioral intentions, consider social and facilitating factors, and integrate both intrinsic and extrinsic motivation.

According to Venkatesh et al. [25], four key constructs are critical for the acceptance and use of information technology: performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI). Many studies have further refined and extended the UTAUT model by integrating additional constructs from other theories or specific contexts. This study employs a further development of the Unified Theory of Acceptance and Use of Technology (UTAUT) model to explore mathematics teachers' intentions and usage behavior regarding AI chatbots. Seven key predictors are examined: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Perceived Risk, and Habit [11,26]. We examine these key factors regarding their influence on mathematics teachers' behavioral intentions and actual use of chatbots. Furthermore, our study investigates how age, gender, and teaching experience moderate these influences.

Performance expectancy

Performance Expectancy (PE) refers to the extent to which individuals believe that using technology will enhance their performance [11]. This construct is akin to the perceived usefulness concept in the Technology Acceptance Model [15]. Research consistently finds PE a significant predictor of technology adoption [31,32]. In this study, mathematics teachers who perceive AI chatbots as beneficial for learning are expected to demonstrate a higher behavioral intention to use them. Based on this, we developed the hypothesis:

H1. PE significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

Effort expectancy

Effort Expectancy (EE) pertains to the perceived ease of technology use [25]. Studies suggest that technology perceived as simple and user-friendly is more likely to be adopted [33,34]. If mathematics teachers find AI chatbots intuitive and easy to integrate into learning, their intention to use them is expected to increase. From this, we derived the following hypothesis:

H2. EE significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

Social influence

Social Influence (SI) measures how individuals perceive that significant others endorse technology use [11]. Research identifies SI as a strong predictor of technology adoption in educational settings [26,35,36]. If mathematics teachers perceive encouragement from peers or mentors, their intention to use AI chatbots may increase. From this, we established the hypothesis:

H3. SI significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

Facilitating conditions

Facilitating Conditions (FC) refer to the availability of technical and organizational support for technology use [11]. Prior studies confirm that FC significantly impacts behavioral intention [37,38]. In this study, FC includes mathematics teachers' knowledge of AI chatbots and the presence of peers who can assist with technical difficulties. Consequently, we proposed the hypotheses:

H4a. FC significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

H4b. FC significantly influences the usage behavior of mathematics teachers to use AI Chatbots positively.

Habit

Habit (HB) denotes the extent to which individuals engage in behavior automatically due to learned patterns [39]. Prior research confirms that individuals accustomed to using technology are more likely to continue its use [40–42]. This study hypothesizes that mathematics teachers with established technology habits are more likely to adopt AI chatbots. Accordingly, the following hypothesis is:

H5. HB significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

Hedonic motivation

Hedonic Motivation (HM) describes the enjoyment of using technology [43]. Studies highlight the prominent role of enjoyment in technology adoption [44,45]. In the context of mathematics education, AI chatbots that provide engaging and novel learning experiences could potentially enhance teachers' satisfaction. This satisfaction, in turn, may positively affect their behavioral intention to adopt these technologies in their instructional practices. Thus, we hypothesize the following:

H6. HM significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

Perceived risk

Perceived Risk (PR) concerns potential negative consequences of technology use, including security and social risks [46]. High perceived risk can deter technology adoption despite its benefits [47,48]. In this study, PR is expected to decrease mathematics teachers' intention to use AI chatbots. As a result, we defined the hypotheses:

H7a. PR significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots negatively.

H7b. PR significantly influences the usage behavior of mathematics teachers to use AI Chatbots negatively.

Behavioral intention and usage behavior

Behavioral Intention (BI) reflects an individual's willingness to use technology and is a key predictor of actual usage [11]. This study represents mathematics teachers' readiness to integrate AI chatbots into their teaching. Actual Usage Behavior (UB) depends on BI and determines how intensively mathematics teachers adopt chatbots in teaching practice [26]. Therefore, our hypothesis is stated as:

H8. BI significantly influences the usage behavior of mathematics teachers to use AI Chatbots positively.

As our study also investigates how age, gender, and teaching experience moderate these constructs presented above, we posit three more hypotheses:

H9. Mathematics teachers' age affects the influences in our research model.

H10. Mathematics teachers' gender affects the influences in our research model.

H11. Mathematics teachers' teaching experience affects the influences in our research model.

Based on Wijaya et al. [26], we present these primary hypotheses in our initial research model in Fig. 1.

Methodological background

Participants of our study

The target group of our study is secondary school mathematics teachers in Austria. In order to reach potential participants of our study, we sent out emails to all secondary school principals in Austria with the request to forward the link to participate in our study to the mathematics teachers at the respective schools. Before contacting the principals of the schools, we obtained permission to conduct our study from the education directorates of the respective federal states and the ethics advisory board of the University of Linz. At the beginning of the data collection, the participating mathematics teachers were informed that participation in our study was voluntary and that they could stop at any time. A total of 625 mathematics teachers started to fill out our questionnaire, and 448 mathematics teachers provided us with such extensive data that it was taken into account in our analyses. For further analyses, we used those data sets of mathematics teachers who had answered at least 75% of the items overall and at least two-thirds of the items for each construct. Detailed demographic information on the participants in our study can be found in Table 1.

Prior to data collection, we obtained approval from the educational directorates of the Austrian federal states and the ethics advisory board of blinded for revision University. To recruit participants, we distributed invitations via email to school principals of all Austrian secondary schools that include upper secondary education (Sekundarstufe II), kindly asking that they forward the survey link to their mathematics teachers. This approach applied a voluntary sampling technique, a widely used method in empirical social research [49]. Voluntary

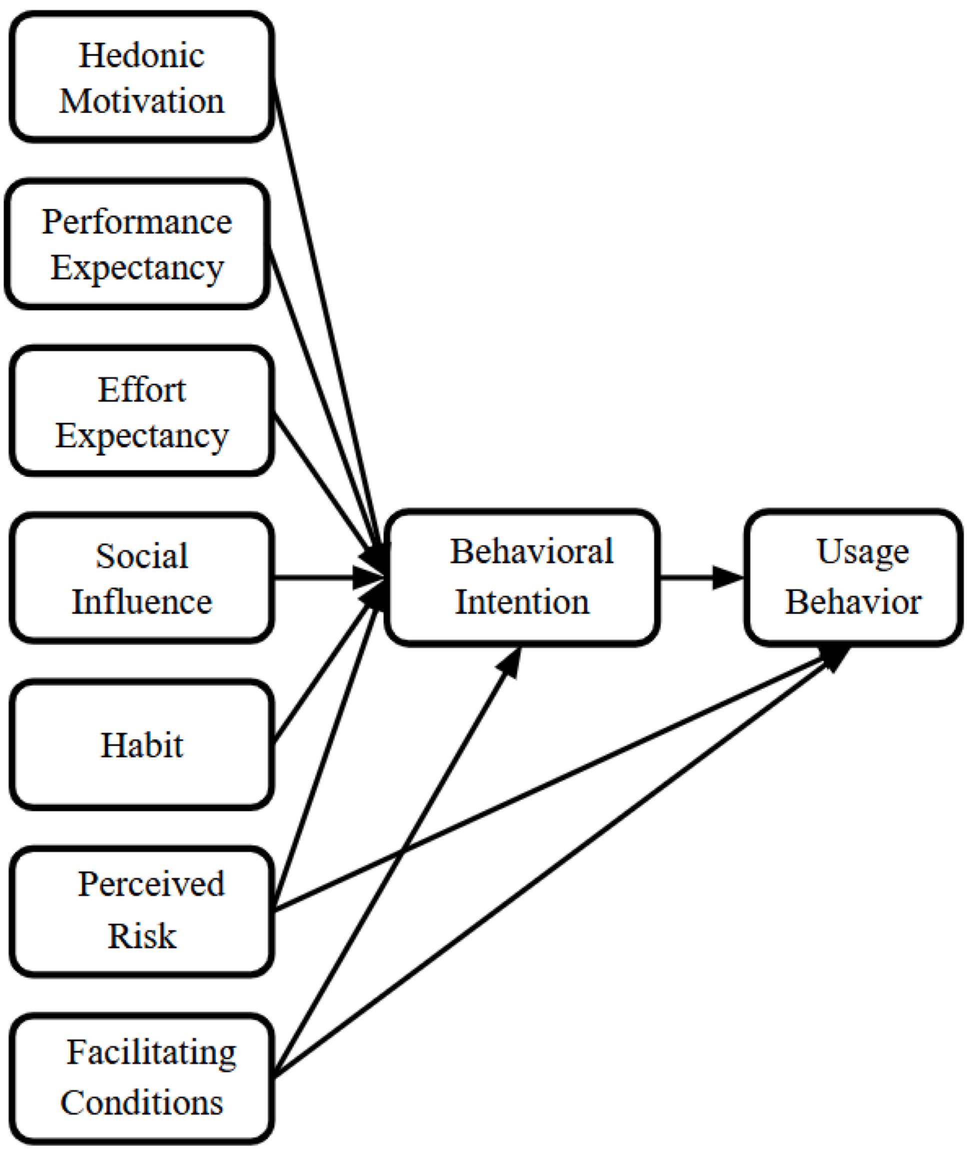

Fig. 1. The initial UTAUT research model of our study adopted from Wijaya et al. [26].

Table 1
Demographic information on the participants in our study.

Age Group			Gender			Teaching experience		
years	N	%		N	%	years	N	%
20–30	63	14.1	female	258	57.6	1–5	92	20.5
31–40	118	26.3	male	163	36.4	6–10	80	17.9
41–50	101	22.5	non-binary	2	0.44	11–15	66	14.7
51–60	121	27.0	do not want to answer	25	5.6	16–20	44	9.8
>60	25	5.6				21–25	38	8.5
do not want to answer	20	4.5				>25	109	24.3
						do not want to answer	19	4.2

sampling in online surveys offers several advantages, including cost-effectiveness compared to traditional survey methods [49,50] and the ability to access large and geographically dispersed populations [51,52]. In our case, this was particularly useful for reaching mathematics teachers from across Austria.

Measures

We used a modified version of the UTAUT [26] with seven predictors to identify why mathematics teachers use chatbots for teaching purposes. The mathematics teachers participating in our study were asked to answer the items attributed to the UTAUT using a five-point Likert scale. In this context, the value 1 indicates the lowest level of agreement (strongly disagree) and the value 5 the highest level of agreement (strongly agree).

With the collected data, we conducted a confirmatory factor analysis with all UTAUT constructs to determine why mathematics teachers use chatbots for teaching purposes (Appendix A). The fit indices such as CFI = 0.893, TLI = 0.868, SRMR = 0.075 and RMSEA = 0.076 are close to but do not meet the required cut-off values by experts such as Hair et al. [53] and Hu and Bentler [54] and thus indicate that our initial research model needs to be better adjusted to the collected data, what we outline in the next section. To achieve an acceptable model fit, we allowed theoretically plausible residual correlations. This adjustment improved the fit indices to TLI = 0.887, CFI = 0.909, RMSEA = 0.070 (90% CI [.065, 0.076]), and SRMR = 0.076, bringing RMSEA, CFI, and SRMR into the acceptable range. Furthermore, the individual constructs demonstrated sufficiently high factor loadings, supporting the adequacy of the measurement model. Next, we analyzed the internal consistency and reliability of our measurement scale. Therefore, we utilized McDonald's ω according to Hayes and Coutts [55]. Except for Facilitating Conditions, the values for McDonald's ω are substantially >0.07 (see Appendix A), which indicates a high internal consistency and reliability of our measurement scale. In this context, Dunn et al. [56] emphasize that the value of >0.7 was never intended as a “gold standard”, and other studies in the educational context sometimes use lower cut-off values such as >0.65 or >0.60 (e.g., [57,58]), according to which all constructs of our study show good internal consistency and reliability.

Finally, we determined the correlation matrix of all UTAUT constructs (see Appendix B). As our data is ordinally scaled (Likert scale), the correlation coefficients were determined according to Spearman [59]. The correlation table shows that the UTAUT constructs correlate significantly with each other, in some cases with very high values (e.g., BI and HM with 0.717; $p < .001$).

Several steps were undertaken to ensure the validity and reliability of our instrument. The questionnaire items were adapted from validated UTAUT scales [11,26] and translated into German following a forward–backward translation procedure to ensure semantic equivalence. Before finalizing the instrument, its clarity and relevance were evaluated by three experts in mathematics education and five practicing secondary school mathematics teachers, all of whom confirmed the comprehensibility and appropriateness of the items. Additionally, the instrument was piloted with 25 secondary mathematics teachers to refine item wording and response scales. Construct validity was supported through confirmatory factor analysis (see Appendix A and C), which demonstrated acceptable fit indices across the UTAUT constructs. Internal consistency and reliability were confirmed via McDonald’s ω, with all constructs meeting or exceeding recommended thresholds for educational research [55].

Determining the research model

In the first step, we aimed to determine the research model for our study. Regarding predictors, we were guided by the original UTAUT model ([25], Fig. 2) and its adaptation to mathematics teachers and chatbot use by Wijaya et al. [26]. We adapted the model for our study by using the model of Wijaya et al. [26]. Then, we tried to achieve the best possible fit for our data by omitting predictors in favor of the model of Venkatesh et al. [25]. When analyzing the different models with different predictors (see Table 2), we found that the model with the predictors from Venkatesh et al. [25] and Perceived Risk (PR) had the best fit indices according to the Chi-Squared Difference Test (see Table 3). Consequently, for our further analyses, we employed the predictors Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC) in line with the original model of Venkatesh et al. [25] with the extension Perceived Risk (PR) (see Fig. 3) to determine why mathematics teachers would employ chatbots for teaching purposes.

Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Habit (HB), Hedonic Motivation (HM), Perceived Risk (PR), Behavioral Intention (BI), Usage Behavior (UB)

In the next step, we investigated the skewness and kurtosis of the UTAUT constructs in our study (see Table 4). On the one hand, the central literature on structural equation modelling (e.g. [34,60,61]) suggests that structural equation analyses exhibit robustness to violations of skewness and kurtosis. This robustness is supported by empirical studies that demonstrate the resilience of SEM methods to non-normal data distributions. On the other hand, except for SI, our study’s skewness and kurtosis values are close to 0, suggesting that structural equation analyses can be performed [62].

These analyses lead to the following reduced and adjusted research hypotheses for our study:

H1. PE significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

H2. EE significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

H3. SI significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots positively.

H4. FC significantly influences the usage behavior of mathematics teachers to use AI Chatbots positively.

H5a. PR significantly influences the behavioral intentions of mathematics teachers to use AI Chatbots negatively.

H5b. PR significantly influences the usage behavior of mathematics teachers to use AI Chatbots negatively.

H6. BI significantly influences the usage behavior of mathematics

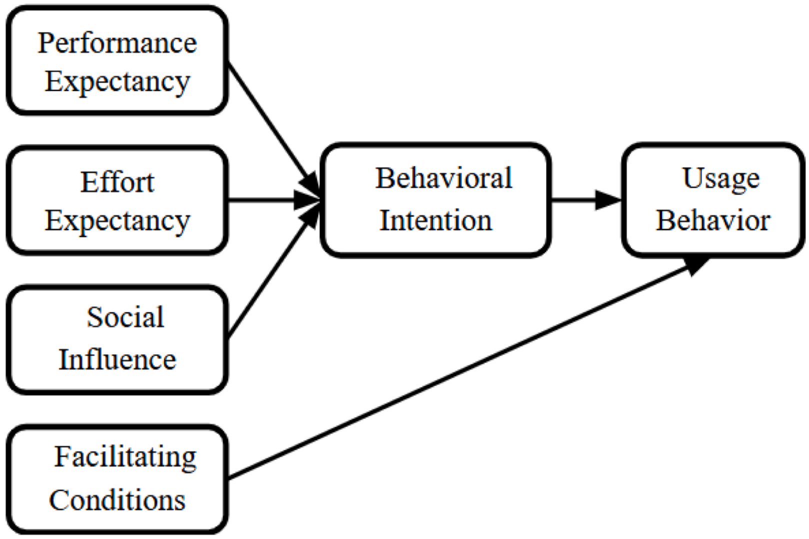

Fig. 2. Initial, simplified UTAUT model according to Venkatesh et al. [25].

Table 2
The different research models analyzed in our study.

	Path in our Model	
	Predictors	Outcome
Model 1	PE, EE, SI, FC*	BI ~ PE + EE + SI + FC + PR + HM + HB
	PR, HM, HB**	UB ~ BI + FC + PR
Model 2	PE, EE, SI, FC*	BI ~ PE + EE + SI + FC + PR + HM
	PR, HM**	UB ~ BI + FC + PR
Model 3	PE, EE, SI, FC*	BI ~ PE + EE + SI + FC + PR + HB
	PR, HB**	UB ~ BI + FC + PR
Model 4	PE, EE, SI, FC*	BI ~ PE + EE + SI + FC + PR
	PR**	UB ~ BI + FC + PR
Model 5	PE, EE, SI, FC*	BI ~ PE + EE + SI + PR
	PR**	UB ~ BI + FC + PR
Model 6	PE, EE, SI, FC*	BI ~ PE + EE + SI + FC + HM
	HM**	UB ~ BI + FC
Model 7	PE, EE, SI, FC*	BI ~ PE + EE + SI + FC + HB
	HB**	UB ~ BI + FC

* Original predictors according to Venkatesh et al. [25]
** Additional predictors according to Wijaya et al. [26]

teachers to use AI Chatbots positively.

H7. Mathematics teachers' age affects the influences in our research model.

H8. Mathematics teachers' gender affects the influences in our research model.

H9. Mathematics teachers' teaching experience affects the influences in our research model.

Analytic procedure

To test our hypotheses, we employed a structural equation modelling (SEM) approach using the R package "lavaan 0.6.17″ (Rosseel, 2012). First, we analyzed which of the UTAUT constructs served as predictors for the behavioral intentions (BI), or the usage behavior (UB) of mathematics teachers to use AI Chatbots (H1-H6). Specifically, we examined whether Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) significantly influence the behavioral intentions (BI) of mathematics teachers to use AI Chatbots (H1–H3). We then assessed whether Facilitating Conditions (FC) positively affect the actual usage behavior (UB) of these chatbots (H4). In addition, we tested the negative impacts of Perceived Risk (PR) on both BI (H5a) and UB (H5b) and confirmed the positive influence of BI on UB (H6). Second, we investigated potential moderating effects to address the remaining hypotheses (H7-H9). In this step, we examined whether mathematics teachers' age (H7), gender (H8), and teaching experience (H9) influence the relationships specified in our research model. Throughout all analyses, we applied a robust maximum likelihood estimator to account for any deviations from normality [63]. Although missing values were minimal, with no item exceeding ten percent, we utilized full-information maximum likelihood estimation, assuming that the data were Missing at Random (MAR) [64].

Results

Before performing structural equation analyses, we assessed the model fit using established fit indices. For our research model (see Fig. 3), the RMSEA is 0.071 with a 90% confidence interval of [.064, 0.078]; values below 0.08 are considered acceptable [54]. The SRMR value of 0.067 shows a good fit to the data. The incremental fit indices CFI = 0.913 and TLI = 0.892 are acceptable [53,65]. Based on the fit

Table 3
Chi-squared difference test concerning the models tested in our study.

	Df	AIC	BIC	Chisq	Chisq diff	RMSEA	Df diff	Pr (>Chisq)
fit_KI5	123	58,856	59,202	1207.9				
fit_KI6	172	66,876	67,296	1487.9	280.04	0.057563	49	< 0.001***
fit_KI7	172	66,345	66,764	1650.6	162.62	0.000000	0	
fit_KI2	228	78,251	78,756	1707.4	56.88	0.003323	56	0.4421
fit_KI3	228	77,716	78,221	1847.6	140.19	0.000000	0	
fit_KI4	229	74,356	74,854	1961.4	113.81	0.281556	1	< 0.001***
fit_KI1	293	85,719	86,308	2179.1	217.65	0.041074	64	< 0.001***

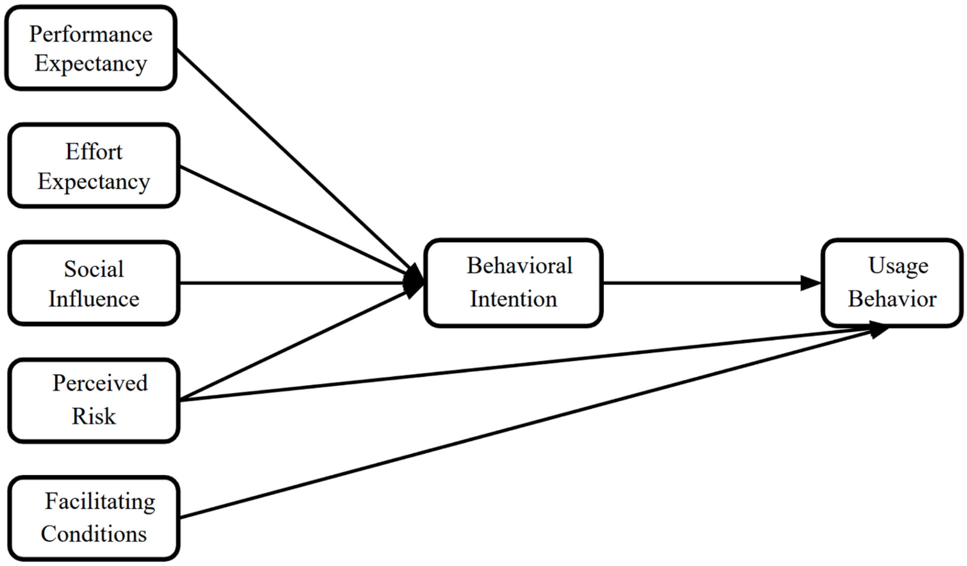

Fig. 3. Adapted UTAUT research model of our study.

Table 4
Descriptive statistics and correlations of the constructs used in our study.

	M	SD	SK	K	PR	PE	EE	SI	FC	BI	UB
PR	2.07	0.84	0.54	−0.22	—						
PE	2.70	0.93	0.06	−0.56	0.254***	—					
EE	3.02	1.01	−0.05	−0,74	0.156**	0.255***	—				
SI	1.51	0.86	2.48	6.52	0.210***	0.298***	0.156**	—			
FC	2.57	1.00	0.31	−0.64	0.232***	0.247***	0.591***	0.342***	—		
BI	2.17	1.05	0.66	−0.40	0.333***	0.609***	0.420***	0.416***	0.415***	—	
UB	1.89	1.03	1.22	0.75	0.206***	0.468***	0.547***	0.300***	0.480***	0.659***	—

Note. * p < .05.
** p < .01.
*** p < .001; SK = Skewness; K = Kurtosis.

indices, our model shows an acceptable fit [66].

Next, we conducted another confirmatory factor analysis (see Appendix C) as well as descriptive statistics and a correlation analysis (see Table 4) with only those constructs that we included in our research model (see Fig. 3). The values of the confirmatory factor analysis of the constructs of our research model (χ^2 = 476; df = 149; p < .001; CFI = 0.917; TLI = 0.895; SRMR = 0.066; RMSEA = 0.070 [lower = 0.063, upper = 0.077]; AIC 22,783; BIC = 23,115) show that the structure of the latent variables of our study corresponds well with the model. The Spearman correlation matrix of the UTAUT constructs of our model again shows significant correlations of the constructs (p < .01 or p < .001), whereby lower correlation values of the constructs can now be determined. Then, we analyzed our model concerning multicollinearity. Values <2 were obtained for both BI (PE = 1.297; EE = 1.219; SI = 1.195; PR = 1.284) and UB (BI = 1.930; FC = 1.715; PR = 1.284), which indicates that there is no multicollinearity in our model. Hence, it can be concluded that each predictor contributes unique information to our model.

Direct effects

In our model, four predictors (PE, EE, SI, and PR) influence the latent variable Behavioral Intention (BI). PE shows a positive and significant effect (β = 0.473, p < .001), which indicates that a higher performance expectation is associated with a stronger behavioral intention to use chatbots. For EE, there is a significant positive effect (β = 0.287, p < .001). For the effect of SI on BI, our data shows a positive and significant effect (β = 0.398, p < .001), i.e., social influence factors strongly influence the intention to use chatbots. A non-significant effect (β = 0.059, p = .235) was found for the effect of PR on BI, suggesting that perceived risk does not play a role for mathematics teachers' intentions to utilize chatbots.

Three predictors, namely BI, FC, and PR, influence the latent variable Use Behavior (UB). Concerning the influence of BI on UB, there is a strong positive effect (β =0.687, p < .001), which means that a higher intention to use correlates directly with greater actual use. FC shows a minor positive and significant effect (β = 0.297, p < .001), indicating that supportive conditions (e.g., technical infrastructure, resources) have little influence on the actual use of chatbots by mathematics teachers. A negative but non-significant effect (β = −0.076, p = .136) is found for the influence of PR on UB, meaning that perceived risk does not directly affect usage behavior. Taken together, the coefficients indicate that Performance Expectancy (PE) is the most influential predictor of Behavioral Intention (BI), with a larger effect (β = 0.473) than SI (β = 0.398), EE (β = 0.287) or PR (β = 0.059). Practically, this finding suggests that mathematics teachers prioritize demonstrable instructional gains over usability alone when deciding whether to use chatbots. The complete regression table is shown in Table 5 and visualized in Fig. 4.

Indirect effects

The analysis of the indirect effects in our UTAUT model (see Table 6) shows that PE and SI have significant indirect effects on UB via BI. The indirect effect of PE on UB ($\beta = 0.325$, $p < .001$, [.225, 0.410]), of EE on UB ($\beta = 0.197$, $p < .001$, [.134, 0.357]) and that of SI on UB ($\beta = 0.273$, $p < .001$, [.205, 0.473]) are both statistically significant. This effect confirms that PE, EE, and SI play a significant role in mathematics teachers' usage of chatbots. In contrast, the indirect effect of PR ($\beta = 0.040$, $p = .330$, [−0.053, 0.0166]) is not significant. Therefore, this variable has no verifiable indirect influence on UB via BI. The total indirect effect ($\beta = 0.835$, $p < .001$, [.675, 1.179]) shows that BI plays a significant role as a mediator and strengthens the overall effect of the predictors on UB. The significant indirect effects for PE, EE, and SI via BI on UB underscore the central role of intention formation in translating perceptions into actual use. In practical terms, interventions that raise teachers' expectations of learning benefits (PE), reduce perceived effort (EE), and leverage peer norms (SI) are especially likely to increase classroom use by first strengthening BI.

Moderation effects

Concerning a possible moderation of the relationships in our research model, we analyzed age, gender, and teaching experience as moderating variables (see Table 7).

The moderation analyses for age and experience indicate that none of the predictors has a significant impact on the influences on BI or UB. In contrast, the moderation analysis for gender [1 = *female* – 2 = *male*] reveals that the influence of BI on UB is significant and negative ($\beta = -0.304$, $p = .012$), and the influence of PR on UB is marginally non-significant and positive ($\beta = 0.203$, $p = .057$).

Hence, the results of the moderation analysis indicate that gender is a partially significant moderator in our model, while age and experience are not significant moderators for the relationships between the predictors and the dependent variables. These results suggest that gender differences in technology use and acceptance may exist and should be further investigated in prospective studies. Although age and experience were not significant moderators, the partial moderation by gender suggests that intention-to-use may convert into practice differently for male and female teachers.

Discussion

The results of our study confirm the UTAUT model initially developed by Venkatesh et al. [25] with Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) as predictors of Behavioral Intention (BI), and BI together with Facilitating Conditions (FC) as predictors of Use Behavior (UB). All relationships regarding the original UTAUT model were highly significant in our model (p<.001), which reinforces the model's applicability in the context of mathematics teachers' chatbot use in the classroom. Similarly, our findings confirm Wijaya et al. [26] in that PE is the strongest predictor of BI and that BI in turn influences UB. These findings can also be linked to the study by Beyer et al. [8], which showed that the perceived usefulness of an intent-based chatbot plays a central role in its use during planning. Teachers' perception that chatbots can effectively support their instructional goals, whether through personalized content delivery [2], the outsourcing of routine tasks [16], or by providing supplemental information [17], appears to be central to their decision to integrate these tools into their lessons. However, in contrast to Wijaya et al. [26], our study demonstrated that EE and SI are also highly significant predictors of BI, effects that were not established in their research. The analysis of indirect effects as well as the moderation effects of age, gender, and teaching experience can be interpreted as a further development of the investigations by Wijaya et al. [26]. This further development suggests that not only is the perceived usefulness of chatbots important, but their ease of use and the social context in which they are adopted also play crucial roles.

The determinants of BI largely correspond to the UTAUT model [25], whereby PE, EE, and SI are confirmed as central predictors. Perceived Risk (PR), on the other hand, has no significant influence on BI and a negative but non-significant effect on UB. These results confirm the central assumptions of the UTAUT model, especially the importance of BI and FC for actual behavior [11]. The non-significant role of PR in our study is particularly notable given that some previous research (e.g. [16, 47,48]) has suggested that teachers' concerns about data privacy, information accuracy, and other risks can deter technology adoption.

Furthermore, studies suggest that technology perceived as simple and user-friendly (EE) is more likely to be adopted [33,67]. In our study, if mathematics teachers find AI chatbots intuitive and easy to integrate into learning environments, their intention to use these tools increases, as evidenced by the significant positive effect of EE on BI. This finding aligns with Chocarro et al. [14], who identified the perceived simplicity and usefulness of chatbots as decisive factors for their acceptance.

Our findings confirm this relationship, as FC shows a positive and significant effect on UB and a strong connection between BI and UB. Supportive conditions, such as adequate technical support and the provision of time within schools for technology use, are therefore key factors that promote the use of chatbots among mathematics teachers. Hindering factors like technical problems, as highlighted by Beyer et al. [8], can have a negative influence on BI. These results can also be linked to the findings of Bii et al. [17], who observed that teachers are more likely to adopt chatbots when time is explicitly provided in schools or the curriculum for technology integration.

Social Influence (SI) has been identified as a strong predictor of technology adoption in educational settings in the literature [35,36,68]. Our study corroborates these findings by showing a positive and significant effect of SI on the intention to use chatbots, which confirms that the social context and peer influences play an important role in technology adoption decisions.

Next to the traditional constructs included in the UTAUT model, prior research confirms that individuals accustomed to using technology

Table 5
Direct effects in our research model.

	Est.	Std.Err	z	p	ci.lower	ci.upper	Std.lv	Std.all
BI ~								
PE	0.442	0.046	9.649	< 0.001	0.353	0.532	0.473	0.473
EE	0.319	0.053	6.050	< 0.001	0.216	0.422	0.287	0.287
SI	0.464	0.054	8.521	< 0.001	0.357	0.571	0.398	0.398
PR	0.074	0.062	1.188	0.235	−0.048	0.195	0.059	0.059
UB ~								
BI	0.711	0.071	9.984	< 0.001	0.572	0.851	0.687	0.687
FC	0.387	0.080	4.811	< 0.001	0.229	0.545	0.297	0.297
PR	−0.099	0.067	−1.490	0.136	−0.229	0.031	−0.076	−0.076

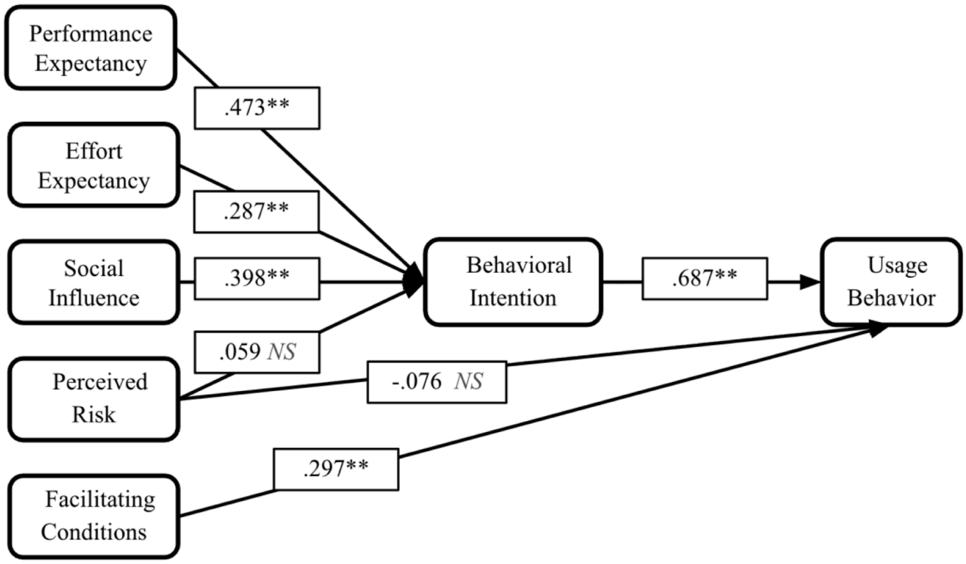

Fig. 4. Path coefficients in our research model.

Table 6
Indirect and total indirect effect in our research model.

Effects	unst. Est.	S.E.	*z* value	*p* value	lower 95% CI	Upper 95% CI	std. Est.
Indirect Effects							
PE → BI → UB	0.315	0.046	6.829	< 0.001	0.225	0.410	0.325
EE → BI → UB	0.227	0.054	4.163	< 0.001	0.134	0.357	0.197
SI → BI → UB	0.330	0.066	4.963	< 0.001	0.205	0.473	0.273
PR → BI → UB	0.052	0.054	0.974	0.330	−0.053	0.166	0.040
Total Indirect Effects	0.924	0.131	7.077	< 0.001	0.675	1.179	0.835
Total Effects							
… for PE	0.315	0.046	6.829	< 0.001	0.225	0.410	0.325
… for EE	0.227	0.054	4.163	< 0.001	0.134	0.357	0.197
… for SI	0.330	0.066	4.963	< 0.001	0.205	0.473	0.273
… for PR	0.440	0.097	4.510	< 0.001	0.230	0.618	0.338
… for FC	−0.099	0.084	−1.176	0.240	−0.292	0.049	−0.076

Note. The 95% CI represents the bias-corrected bootstrap interval.

are more likely to continue its use [40–42]. Although our model did not include a measure of habit, this factor is influential in sustained technology adoption and should be considered in future research. Similarly, studies highlight the prominent role of enjoyment or hedonic motivation in technology adoption [44,45]. While hedonic aspects were found to be a prominent driver in other studies, our model did not incorporate a measure of positive affect or enjoyment. This absence is notable, particularly in light of Bii et al. [17], who argue that a positive attitude toward chatbots, which would reflect hedonic motivation, along with their integration into the curriculum, can further encourage teachers' use. In our model, a positive attitude (as a construct reflective of hedonic motivation) emerged as significant. This suggests that, at least within our sample, pragmatic factors such as performance expectancy, ease of use, and social influence are more dominant drivers of chatbot adoption among mathematics teachers.

In addition to the primary relationships examined in our study, we also explored the moderating effects of age, gender, and teaching experience on the model's predictive relationships. Our analyses revealed that age and teaching experience did not significantly influence these relationships. However, gender emerged as a noteworthy moderator that affects the strength and direction of BI on UB. This indicates that male and female teachers may experience different dynamics in how their intentions and perceptions translate into actual technology use.

Conclusion

This study examined the adoption of chatbots in mathematics classrooms through the lens of the UTAUT model, as well as including constructs such as Perceived Risk (PR), while also considering the broader literature on technology adoption. Our results robustly confirm that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) are significant predictors of teachers' Behavioral Intention (BI) to use chatbots, and that BI, along with Facilitating Conditions (FC), plays a decisive role in actual Use Behavior (UB). In contrast, while Perceived Risk (PR) has been highlighted in earlier studies as a deterrent to technology adoption, our study found no significant influence of PR on either BI or UB. This divergence may reflect context-specific factors or evolving teacher perceptions as familiarity with chatbots increases. Furthermore, while literature underscores the roles of habit, hedonic motivation, and a positive attitude toward technology in fostering sustained use, these factors did not emerge as significant within our model. Their absence suggests that pragmatic concerns, such as the efficiency, ease of use, and social support for technology, predominate in influencing adoption decisions.

Notably, Performance Expectancy (PE) emerged as the strongest predictor of Behavioral Intention (BI) compared with Effort Expectancy (EE) and Social Influence (SI), with a larger effect size for PE ($\beta = 0.473$) than for SI ($\beta = 0.398$) and EE ($\beta = 0.287$). This pattern likely reflects mathematics teachers' prioritization of demonstrable instructional gains, such as faster preparation of scaffolded tasks or improved

Table 7
Moderation effects of age, gender, and teaching experience.

Age								
Regressions	Estimate	Std.Err	z-value	*p*-value	ci.lower	ci.upper	Std.lv	Std.all
PE→BI	−0.001	0.036	−0.026	0.98	−0.074	0.066	−0.001	−0.003
EE→BI	0.001	0.032	0.038	0.97	−0.062	0.061	0.001	0.005
SI→BI	−0.032	0.059	−0.532	0.595	−0.134	0.099	−0.034	−0.063
PR→BI	0.026	0.047	0.541	0.588	−0.065	0.12	0.027	0.068
BI→UB	0.041	0.042	0.966	0.334	−0.044	0.122	0.041	0.099
PR→UB	−0.052	0.038	−1.381	0.167	−0.128	0.024	−0.053	−0.133
FC→UB	0.026	0.029	0.887	0.375	−0.028	0.082	0.026	0.081
Gender								
Regressions	Estimate	Std.Err	z-value	*p*-value	ci.lower	ci.upper	Std.lv	Std.all
PE→BI	0.127	0.074	1.728	0.084	−0.031	0.263	0.139	0.206
EE→BI	−0.038	0.049	−0.767	0.443	−0.141	0.06	−0.041	−0.071
SI→BI	−0.128	0.113	−1.134	0.257	−0.33	0.117	−0.14	−0.123
PR→BI	−0.014	0.089	−0.162	0.871	−0.186	0.166	−0.016	−0.018
BI→UB	−0.263	0.105	−2.501	0.012	−0.473	−0.064	−0.273	−0.304
PR→UB	0.168	0.088	1.904	0.057	−0.008	0.324	0.174	0.203
FC→UB	0.025	0.051	0.499	0.618	−0.053	0.148	0.026	0.042
Teaching Experience								
Regressions	Estimate	Std.Err	z-value	*p*-value	ci.lower	ci.upper	Std.lv	Std.all
PE→BI	−0.017	0.023	−0.741	0.459	−0.064	0.028	−0.018	−0.097
EE→BI	−0.011	0.019	−0.569	0.569	−0.047	0.030	−0.012	−0.066
SI→BI	−0.001	0.034	−0.021	0.983	−0.063	0.069	−0.001	−0.002
PR→BI	0.042	0.027	1.587	0.112	−0.012	0.097	0.045	0.184
BI→UB	0.018	0.028	0.659	0.510	−0.042	0.069	0.019	0.077
PR→UB	−0.039	0.024	−1.654	0.098	−0.084	0.012	−0.040	−0.164
FC→UB	0.013	0.019	0.713	0.476	−0.024	0.051	0.014	0.070

feedback, over usability alone when deciding whether to adopt chatbots. Practically, this finding implies that adoption efforts should foreground evidence of instructional impact (e.g., vetted exemplars, alignment to curricular goals, student learning indicators) while still ensuring low-friction onboarding. In short, perceived usefulness appears to carry more weight than incremental usability improvements in this context.

These findings not only reinforce the core tenets of the UTAUT model but also extend our understanding of technology acceptance in educational contexts. The practical implications of our findings are clear. For educational institutions aiming to integrate chatbots effectively, it is essential to ensure that these tools are not only functionally useful (PE) but also user-friendly (EE) and supported by a conducive technological and social environment (FC and SI). By addressing these areas, schools can facilitate the seamless incorporation of chatbots into the curriculum, thereby potentially reducing teacher workload and enriching the learning experience. Translating these findings into practice, institutions seeking to foster uptake should prioritize: (a) showcasing concrete, curriculum-aligned use cases that highlight learning benefits (PE), (b) reducing early barriers through quick-start resources, templates, and brief training (EE), and (c) amplifying peer endorsement and norm-setting via teacher champions and department-level routines (SI). Reliable, school-supported access and guidance (FC) could facilitate intentions convert into actual use. Although Perceived Risk (PR) was not significant in this study, maintaining clear data governance and compliant workflows remains advisable to preempt context-dependent concerns. Together, emphasizing demonstrable impact while minimizing early effort and leveraging social support offers a balanced path to sustainable adoption.

As classrooms worldwide navigate the challenges of modern learning, this research stands as a call for utilizing the power of intelligent technology to transform teaching practices and unlock the full potential of every learner.

Limitations and future research

Our research provides several contributions, yet it also has certain limitations that need consideration. These limitations may prompt further research. First, our study was conducted in Austria. The cultural and institutional contexts may differ significantly in other countries, which means the findings may not be generalizable worldwide. Future research could explore similar themes in diverse cultural settings to examine whether the motivations align or differ across different contexts. Secondly, the use of a cross-sectional methodology in this study limits the capacity to establish causal linkages between variables. The methodology employed in our study captures a snapshot in time and does not account for changes over time or the directionality of the relationships observed. Longitudinal studies or experimental designs may be necessary to confirm the causality and sequence of events suggested by the findings. Lastly, the reliance on self-reported data obtained through a questionnaire introduces possible biases, such as social desirability or response biases, where participants may answer in a way they believe is expected or favorable rather than how they truly feel or behave. Future studies could incorporate multiple data sources, such as observations or interviews, to triangulate data and provide a more comprehensive understanding of the issues at hand.

Disclosure of funding

No funds, grants, or other support were received.

Data availability statement

The data used in the study will be made available by the corresponding author in response to justified requests.

Ethics statement

The authors declare that all procedures leading to this paper are ethically rigorous and in line with the standards of the University Linz concerning conducting educational research. Permission to conduct the study at hand and to collect data was granted by the Ethics Advisory Board of the University Linz (JKU EC-11–2024).

Data statement

The data used in the study will be made available by the corresponding author in response to justified requests.

CRediT authorship contribution statement

Robert Weinhandl: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Branko Andic:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Data curation, Conceptualization. **Tommy Tanu Wijaya:** Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Valentina Bleckenwegner:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Viktoria Riegler:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Selina Baldinger:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Jonas Mayrhofer:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Conceptualization. **Christoph Helm:** Software, Methodology, Formal analysis, Data curation.

Declaration of competing interest

All authors confirm that they have nothing to declare.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.caeo.2026.100359.

References

[1] Kuhail MA, Alturki N, Alramlawi S, Alhejori K. Interacting with educational chatbots: a systematic review. Educ Inf Technol 2023;28(1):973–1018.
[2] Labadze L, Grigolia M, Machaidze L. Role of AI chatbots in education: systematic literature review. Int J Educ Technol High Educ 2023;20(1):56.
[3] Nee CK, Rahman MHA, Yahaya N, Ibrahim NH, Razak RA, Sugino C. Exploring the trend and potential distribution of chatbot in education: a systematic review. Int J Inf Educ Technol 2023;13(3):516–25.
[4] Wollny S, Schneider J, Di Mitri D, Weidlich J, Rittberger M, Drachsler H. Are we there yet? A systematic literature review on chatbots in education. Front artif intell 2021;4:654924.
[5] Hwang GJ, Tu YF. Roles and research trends of artificial intelligence in mathematics education: a bibliometric mapping analysis and systematic review. Mathematics 2021;9(6):584.
[6] Opesemowo OAG, Adewuyi HO. A systematic review of artificial intelligence in mathematics education: the emergence of 4IR. Eurasia J Math Sci Technol Educ 2024;20(7):em2478.
[7] Almarashdi HS, Jarrah AM, Khurma OA, Gningue SM. Unveiling the potential: a systematic review of ChatGPT in transforming mathematics teaching and learning. EURASIA J Math Sci Technol Educ 2024;20(12):em2555.
[8] Beyer S, Grave-Gierlinger F, Meyer-Jenßen L. Twenty reasons why: investigating use-related beliefs and reasons of preservice teachers for (Not) using an intent-based chatbot during lesson planning. Contemp Issues Technol Teach Educ 2024;24(3):359–83.
[9] Birenbaum M. The chatbots' challenge to education: disruption or destruction? Educ Sci 2023;13(7):711.
[10] Drijvers P. Digital technology in mathematics education: why it works (or doesn't). In: Selected regular lectures from the 12th international congress on mathematical education. Springer International Publishing; 2015. p. 135–51.
[11] Venkatesh V, Thong JYL, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology (UTAUT2). MIS Q 2012;36(1):157–78.
[12] Lee D, Yeo S. Developing an AI-based chatbot for practicing responsive teaching in mathematics. Comput Educ 2022;191:104646.
[13] Egara FO, Mosimege M. Exploring the integration of artificial intelligence-based ChatGPT into mathematics instruction: perceptions, challenges, and implications for educators. Educ Sci 2024;14(7):742.
[14] Chocarro R, Cortiñas M, Marcos-Matás G. Teachers' attitudes towards chatbots in education: a technology acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics. Educ Stud 2023;49(2):295–313.
[15] Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS q 1989:319–40.
[16] Limna P, Kraiwanit T, Jangjarat K, Klayklung P, Chocksathaporn P. The use of ChatGPT in the digital era: perspectives on chatbot implementation. J Appl Learn Teach 2023;6(1):64–74.
[17] Bii PK, Too JK, Mukwa CW. Teacher attitude towards use of chatbots in routine teaching. Univers J Educ Res 2018;6(7):1586–97.
[18] Scherer R, Siddiq F. Revisiting teachers' computer self-efficacy: a differentiated view on gender differences. Comput Hum Behav 2015;53:48–57.
[19] Thurm D. Digitale werkzeuge im mathematikunterricht integrieren: zur rolle von lehrerüberzeugungen und der wirksamkeit von fortbildungen. Springer; 2020.
[20] Wong KT, Teo T, Russo S. Influence of gender and computer teaching efficacy on computer acceptance among Malaysian student teachers: an extended technology acceptance model. Australas J Educ Technol 2012;(7):28.
[21] Buabeng-Andoh C. Factors influencing teachers adoption and integration of information and communication technology into teaching: a review of the literature. Int J Educ Dev using ICT 2012;8(1).
[22] Kaur M, Singh B. Teachers' attitude and beliefs towards use of ICT in teaching and learning: perspectives from India. In: Proceedings of the Sixth International Conference on Technological Ecosystems for Enhancing Multiculturality; 2018. p. 592–6.
[23] Knüsel Schäfer D. Überzeugungen von lehrpersonen zu digitalen medien: eine qualitative untersuchung zu entstehung, bedingungsfaktoren und typenspezifischen entwicklungsverläufen. Verlag Julius Klinkhardt; 2020. p. 288.
[24] Lau BT, Sim CH. Exploring the extent of ICT adoption among secondary school teachers in Malaysia. Int J Comput ICT res 2008;2(2):19–36.
[25] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. MIS Q 2003;27(3):425–78.
[26] Wijaya TT, Su M, Cao Y, Weinhandl R, Houghton T. Examining Chinese preservice mathematics teachers' adoption of AI chatbots for learning: unpacking perspectives through the UTAUT2 model. Education and information technologies. 2024. p. 1–29.
[27] Šumak B, Šorgo A. The acceptance and use of interactive whiteboards among teachers: differences in UTAUT determinants between pre-and post-adopters. Comput Hum Behav 2016;64:602–20.
[28] Alkhwaldi AF. Understanding the acceptance of business intelligence from healthcare professionals' perspective: an empirical study of healthcare organizations. Int J Organ Anal 2024;32(9):2135–63. https://doi.org/10.1108/IJOA-10-2023-4063.
[29] Alkhwaldi AF, Abdulmuhsin AA, Masa'deh R, Abu-AlSondos IA. Business intelligence adoption in higher education: the role of data-driven decision-making culture and UTAUT. J Int Educ Bus 2025;18(4):484–504. https://doi.org/10.1108/JIEB-08-2024-0110.
[30] Alkhwaldi AF, Alidarous MM, Alharasis EE. Antecedents and outcomes of innovative blockchain usage in accounting and auditing profession: an extended UTAUT model. J Organ Change Manag 2024;37(5):1102–32. https://doi.org/10.1108/JOCM-03-2023-0070.
[31] Cai Q, Lin Y, Yu Z. Factors influencing learner attitudes towards ChatGPT-assisted language learning in higher education. Int J Hum Comput Interact 2023;0(0):1–14. https://doi.org/10.1080/10447318.2023.2261725.
[32] Yang C, Guo R, Cui Y. What affects vocational teachers' acceptance and use of ICT in teaching? A large-scale survey of higher vocational college teachers in China. Behav Sci 2023;13(1):77. https://doi.org/10.3390/bs13010077.
[33] Foroughi B, Nhan PV, Iranmanesh M, Ghobakhloo M, Nilashi M, Yadegaridehkordi E. Determinants of intention to use autonomous vehicles: findings from PLS-SEM and ANFIS. J Retail Consum Serv 2023;70:103158. https://doi.org/10.1016/j.jretconser.2022.103158.
[34] Yuan KH, Bentler PM, Zhang W. The effect of skewness and kurtosis on mean and covariance structure analysis: the univariate case and its multivariate implication. Sociol Methods Res 2005;34(2):240–58.
[35] Geng Y, Fei W, Tang Z, Wang S, Yu J, Zhang M, Zhang T. Parental care and depressive symptoms among Chinese medical students: roles of empathy and gender. BMC Med Educ 2022;22(1). https://doi.org/10.1186/s12909-022-03524-2.
[36] Wang Q, Cui S, Barnhart WR, Liu Y, Yu Y, Cui T, He J. Relationships between retrospective parental feeding practices and Chinese university students' current appetitive traits, weight status, and satisfaction with food-related life. Appetite 2022:175. https://doi.org/10.1016/j.appet.2022.106061.
[37] Dahri NA, Vighio MS, Bather J, Das, Arain AA. Factors influencing the acceptance of mobile collaborative learning for the continuous professional development of teachers. Sustain (Switz) 2021;13(23):1–23. https://doi.org/10.3390/su132313222.
[38] Tosuntaş B, Karadağ E, Orhan S. The factors affecting acceptance and use of interactive whiteboard within the scope of FATIH project: a structural equation model based on the unified theory of acceptance and use of technology. Comput Educ 2015;81:169–78. https://doi.org/10.1016/j.compedu.2014.10.009.
[39] El-Masri M, Tarhini A. Factors affecting the adoption of e-learning systems in Qatar and USA: extending the unified theory of acceptance and use of technology 2 (UTAUT2). Educ Technol Res Dev 2017;65(3):743–63. https://doi.org/10.1007/s11423-016-9508-8.
[40] Martins M, Farias JS, Albuquerque PHM, Pereira DS. Adoption of technology for reading purposes: a study articles of e-books acceptance. Braz Bus Rev 2018;15(6):568–88. https://doi.org/10.15728/bbr.2018.15.6.4.
[41] Taamneh A, Alsaad A, Elrehail H, Al-Okaily M, Lutfi A, Sergio RP. University lecturers acceptance of moodle platform in the context of the COVID-19 pandemic. Glob Knowl Mem Commun 2022;72(6/7):666–84.

[42] Zhou Y, Li X, Wijaya TT. Determinants of behavioral intention and use of interactive whiteboard by K-12 teachers in remote and rural areas. Front Psychol 2022;13:1–19. https://doi.org/10.3389/fpsyg.2022.934423.

[43] Nikolopoulou K, Gialamas V, Lavidas K. Acceptance of mobile phone by university students for their studies: an investigation applying UTAUT2 model. Educ Inf Technol 2020:4139–55. https://doi.org/10.1007/s10639-020-10157-9.

[44] Choi H, Hoo-Jo H. Influential factors on elementary school teachers' intention to use MOOC. Teach Educ Res 2018;57(1):16–29. https://doi.org/10.15812/ter.57.1.201803.16.

[45] Garg A. Investigating the moderating effects of age and gender on customers' use of tablet menu in casual dining restaurants. J Qual Assur Hosp Tour 2021:1–39. https://doi.org/10.1080/1528008X.2021.2002786.

[46] Lee B, Fenoff R, Paek SY. Correlates of participation in e-book piracy on campus. J Acad Librariansh 2019;45(3):299–304. https://doi.org/10.1016/j.acalib.2019.04.002.

[47] García de Blanes Sebastián M, Sarmiento Guede JR, Antonovica A. Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. Front Psychol 2022;13. https://doi.org/10.3389/fpsyg.2022.993935.

[48] Hu J, Liu M, Yang R, Wang L, Liang L, Yang Y, Jia S, Chen R, Liu Q, Ren Y, Zhu L, Cai M. Effects of high-intensity interval training on improving arterial stiffness in Chinese female university students with normal weight obese: a pilot randomized controlled trial. J Transl Med 2022;20(1). https://doi.org/10.1186/s12967-022-03250-9.

[49] Couper MP. Web surveys: a review of issues and approaches. Public Opin Q 2000;64(4):464–94.

[50] Kaplowitz MD, Hadlock TD, Levine R. A comparison of web and mail survey response rates. Public Opin Q 2004;68(1):94–101.

[51] Bethlehem J. Selection bias in web surveys. Int Stat Rev 2010;78(2):161–88.

[52] Van Selm M, Jankowski NW. Conducting online surveys. Qual Quant 2006;40(3):435–56.

[53] Hair JF, Anderson RE, Tatham RL, Black WC. Multivariate data analysis. Cengage Learn EMEA 2019;87. Annabel Ainscow.

[54] Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct Equ Model 1999;6(1):1–55.

[55] Hayes AF, Coutts JJ. Use omega rather than Cronbach's alpha for estimating reliability. But…. Commun Methods Meas 2020;14(1):1–24. https://doi.org/10.1080/19312458.2020.1718629.

[56] Dunn TJ, Baguley T, Brunsden V. From alpha to omega: a practical solution to the pervasive problem of internal consistency estimation. Br J Psychol 2014;105(3):399–412.

[57] Ackermans K, Bakker M, Gorissen P, van Loon AM, Kral M, Camp G. Development and validation of a test for measuring primary school students' effective use of ICT: the ECC-ICT test. J Comput Assist Learn 2024;40(3):960–72.

[58] Popa NL, Assante GM. Explanatory factors of digital citizenship among university students. A cross-national dataset. Data Br 2024;57:111011. https://doi.org/10.1016/j.dib.2024.111011.

[59] De Winter JC, Gosling SD, Potter J. Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: a tutorial using simulations and empirical data. Psychol Methods 2016;21(3):273.

[60] Ryu E. Effects of skewness and kurtosis on normal-theory based maximum likelihood test statistic in multilevel structural equation modeling. Behav Res Methods 2011;43:1066–74.

[61] Yuan KH, Bentler PM. Asymptotic robustness of standard errors in multilevel structural equation models. J Multivar Anal 2006;97(5):1121–41.

[62] Demir S. Comparison of normality tests in terms of sample sizes under different Skewness and Kurtosis coefficients. Int J Assess Tools Educ 2022;9(2):397–409.

[63] Finney SJ, DiStefano C. Nonnormaland categorical data in structural equation modeling. In: Structural equation modeling. Sec Cour 2013. https://doi.org/10.1108/978-1-62396-246-320251015.

[64] Rioux C, Little TD. Missing data treatments in intervention studies: What was, what is, and what should be. Int J Behav Develop 2021;45(1):51–8. https://doi.org/10.1177/0165025419880609.

[65] Bentler PM. Comparative fit indexes in structural models. Psychol Bull 1990;107(2):238–46.

[66] Byrne BM. Structural equation modeling with mplus. Routledge; 2013.

[67] Yuan Z, Liu J, Deng X, Ding T, Wijaya TT. Facilitating Conditions as the Biggest Factor Influencing Elementary School Teachers' Usage Behavior of Dynamic Mathematics Software in China. Mathematics 2023;11(6). https://doi.org/10.3390/math11061536.

[68] Wijaya TT, Cao Y, Weinhandl R, Yusron E, Lavicza Z. Applying the UTAUT model to understand factors affecting micro-lecture usage by mathematics teachers in China. Mathematics 2022;10(7):1008.