Pre-service teachers' AI usage:

The effects of perceived usefulness, subjective norm, behavioral intention, and self-efficacy

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Abstract The use of artificial intelligence in teacher education is seen as having great potential. AI tools can help relieve teachers' workloads and support learners individually in the classroom. However, they are still relatively rarely used by practicing teachers and currently, there are nearly no empirical findings regarding the use of AI tools as well as the factors influencing AI usage behavior among pre-service teachers. Using the Theory of Planned Behavior, the following article examines which factors can explain the weekly use of AI by pre-service teachers. In an empirical-quantitative study, *n*=931 pre-service teachers across Germany were asked about their perceived usefulness, their perceived subjective norm, their self-efficacy beliefs and their behavioral intention to use AI tools in their future work as teachers in schools. Pre-service teachers also provided information about their average weekly AI usage time. The results of a structural equation model show that the behavioral intention to use AI tools in the future can be highly significantly explained by the perceived usefulness of AI tools, the subjective norm of AI use, and the participants' self-efficacy beliefs. In addition, pre-service teachers' behavioral intention and self-efficacy beliefs are significant predictors of the weekly duration of AI use. Specifically, the correlation between pre-service teachers' self-efficacy beliefs and their weekly AI use is mediated by their behavioral intention. The results of the study thus provide important insights into how to promote the use of AI tools in teacher education.

Keywords: Artificial Intelligence, theory of planned behavior, perceived usefulness, subjective norm, self-efficacy, behavioral intention, pre-service teachers, teacher education, usage behavior, Germany

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1 Introduction

Artificial intelligence (AI) is considered to have comprehensive implications for teachers and teaching (Heeg & Avraamidou, 2023). AI tools understood as "a technology that enables machines to imitate various complex human skills" (Sheikh et al., 2023, p. 15) offer a wide range of innovative applications for teachers, from providing more personalized support to students to assisting and alleviating teachers in their pedagogical practices (Delcker et al., 2024; Mah et al., 2019). For example, AI systems can analyze students' learning progress and create individualized learning plans. They can also be used as feedback tools to support teachers in the classroom and thus effectively support learners in their individual learning processes (Fleckenstein et al., 2023). This opens up a whole new range of opportunities for teachers in the digital age (e.g., Hansen et al., 2024; Mah et al., 2023; Martin et al., 2024).

Unlike previous educational technologies, which were often slow to be adopted by educators (Liu et al., 2020; Mah, 2016), especially Generative AI (GenAI) stands out due to its accessibility, adaptability, and widespread societal impact (e.g., Kasneci et al., 2023). As a result, GenAI is already reshaping the educational landscape and is believed to play a significant role for the teaching profession (e.g., Hodges & Kirschner, 2024). However, as of yet, AI tools are still used relatively infrequently in schools and classrooms (e.g., Galindo-Dominguez et al., 2024). At the same time, school students are increasingly using AI tools in and outside the classroom (e.g., Johnston et al., 2024). Despite its potential of being a "transformative technology in education" (Kasneci et al., 2023, p. 8), AI tools require cautious and mindful integration into teaching and learning processes to mitigate negative effects (e.g., Hansen et al., 2024; Kasneci et al., 2023). Teachers will play a crucial role in implementing AI in schools and modeling the critical use of AI tools for their students. Hence, already during teacher education, pre-service teachers need to be prepared for this process (Mishra et al., 2024). Therefore, the focus should be on current pre-service teachers who will be working in schools in the future and who will face a variety of challenges in this area due to the expected rapid progress of AI technologies in schools. It is therefore paramount to understand factors impacting pre-service teachers' use of AI tools to redesign teacher education programs.

To explore factors impacting pre-service teachers' use of AI tools, this study applies the theory of planned behavior (Ajzen, 1985). The intention to perform a behavior, and consequently the actual behavior exhibited by individuals, can be explained by a variety of factors. To date, there is a lack of research regarding the use of AI tools by pre-service teachers. Recent studies from other domains (e.g., An et al., 2023; Gado et al., 2021; Ivanov et al., 2024) or the pre-ChatGPT era in teacher education (e.g., Zhang et al., 2023) show that attitudes, subjective norms, or behavioral control variables can have a significant effect on the behavioral intention to use AI among

participants. However, with few exceptions (e.g. Sanusi et al., 2024), the current studies have rarely included indicators of the actual behavior exhibited by individuals.

A deeper understanding of the underlying relationships offers the opportunity to support pre-service teachers individually in their specific needs and to develop appropriate support measures. Ultimately, this could help to realize the full potential of AI use in schools and improve the overall quality of teaching. Therefore, our study addresses this research gap. Using a quantitative cross-sectional design, we collected data from *n*=931 pre-service teachers across universities in Germany and investigated, how their socio-demographic characteristics (e.g., gender, age) and their motivational-emotional characteristics (e.g., attitudes towards AI, subjective norms, self-efficacy) effect their behavioral intention to use AI as well as their actual use of AI tools.

2 Theoretical background

2.1 AI in education

AI is not only reshaping many industries, but also education by using technologies such as machine learning and natural language processing to enhance individual learning processes (Harry & Sayudin, 2023; Wu & Yu, 2024). Accordingly, the application of AI in higher education has expanded rapidly over the past five years (Crompton & Burke, 2023; Delcker et al., 2024; Mah et al., 2023) and AI-based tools like ChatGPT and GPT-4 are currently transforming the higher education landscape, leading to widespread discussions about the implications for future teaching and learning (von Garrel & Mayer, 2023). In their systematic review Crompton and Burke (2023) identified 138 studies about AI in higher education from 2016 to 2022 conducted across 31 countries. However, the distribution of these studies was uneven across continents. Asia accounted for the largest share, with 41% of the studies on AI in higher education taking place there, whereas Europe followed with 30% of the studies, spanning 15 countries, each contributing between one and eight studies. Studies from Germany were not identified in this review, which suggests that Germany is lagging somewhat behind. Nevertheless, up to date, there are a few studies which investigate the use of AI in higher education in Germany. For example, von Garrel and Mayer (2023) conducted a nationwide survey of over 6,300 students in Germany to assess how AI-based tools are used in academic settings and daily life. The results revealed that nearly two-thirds of the respondents have used or currently use AI-based tools, especially ChatGPT or GPT-4. AI-based tools are most used by students in engineering, mathematics, and natural sciences. Based on a survey conducted as part of the CHE University Ranking 2024 during the winter semester of 2023/24, Huesch et al. (2024) surveyed a total of 34,147 students enrolled in undergraduate programs from their third semester onward at 165 universities and vocational academies across Germany and Austria. Also in this study, approximately half of the surveyed students reported using AI

tools occasionally to daily. However, it is important to note that there are significant differences in AI usage across various academic disciplines. The use of AI tools is particularly prevalent among computer science students, especially for programming tasks. However, in their recent review about potential benefits of using AI in education, Harry and Sayudin (2023) point out, that tools such as intelligent tutoring systems, chatbots, and automated grading and assessment should be implemented in teacher education, because they can save time and boost efficiency of educators. In line with this, we found in a previous study, that AI based feedback can offer a cost-effective and high-quality alternative to expert feedback in the context of higher education (Jacobsen & Weber, 2023). However, the use of AI in education also brings challenges, including concerns about privacy, security, trust, cost, and potential biases (Harry & Sayudin, 2023). Therefore, teachers as well as pre-service teachers should be trained to understand these challenges and to use AI tools in efficient and intelligent ways. This is not only important for the teachers themselves, but also for their future students. Accordingly, teachers should be role models for that, and it is of importance to know which factors influence their intention as well as their actual use of AI. Both von Garrel and Mayer (2023) and Huesch et al. (2024) surveyed students with various academic disciplines and moreover investigated only the use of AI tools and not factors which are supposed to predict AI usage of students. Therefore, there is still a research gap regarding AI usage behavior of pre-service teachers as well as potential predictors of the use of AI tools.

2.2 Factors influencing the use of AI

A well-known and often cited model for explaining human behavior is Ajzen's (1985) theory of planned behavior. In his theoretical assumptions, the author assumes that several distal factors underlie the intention to perform a certain behavior and its explicit execution. It is assumed that individual behavioral intention can be explained by people's specific attitudes, their perceived subjective norm, and their perceived behavioral control. The behavior intention as well as by person's perceived behavioral control then in turn determine their actual behavior (Ajzen, 1985, 1991, 2012). According to Eagly and Chaiken (1993, p. 1), attitudes can be understood as "a psychological tendency that manifests itself in evaluating a particular entity with a certain degree of favor or disfavor". Thus, for example, the perceived usefulness of a particular technology regarding the profession as teacher can be seen as part of a person's attitude (cf. Davis, 1989). According to Ajzen (2012), perceived behavioral control for the successful performance of a behavior can be subsumed under several relevant internal and external factors that may positively facilitate or hinder the concrete performance of the behavior. These include the social support of important reference persons, external factors (perceived obstacles or supportive aspects in the execution of the action), the availability of or access to necessary information in the action process, as well as a person's implicit

beliefs. According to Bandura (1997), self-efficacy beliefs can be named as a central component of perceived behavioral control.

2.2.1 Self-efficacy beliefs of using AI in teaching

Self-efficacy beliefs are defined as "people's beliefs about their capabilities to exercise control over their own level of functioning and over events that affect their lives" (Bandura, 1991, p. 255). Hence, self-efficacy significantly impacts personal thought, affect, motivation, and action. Concerning the teaching profession, a large body of research shows that teachers' self-efficacy has comprehensive implications on teachers themselves and their students (Klassen & Tze, 2014; Zee & Koomen, 2016). At teacher level, studies (e.g., Klassen & Tze, 2014; Vieluf et al., 2013), for example, indicate that teachers' self-efficacy has strong positive effects on their teaching performance or their job satisfaction. At student level, research shows that teachers' self-efficacy positively predicts students' overall performance at primary, middle and high school level (Zee & Koomen, 2016). First conceptualized as an omnibus trait (Rotter, 1966), teachers' self-efficacy is now perceived as a task- and domain-specific multidimensional construct (Zee & Koomen, 2016). In the field of technology, task-specific self-efficacy constructs such as computer self-efficacy, internet self-efficacy, technology-integration self-efficacy, or ICT self-efficacy have been studied (e.g., Alt, 2015; Musharraf et al., 2018). With increased implementation of AI tools, researchers have recently conceptualized AI-specific self-efficacy as one's belief in one's ability to successfully apply AI technologies (Wang & Chuang, 2024).

To date, studies concerning pre-service teachers' AI-specific self-efficacy are still scarce, especially focusing on the post-ChatGPT era. A study by Al Darayseh (2023) from the pre-ChatGPT era showed that pre-service science teachers' self-efficacy significantly predicted their behavioral intention to use AI tools in the classroom. Sanusi et al. (2024) explored pre-service teachers' AI-specific self-efficacy with respect to learning about AI post-ChatGPT. Sanusi et al. found that participants' self-efficacy had a significant effect on their intention to learn AI. However, both studies do not focus on the usage of AI tools. Nonetheless, the findings highlight the need to foster pre-service teachers' self-efficacy to increase their engagement with AI: Findings from research focusing on other technology than AI can shed some light on its the association with the use of technology. Kim et al. (2013) showed that teachers' self-efficacy beliefs were related to their technology integration into teaching. Furthermore, studies from fields outside teacher education can provide additional insights into higher education students' current AI self-efficacy beliefs. A recent study by Asio and Gadia (2024) showed higher education students had a moderate level of AI-specific self-efficacy and that their beliefs significantly predicted their attitudes towards AI. These results correspond to Hornberger et al. (2023) who also found that participants' AI-specific self-

efficacy significantly correlated with their AI-related attitudes. Overall, studies concerning (pre-service) teachers' AI or technology self-efficacy highlight the need to foster their self-efficacy to increase engagement and usage of AI or technology.

2.2.2 Subjective norm and perceived usefulness

Knauder and Koschmieder (2019), citing Ajzen (1985, 1991), describe the subjective norm as an individual's belief that important reference persons (e.g., friends, family members) will positively or negatively sanction a displayed behavior. Based on this subjective perception, a person may be inclined to conform their behavior to the social expectations of those around them. Perceived usefulness on the other hand refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). Both subjective norm and perceived usefulness are considered to explain human behavior according to Ajzen's (1985) theory of planned behavior and therefore may have an impact on pre-service teachers' use of AI. Previous research already showed that perceived usefulness as well as subjective norms have an impact on attitudes toward computer use among pre-service teachers (Teo, 2009). In a more recent study, Ursavaş et al. (2019) examined the impact of subjective norms on the perceptions, attitudes, and behavioral intentions of pre-service and in-service teachers to use technology in Turkey. The findings indicated that subjective norms had a substantial overall effect on the behavioral intentions of pre-service teachers, this effect was smaller among in-service teachers. Additionally, subjective norms were crucial in shaping the attitude towards technology use among pre-service teachers. Another study from China examined the general public's acceptance of the application of AI in medical settings (Ye et al., 2019). The intention to use ophthalmic AI devices was significantly influenced by subjective norms as well as perceived usefulness. Subjective norms and perceived behavioral control also indirectly affected the intention to use through perceived usefulness and perceived ease of use. In another recent study, Ma and Lei (2024) explored diverse factors that influence Chinese pre-service teachers in Information-Based Teaching to adopt AI technologies. They identified perceived usefulness as one of the key factors influencing the behavioral intention to use AI. Li (2023) found the same effect for college students in China and could show, that perceived usefulness positively affected students' attitudes, behavioral intentions as well as their actual use of these systems. Sanusi et al. (2024) surveyed pre-service teachers from Nigerian universities and could show, that subjective norm emerged as one of the most significant determinants of pre-service teachers' intentions to learn AI. In addition, An et al. (2023) surveyed English teachers in China and showed that the behavioral intention to use AI tools could be significantly explained by perceived usefulness and subjective norms of the participants. Similar results were found in the study of Zhang et al. (2023) with pre-service teachers in Germany and in those of the non-site specific

studies by Gado et al. (2021) and Ivanov et al. (2024) with university students. However, most of the studies investigated only the intentions to use AI and with few exceptions (e.g., Zhang et al., 2023) none of the above-mentioned studies was conducted in Germany. Accordingly, there is still a research gap regarding factors which influence behavioral intentions as well as AI usage behavior among preservice teachers in Germany.

2.3 Theoretical model

In summary, the current state of research shows that there are correlations between people's self-efficacy beliefs, their assessment of the usefulness of AI tools, and their perceived subjective norm for AI use on the one hand, and their intention to use AI in the future on the other. However, with regard to the distal indicators of the Theory of Planned Behavior (Ajzen, 1985, 1991, 2012), Few studies have currently examined indicators to assess current behavior in dealing with AI, which can be seen as a present research desideratum. Exceptions are the studies by Ivanov et al. (2024) with students from different professions and countries and Sanusi et al. (2024) with Nigerian pre-service teachers. Both studies concluded that respondents' AI-related self-efficacy beliefs, their perceived subjective norms for using AI tools, and their perceived usefulness of AI tools/attitudes towards AI tools can significantly explain their behavioral intention to use AI in the future. However, the latter is only a significant predictor of their current AI usage behavior in the study by Ivanov et al. (2024), but not in that by Sanusi et al. In contrast, Delcker et al. (2024) were able to demonstrate a relationship between students' behavioral intentions and their actual AI use, albeit almost without including distal indicators from the Theory of Planned Behavior. The current state of research on this topic is therefore inconsistent. Another current research desideratum is whether and to what extent the relationship between people's AI-related self-efficacy beliefs and their actual AI usage behavior is mediated by their behavioral intentions. This aspect is not considered by Ivanov et al. (2024) or Sanusi et al. (2024). Furthermore, neither of the two studies explicitly refers to pre-service teachers in European/German-speaking countries. These research desiderata are addressed in our study. In order to examine the precise relationships between pre-service teachers' perceived usefulness, perceived subjective norm, self-efficacy beliefs, behavioral intentions and actual weekly AI use, a structural equation model was calculated. Referring to the assumptions of the Theory of Planned Behavior (Ajzen, 1985, 1991, 2012) and the current research findings, we assume that the behavioral intentions of pre-service teachers to use AI tools in the future is significantly effected by their AI-related self-efficacy beliefs (Al Darayseh, 2023; Sanusi et al., 2024), perceived subjective norms (An et al., 2023; Gado et al., 2021; Ivanov et al., 2024; Ursavaş et al., 2019; Ye et al., 2019; Zhang et al., 2023) and assumptions about the usefulness of AI in the future teaching profession (An et al., 2023; Gado et al., 2021; Ivanov et al., 2024; Li, 2023; Ma & Lei, 2024; Zhang et al., 2023). Furthermore, we assume that pre-service teachers'

behavioral intentions to use AI tools in their future teaching career (Delcker et al., 2024; Ivanov et al., 2024) and their self-efficacy beliefs about AI use (Kim et al., 2013) are significant predictors of their current AI usage behavior. Additionally, in line with the Theory of Planned Behaviour (Ajzen, 1985, 1991, 2012), it is assumed that the effects of students' self-efficacy beliefs on their current AI use behavior can be significantly explained by their behavioral intentions to use AI tools in their future careers as teachers. In order to avoid bias in the results, participants' gender, their current number of semesters and their teaching profession were included as control variables in the analyses. We believe this is necessary as there is empirical evidence that the above variables can have an impact on the use of AI by (pre-service) teachers (OECD, 2023; Zhang et al., 2023). The assumed relationships between the variables are summarised in a theoretical model (Figure 1).

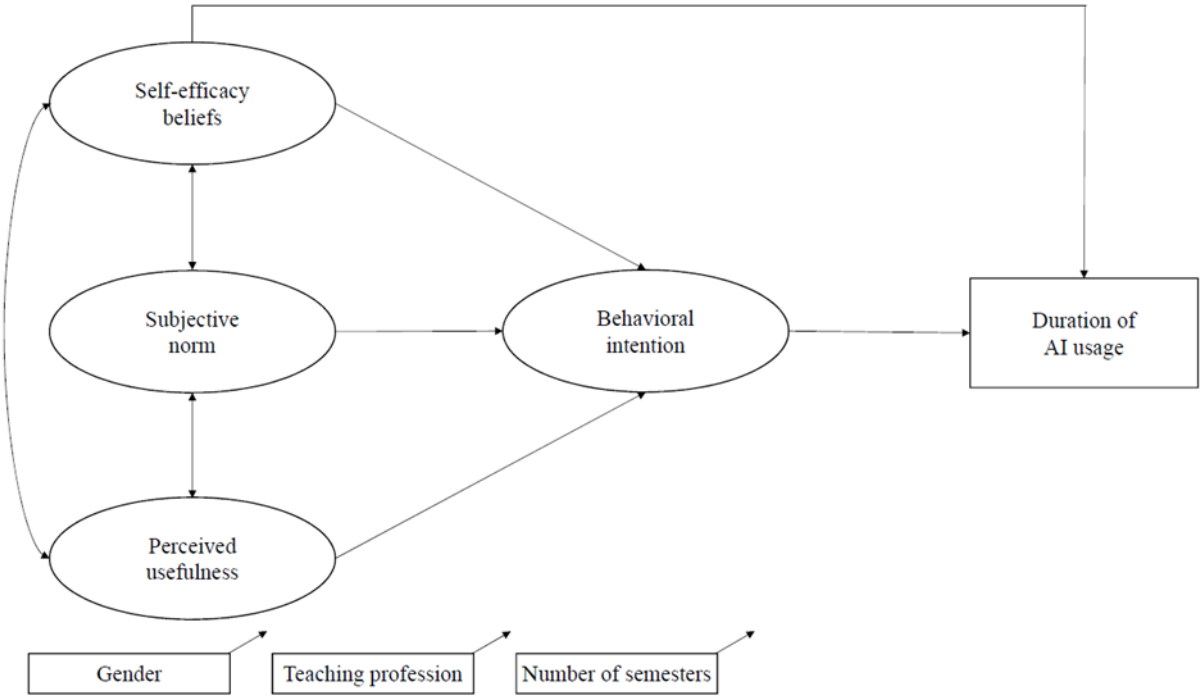


Figure 1 Theoretical model

3 Method

3.1 Sample

In a quantitative cross-sectional study, 931 pre-service teachers (192 male, 729 female, 7 identifying as diverse, and 3 with missing data) from 21 universities in Germany completed a survey. The participants were categorized as follows: 626 pre-service teachers were enrolled in primary school teacher degrees, 58 in special education

degrees, 50 in lower secondary school degrees, 88 in secondary school degrees, and 105 in vocational teaching degrees (with 4 missing data). Participants were on average in their 4th semester (*M*=3.71; *SD*=2.85; *Min*=1.00; *Max*=17.00). The majority of pre-service teachers were between 18 and 20 years old (*n*=368) or between 21 and 24 years old (*n*=366). Additionally, 127 pre-service teachers were aged between 25 and 29 (*n*=68 30 years old or older; *n*=2 under 18 or no age provided). A total of 274 participants indicated that they had no prior teaching experience. Conversely, 487 respondents had already completed practical phases in schools as part of their studies, and 131 pre-service teachers had independently taught as schoolteachers.

3.2 Instruments

As part of a questionnaire survey, the participants were asked to provide information about their perceived usefulness of AI use in their future profession as a teacher (4 items; *M*=4.16; *SD*=1.02; *Min*=1.00; *Max*=6.00; α=.88; sample item: "Learning AI will help me get a good job in the future."), their self-efficacy beliefs regarding general AI use (4 items; *M*=3.85; *SD*=0.89; *Min*=1.00; *Max*=6.00; α=.88; sample item: "I am confident I will perform well on AI related tasks.") and their behavioral intention to use AI tools in the future (3 items; *M*=3.99; *SD*=0.97; *Min*=1.00; *Max*=6.00; α=.83; sample item: "I will continue to use AI in the future."). Existing constructs from Ng et al. (2023) were used for this purpose. In addition, pre-service teachers were queried about their perceived subjective norm regarding AI use (2 items; *M*=2.87; *SD*=1.18; *Min*=1.00; *Max*=6.00; α=.84; sample item: "People who are important to me think that I should use the system."). Previously tested instruments by Venkatesh and Davis (2000) were used. A six-point Likert scale (1=strongly disagree to 6=strongly agree) was implemented. In addition, participants indicated how often they would use AI tools (e.g. ChatGPT, DALL-E) on average per week on a self-developed 7-point Likert scale (1=0 h; 2≤1 h; 3=1-3 h; 4=4-7 h; 5= 8-11 h; 6= 12-15 h; 7=>15 h; *M*=2.06; *SD*=0.77; *Min*=1.00; *Max*=7.00).

3.3 Data Analysis

The statistical software programs SPSS (version 29.0.0.0; IBM 2023) and Mplus (version 7, Muthèn & Muthén, 2015) were used for data analysis. The structural equation model employed the Maximum Likelihood (ML) estimator. To assess the fit of the structural equation model the Tucker-Lewis Index (TLI), the Comparative Fit Index (CFI), the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Residual (SRMR) were used. This means that both absolute and incremental methods are used to check the quality of the model, which allows for a more robust and reliable interpretation of the results when the model fit is good (Weiber & Muehlhaus, 2014). In assessing the model fit, we were guided by the cut-off values commonly used in the

literature. The CFI and TLI should have values between 0.90 and 0.95, respectively, to indicate a good model fit. Values above 0.95 indicate excellent model fit (Byrne, 2001; Hu & Bentler, 1999). For RMSEA, values below .06 are considered excellent (Byrne, 2001; Hu & Bentler, 1999) and between .06 and .08 (Browne & Cudeck, 1993) are regarded as good to acceptable (Kyndt & Onghena, 2014), while values below .08 are deemed good when assessing model fit by SRMR (Hu & Bentler, 1999).

4 Results

As highlighted in the descriptive statistics presented in Chapter 4.2, pre-service teachers generally perceive AI tools as beneficial for their work. They also exhibit a moderately positive sense of self-efficacy regarding AI usage, believing that proficient use of these tools could provide them with a competitive edge in their future teaching profession. However, pre-service teachers were less convinced that their peers would expect them to incorporate AI tools into their work. The findings on AI usage reveal that these tools are still relatively underutilized in teacher education. On average, participants reported spending less than one hour per week using AI. To further explore these insights, correlations were calculated to assess the strength and direction of relationships between the used variables. The results of these analyses are presented in Table 1.

Table 1 Intercorrelation matrix of the variables used

	(2)	(3)	(4)	(5)
(1) Self-efficacy beliefs [a]	.24***	.39***	.59***	.41***
(2) Subjective norm [a]		.40***	.42***	.22***
(3) Perceived usefulness [a]			.65***	.34***
(4) Behavioral intention [a]				.46***
(5) Duration of AI usage [b]				

Annotations: [a] 1=strongly disagree to 6=strongly agree; [b] 1=0 h; 2=<1 h; 3=1-3 h; 4=4-7 h; 5=8-11 h; 6=12-15 h; 7=>15 h; *$p \leq .05$; **$p \leq .01$; ***$p \leq .001$

With reference to Cohen (1988), there are small to medium positive effects between the variables. The effects show a highly significant level ($p \leq .001$). The behavioral intention to use AI tools in future teaching reported by pre-service teachers shows the highest correlation with the duration of the average weekly AI usage time. There were also moderate effects between the duration of AI use and self-efficacy beliefs, the subjective norm and the perceived usefulness of the AI tools.

A structural equation model was calculated to test the hypothetical assumptions made in Chapter 3. In relation to Hair et al. (2010), the measurement model (see Table 2 below) shows that all manifest indicators have high ($\lambda \geq .70$) to moderate (λ between .50 and .70) factor loadings to explain the latent variables.

Table 2 Standardized factor loadings in the structural equation model

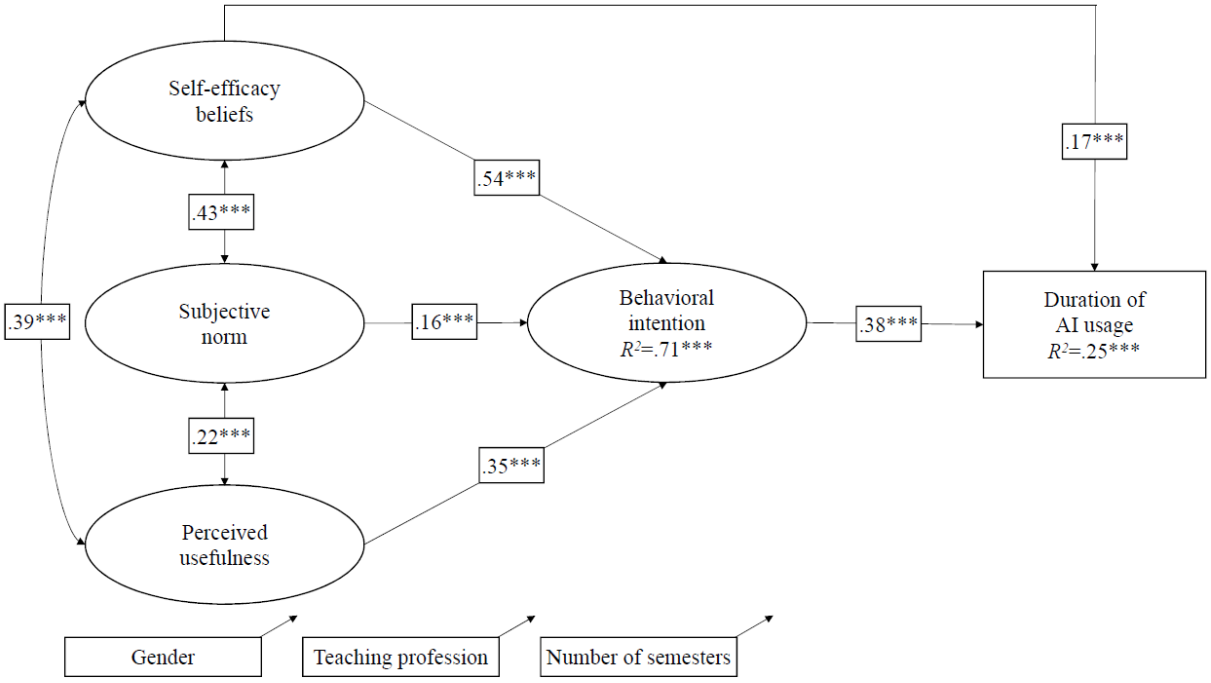
Latent variable	Indicators	β	*S.E.*
Self-efficacy beliefs	1	.90	.01
	2	.89	.01
	3	.86	.01
	4	.60	.02
Subjective norm	1	.87	.03
	2	.84	.02
Self-efficacy beliefs	1	.90	.01
	2	.88	.01.
	3	.72	.02
	4	.71	.02
Behavioral intention	1	.84	.01
	2	.77	.02

	3	.73	.02

Annotations: All factor loadings show a highly significant level.

The overall model also shows consistently satisfactory values for CFI, TLI, RMSEA and SRMR and thus indicates a good model fit (Browne & Cudeck, 1993; Byrne, 2001; Hu & Bentler, 1999; Kline, 2016; Kyndt & Onghena, 2014). Consequently, it could be shown that the theoretical assumptions in the model can be adequately mapped using the underlying database. The exact relationships between the latent variables can be seen in Figure 2.

Figure 2 Structural equation model



Note: *$p \leq .05$; **$p \leq .01$; ***$p \leq .001$; *CFI*=.95; *TLI*=.93; *RMSEA*=.64; SRMR=.038

Differences in pre-service teachers' behavioral intention to use AI tools in the future can be significantly explained (controlling for participants' gender, number of semesters, and teaching degree) by their perceived usefulness for their future profession as teachers, their perceived subjective norm for using AI tools, and their self-efficacy beliefs for using AI tools. These variables explain 71 percent of the variance in participants' behavioral intentions. In addition, the weekly use of AI tools can be highly significantly explained by pre-service teachers' behavioral

intention and their self-efficacy beliefs. These two variables can explain 25 percent of the participants' weekly AI use. In addition to the reported direct effects, the relationship between self-efficacy beliefs and AI usage duration is significantly mediated by participants' behavioral intentions ($\beta_{indirect}$=.13***; β_{total}=.31***).

5 Discussion

5.1 Findings

In this study, the Theory of Planned Behavior (Ajzen, 1985, 1991, 2012) was utilized to examine the factors that can explain the duration of AI tool usage among pre-service teachers. The results from the structural equation model indicate that the differences in pre-service teachers' behavioral intentions to use AI tools in the future could be significantly explained by their perceived usefulness of AI tools, subjective norm and self-efficacy beliefs in using AI tools. Therefore, our results are in line with previous research (e.g. An et al., 2023; Ma & Lei, 2024; Sanusi et al., 2024, Zhang et al., 2023) and our hypothetical model can be verified. Additionally, the weekly use of AI tools was significantly predicted by pre-service teachers' behavioral intentions and their self-efficacy beliefs. This suggests that beyond the intention to use AI, confidence in one's ability to use these tools plays a crucial role in determining how frequently they are used. The mediation effect observed between self-efficacy beliefs and AI usage duration through behavioral intentions further highlights the complex interplay between belief systems and actual behavior.

Concerning AI-specific self-efficacy beliefs, the study showed that pre-service teachers' self-efficacy concerning their ability to successfully use AI tools significantly predicted subjective norms, perceived usefulness, behavioral intention, and duration of AI usage. This aligns with prior research on the adoption of technology. First and foremost, our study is the first to show that pre-service teachers' self-efficacy beliefs have a significant effect on the use of AI tools. This is consistent with findings by Kim et al. (2013). Moreover, our study adds to Al Darayseh's (2023) and Sanusi et al.'s (2024) results regarding pre-service teachers' behavioral intention in a Middle Eastern and African context. Our study extends these results to a European teacher education context. Furthermore, the effect of participants' self-efficacy on their perceived usefulness of AI tools corresponds to the findings by Asio and Gadia (2024) and Hornberger et al. (2023). Hence, our findings suggest teacher education programs need to develop interventions that specifically target pre-service teachers' AI-specific self-efficacy to increase the use of AI tools.

Perceived usefulness as well as subjective norms have consistently been highlighted as key predictors in various contexts and countries such as computer use in Singapore (e.g. Teo, 2009), technology use among Turkish

teachers (e.g. Ursavaş et al., 2019), the application of AI in medical settings in China (e.g. Ye et al., 2019) and the use of AI technologies in the educational context (e.g. Ma & Lei [China], 2024; Sanusi et al., 2024 [Nigeria]; Zhang et al., 2023 [Germany]). The alignment of these findings across different fields and different countries reinforces the robustness of these constructs in technology acceptance models.

To sum it up, the effects of perceived usefulness as well as subjective norm on behavioral intention is well-established in the literature, particularly within technology acceptance models. In our findings, perceived usefulness of AI tools also emerged as a critical determinant, suggesting that when pre-service teachers perceive AI tools as beneficial for their future profession, they are more likely to develop intentions to use them. Our study also found that subjective norms significantly influence pre-service teachers' behavioral intention to use AI. This underlines that the influence from faculty, peers and educational culture plays a pivotal role in pre-service teachers' intention to use AI. If university teachers consistently integrate AI tools into their teaching, it sets a precedent for pre-service teachers to follow, and pre-service teachers internalize the expectation that AI is an essential tool in modern education. However, in Germany even the university teachers who actively experiment with AI and, in some cases, regularly use specific applications for preparing and reviewing their teaching, rarely reported incorporating AI tools into their actual courses (Go, 2024). Therefore, pre-service teachers lack role models which could also explain why subjective norms as well as perceived usefulness only predicted the intention to use AI but not the actual usage.

Regarding the different phases of teacher education, it seems that the role of subjective norms differs across professional stages. For example, Ursavaş et al. (2019) observed that subjective norms played a smaller role in shaping in-service teachers' behavioral intentions compared to pre-service teachers. This suggests that as teachers gain experience, they might rely more on the perceived practical benefits of AI rather than on peer or social influences. Our study, focusing on pre-service teachers, found subjective norms to be a strong factor, in line with this distinction. These findings suggest a potential shift in focus for professional development programs, as the factors influencing the intention to use AI may evolve with teaching experience.

5.2 Implications

In a recent publication, UNESCO (2024) presented the first global framework on AI competencies for teachers. This underscores the profound impact of AI on educational practices and, consequently, on the responsibilities and skill sets required of (pre-service) teachers in the context of teaching and learning. Our findings have practical implications for teacher education programs and therefore address the above-mentioned AI competencies. To foster the integration of AI tools into teaching practice, it is essential to enhance pre-service teachers' perceptions of the usefulness of these tools, cultivate a supportive environment that endorses AI use, and

build pre-service teachers' confidence in their ability to use AI effectively. This could be achieved through targeted training and professional development initiatives that not only introduce pre-service teachers to AI tools but also provide hands-on experience and emphasize the practical benefits of AI in educational settings. Participation in AI and technology-related training is necessary for both pre-service and in-service teacher education. Fuetterer et al. (2023) found that the perceived usefulness of technology in the classroom was a strong predictor of teachers' participation in technology-related professional development. Thus, university seminars should address the potential and benefits of using AI for teaching and learning, while also discussing challenges and addressing critical issues such as ethics (e.g., Shao et al., 2024). By emphasizing AI's utility, pre-service teachers can develop a positive attitude and intention to use these tools. Since self-efficacy beliefs play a critical role, teacher training should focus not only on these topics, but also on fostering pre-service teachers' confidence in using AI tools. Offering hands-on experiences, practice sessions, and opportunities to experiment with AI technologies in a low-stakes environment can significantly enhance self-efficacy. Therefore, curriculum development in higher education is essential in order to integrate AI-related content into pre-service teacher education (Southworth et al., 2023).

Regarding the role of subjective norms, institutions that emphasize innovation and technological advancement create an environment where AI integration is expected and celebrated. Universities with a strong emphasis on educational technology naturally foster a norm where AI usage is seen as integral to teaching. In contrast, universities that are slower to adopt such technologies may find that subjective norms around AI usage remain weak or negative, resulting in lower adoption rates among pre-service teachers. Pre-service teachers often feel insufficiently trained in the use of AI in their teaching profession and express a desire for a greater variety of advanced training opportunities in this area (Helm et al. 2024). Universities should offer these training opportunities and integrate AI more deeply into their university culture (Mah et al., 2023).

5.3 Limitations and future research

There are certain limitations to consider in our study. First, we relied solely on self-reported data from pre-service teachers, rather than directly observing or measuring their actual AI usage behavior. This approach can introduce biases, such as social desirability bias, where participants might over- or underestimate their use of AI tools to align with perceived expectations. As policymakers in German universities tend to be somehow restrictive towards the use of AI (Delcker et al., 2024) participants may have been less likely to admit to using AI tools frequently, fearing potential negative consequences or disapproval from their institutions. This could lead to underreporting of actual usage behavior, resulting in data that does not accurately reflect the extent of AI usage among pre-service teachers. Moreover, restrictive policies at German universities might limit pre-service teachers' opportunities to

experiment with and explore AI tools. Consequently, self-reported data may reflect limited knowledge and experience with AI, which could influence their perceived usefulness and self-efficacy. Second, the mere duration of interaction with AI technologies does not necessarily indicate the quality or depth of how these tools are used by pre-service teachers. Without assessing the qualitative aspects of AI tool usage, it is difficult to draw conclusions about whether pre-service teachers are engaging with AI in meaningful and effective ways. Additionally, a significant number of the participants in this study were primary education pre-service teachers who were in the early stages of their bachelor's programs and had not yet completed extensive practical teaching phases. This lack of practical experience could mean that they have had limited exposure to using AI tools in their studies, potentially influencing their usage behavior and attitudes towards AI. Third, the study was conducted as a cross-sectional study, which limits our ability to draw conclusions about causality. The findings provide a snapshot of the participants' perceptions and behaviors at one point in time, but they do not capture changes over time, or the direction of the relationships observed. Fourth, the study did not assess the participants' actual knowledge of AI. Even if Delcker et al. (2024) found no impact of knowledge on first-year pre-service teachers' intention to use AI, it would have been interesting to replicate these findings with our participants. These limitations suggest that future research should incorporate longitudinal designs, direct measures as well as the quality of AI usage, and assessments of AI knowledge to gain a more comprehensive understanding of AI use among preservice teachers. To gain deeper insights into how AI is being used by pre-service teachers, further research could benefit from conducting in-depth interview studies. Such qualitative approaches would allow for a more nuanced understanding of pre-service teachers' experiences and perceptions of AI, providing richer data on how AI tools are integrated into their learning processes and teaching practices.

5.4 Conclusion

The findings of our study can aid in better understanding the relationships between various factors influencing AI usage of preservice teachers in Germany. These insights could be leveraged in the professional development of teachers to enhance their competency in using AI tools effectively. By understanding the factors that encourage or hinder AI usage among preservice teachers, educational programs can be tailored to foster positive attitudes towards AI, enhance self-efficacy, and promote the perceived usefulness of these technologies. This, in turn, could lead to more effective and widespread adoption of AI tools in education, ultimately benefiting both teachers and pre-service teachers in the learning environment. Further research is required to gain an evidence-based understanding of AI in education, including the perspectives of all stakeholders (e.g., learners, teachers, decision

makers). The development of AI literacy is necessary to ensure the meaningful utilization of AI in teaching and learning in a sovereign, critical-reflective, and empowering manner.

6 Declarations

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4o as well as DeepL in order to improve readability and language of the work. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Fabian Hoya: Conceptualization, Data Collection, Data Curation, Methodology, Writing - Original Draft. Christopher Neil Prilop: Conceptualization, Data Collection, Writing - Original Draft. Dana-Kristin Mah: Conceptualization, Data Collection, Writing - Original Draft. Lucas Jacobsen: Data Collection. Kira Elena Weber: Conceptualization, Data Collection, Writing - Original Draft. All authors read and approved the final manuscript.

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