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RESEARCH ARTICLE

Acceptance of artificial intelligence in education: opportunities, concerns and need for action

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Abstract: The spread of AI text generators such as ChatGPT in education has reached an enormous reach in a short period, which has led to various questions regarding the acceptance of artificial intelligence among teachers and student teachers. This study examines the acceptance of AI among teachers and student teachers. In particular, it considers crucial aspects for planning teaching and teacher training. The results show that despite fundamentally positive attitudes towards AI applications, there are concerns regarding data ethics and legal standards. The correlation between the intention to use AI and trust in AI is significant. The findings should help gain a more comprehensive understanding of the acceptance of AI in the education sector and help teachers plan training and further education accordingly.

Keywords: artificial intelligence, AI applications, student teachers, AI acceptance

1 Problem statement

Research on accepting artificial intelligence (AI) in education is essential due to the rapid spread of AI applications and the associated challenges. The acceptance of AI faces several challenges. These challenges include ethical risks related to privacy and security concerns arising from the use of big data in education, the potential alienation of students due to algorithmic recommendations, the exacerbation of educational inequality through the 'digital divide', the risk of simplification of educational processes leading to behaviourism, information cocooning through algorithmic recommendations, teachers' fear of AI and emotional deficits in AI applications (Gartner & Krašna, 2023; Ma & Jiang, 2023; Zhang et al., 2023; Zhang & Deng, 2022). In addition, the integration of AI technologies into educational culture and processes is a significant barrier and requires effective communication of complex data insights to support educational practices such as personalisation, assessment and stakeholder engagement in the educational environment (Brandhofer & Tengler, 2024; Ritter & Koedinger, 2023).

AI text generators, such as ChatGPT, have the potential to change the educational landscape fundamentally. For example, ChatGPT can serve as a tool to support language teaching and create a conducive learning environment, especially for students with a migrant or refugee background, and AI can help with inclusion challenges in general (Athanassopoulos et al., 2023; Luckin et al., 2016; Pishtari et al., 2024). While the positive applications of ChatGPT can offer significant benefits, the negative impacts and ethical concerns must be carefully monitored and addressed to ensure a balanced and effective educational environment (İpek et al., 2023). As part of this, understanding teachers' perspectives on AI applications is relevant to overcoming the challenges posed by the increasing spread of AI applications. Proactively shaping the transformation process through integrating AI in education, considering ethical, legal and social issues beyond a rudimentary technology assessment, should be pursued.

This article examines the acceptance of artificial intelligence (AI) among teachers and student teachers. The use of AI applications depends mainly on their acceptance, as already shown by Chao (2019), Niklas (2015) and Venkatesh et al. (2003) was highlighted. Various established models in the literature for analysing technology acceptance have been adapted for researching AI applications in the educational context (Scheuer, 2020; Stützer & Herbst, 2021). Due to the increasing awareness of AI applications, the study used these models to explore the acceptance of AI among teachers and students. This study is distinctive because it examines general attitudes towards AI applications and specific aspects relevant to lesson planning and teacher training. The insights gained will inform the design of tailored teacher training and professional development programmes for educators.

2 Technology acceptance and AI acceptance

Research in technology acceptance focuses on exploring the reasons that lead people to accept or reject certain technologies. It considers various factors influencing these decisions, such as the attitude of users, their knowledge of the technology and the framework conditions for its use (Kollmann, 1998, p. 42). *Acceptance* refers to the recognition, confirmation, approval or agreement of a fact, person or situation. Acceptance results from the relationship of the acceptance construct consisting of the acceptance subject, acceptance object and context (Holzapfel, 2014, p. 85).

Various technology acceptance models have been developed and tested over the years, with the Technology Acceptance Model (TAM) being one of the most significant (Ajzen, 1991; Ajzen & Fishbein, 1980; Davis et al., 1989). It is based on the *Theory of Planned Behavior* and was initially developed to investigate the behaviour of employees regarding the acceptance or rejection of computerised systems. The TAM suggests that the acceptance of technology use is mainly influenced by perceived usefulness and ease of use. Perceived usefulness refers to the belief that using a particular information technology improves job performance, while perceived ease of use refers to the extent to which a technology is perceived to be effortless. According to various studies, a positive assessment of these two factors increases users' probability of using a technology. Thus, perceived usefulness and ease of use influence the attitude towards technology use that precedes actual use. Since the original publication of the TAM, numerous other acceptance models for technology use have been presented, including the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). The UTAUT model combines eight of the most prominent models, including the *Theory of Planned Behavior* and the TAM, and aims to evaluate the acceptance of innovations by users based on four main factors. Based on TAM 3, Scheuer (2020) developed an acceptance model for the use of artificial intelligence (AI) called KIAM (Scheuer, 2020, p. 57). Tappe (2019) has, in turn, developed the UTAUT model (Venkatesh et al., 2003) and examined which factors promote or inhibit the use of digital media in the classroom (Tappe, 2019). He focuses on applying the UTAUT model to a didactic environment. Stützer and Herbst (2021, S. 298) have attempted to synthesise these models and transfer them to research practice (Stützer & Herbst, 2021, p. 298). This resulted in the model for AI acceptance in higher education.

3 The model for AI acceptance in education

The model for AI acceptance in education is a further development of the model for AI acceptance in higher education by Stützer and Herbst (2021) and its operationalisation by Stützer (2022). Figure 1 shows a brief overview. For further details of the model, please refer to Brandhofer & Tengler (2024).

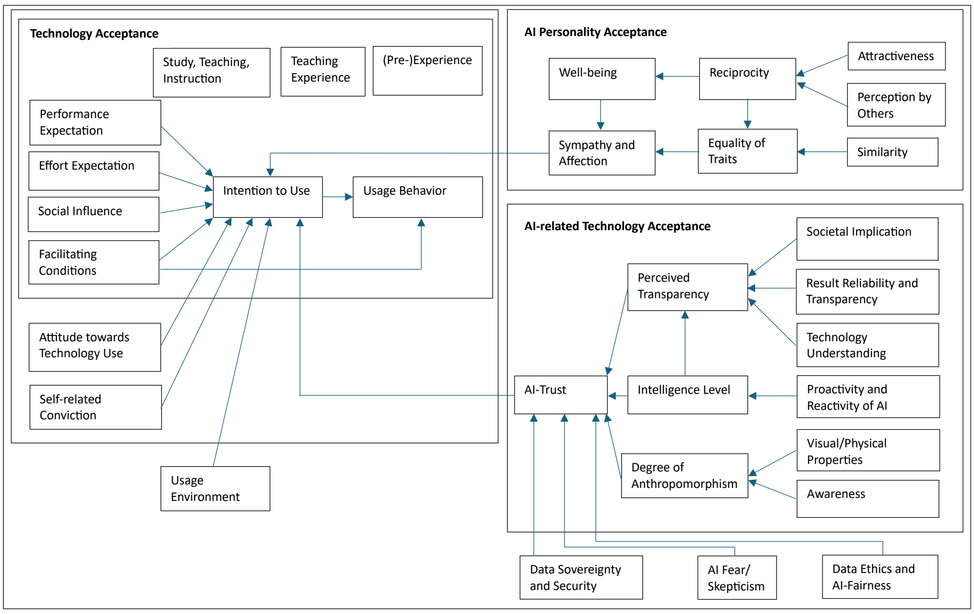

Figure 1 Model for AI acceptance in education (Brandhofer & Tengler, 2024)

The model considers the intention to use it as a latent dependent variable, influenced by technology acceptance, AI-related technology acceptance, and AI personality acceptance. The intention to use, in turn, influences user behaviour. The determinants of technology acceptance were derived from the UTAUT model or the adapted UTAUT model, according to Tappe (2019), which were selected and adapted. AI personality acceptance comprises the constructs of sympathy and affection. In contrast, AI-related technology acceptance subsumes AI trust, which is related to data sovereignty and data security, AI fear and AI scepticism, as well as data ethics and AI fairness. The determinants of AI-related technology acceptance and AI personality acceptance were derived from the KIAM model, according to Scheuer (2020, S. 63) and partially adapted.

An empirical survey was carried out to test the model, with three target groups: Students of the teaching profession at Austrian universities and university colleges, teachers at Austrian schools and university lecturers at Austrian universities in the teaching profession study program. Eight hundred thirteen data sets could be used to evaluate after cleaning (Brandhofer & Tengler, 2024).

3.1 Participant groups and evaluation methodology

Of these 813 people, 631 were female, 168 were male, four were diverse, and ten did not answer this optional question. Three hundred-eleven teachers from different types of schools, 345 student teachers, and 157 university lecturers participated.

This article aims to present selected correlations. Here are essential aspects for planning teaching and further training with artificial intelligence in school education. As parametric tests are subsequently used to examine correlations and differences between the groups, two conditions must be checked in advance. Parametric tests generally require that the sample data have a specific scale level and a particular probability distribution (Albrecht, 1974, p. 106; Bortz & Döring, 2006, p. 218). Therefore, The prerequisites for parametric tests are the mathematical-statistical condition of normal distribution and the homogeneity of variance in several groups.

The Kolmogorov-Smirnov test is usually used to check the normal distribution of samples (Albrecht, 1974, p. 108). As this test is no longer necessary above a sample size of 30 people and also becomes significant very quickly without being meaningful about the normal distribution of the sample, the Kolmogorov-Smirnov test was not used due to the sample size of 813 people. Due to the scope of the study, a normal distribution of the values can be assumed, which is also illustrated by the P-P diagram for the AI confidence construct (Bortz & Lienert, 2003, p. 203). (see in Figure 2)

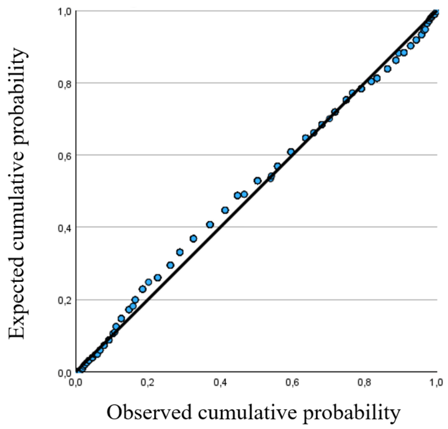

Figure 2 P-P diagram for the AI confidence construct, expected cumulative probability about the observed cumulative probability

The second requirement is the homogeneity of variance. The homogeneity of variance was checked; the Levene test is not significant, and the variance is homogeneous. This means this requirement for parametric tests for hypothesis testing is also fulfilled.

3.2 The use of AI applications

In addition to attitudes towards artificial intelligence, the intensity of the use of AI applications is also of interest for correlating correlations. The analysis shows a specific range in the use of

AI applications; in general, AI applications have been used relatively infrequently. 42.7% of all survey participants use AI applications once a week, and 33.5% do not use them at all. 13.5% work with AI applications 2-3 times a week, 10.5% more often. University lecturers work with AI applications most frequently, followed by school teachers (see Figure 3). Among students, 79.5% do not use AI applications or only once a week.

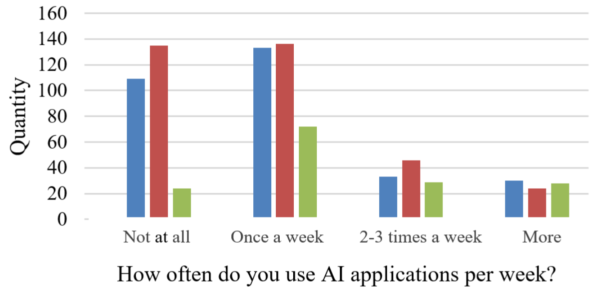

Figure 3 Use of AI applications by the participant groups (1 teacher, two students, three university lecturers

3.3 Technology acceptance

The three categories of the model, technology acceptance, AI-related technology acceptance and AI personality acceptance, will be examined in more detail below. The construct of technology acceptance comprises several determinants, including performance expectations and social influence. The study confirms the theoretical foundation of the model for AI acceptance in education; technology acceptance correlates significantly to integrating AI into everyday life (r_s = 0.522). The enormous effect of this correlation is highly significant at $p < 0.001$ (Bortz, 2005, p. 588).

Technology acceptance is least pronounced among students (*M* = 2.54, *SD* = 1.37). Regarding performance expectations about AI applications, teachers at secondary schools, vocational schools, and general secondary schools are the most optimistic. In contrast, teachers at polytechnic schools, vocational middle and secondary schools, and elementary schools need to be more convinced of the increase in efficiency through AI applications.

3.4 Trust in Artificial Intelligence

Trust in AI technologies is the main factor influencing the acceptance of AI-related technology. According to Scheuer (2020), this trust is mainly determined by perceived transparency, especially the transparency of results. In addition, the external appearance (degree of anthropomorphism) and the level of intelligence (interaction behaviour) significantly influence trust. Another decisive trust factor is the perception of one's control over the behaviour of the AI, which depends on the proactive or reactive behaviour of the system. The AI trust construct is therefore made up of several items (Brandhofer & Tengler, 2024), including data ethics/AI fairness, data sovereignty and data security and AI fear or AI scepticism.

The AI confidence construct was rated similarly in the individual participant groups (teachers *M* = 3.05, students *M* = 3.11, university lecturers *M* = 3.14). The evaluation of the results shows a significant correlation between the intention to integrate AI into one's everyday life and the construct of AI trust (r_s = 0.458). The enormous effect of this correlation is highly significant at $p < 0.001$ (Bortz, 2005, p. 588).

We want to take a closer look at one aspect of this construct. This relates to data ethics and AI fairness. Suppose this is set about teaching experience in a group of teachers. In that case, the most significant concerns regarding data protection and AI fairness are shown by the teachers with more than 39 years of teaching experience, followed by those with 10 - 19 years of teaching experience. A linear relationship between teachers' teaching experience and scepticism regarding data protection cannot be derived from the data.

3.5 AI personality acceptance

Affective aspects of the intention to use are taken into account in models of AI acceptance (Scheuer, 2020; Stützer, 2022; Stützer & Herbst, 2021) as well as the one on which this is based (Brandhofer & Tengler, 2024) combined in the AI personality acceptance construct. The contribution of the determinants of AI personality acceptance to explaining the intention to use depends primarily on whether the AI technology is perceived as an independent personality and whether the use of the technology is more rational or emotional. This is characterised by sympathy and affection and is operationalised by the reciprocal reference in communication and the equality of character traits.

The AI personality acceptance construct was rated most positively by the participant groups among school teachers (M = 2.93, SD = 1.04) and again particularly positively among teachers at elementary school (M = 2.76, SD = 1.12). A significant correlation with the intended use of AI was also confirmed here (r_s = 0.476). The evaluation of the items from this construct shows that the item understanding of technology was rated most positively, while the degree of anthropomorphism has the highest mean value. (Table 1)

Table 1 Mean values for the items surveyed from the AI personality acceptance construct

No.	Item	Mean Value	N	Std. Deviation
14	Social implication	2.98	811	1.187
15	Reliability and transparency of results	3.40	807	1.147
16	Understanding of technology	2.22	798	1.407
17	Proactivity and reactivity of the AI	2.76	805	1.449
18	Visual/physical characteristics	2.66	805	1.369
19	Awareness	2.96	807	1.724
26	Intelligence level	2.65	805	1.266
27	Degree of anthropomorphism	4.20	803	1.285
25	Perceived transparency	2.69	807	1.326

The sympathy and affection item from the AI personality acceptance construct was rated most positively by teachers at vocational schools (M = 2.34, SD = 1.59). In the evaluation by experience cohort, teachers with 0 - 10 years of teaching experience find AI applications the most likeable (M = 2.71, SD = 1.44). The evaluation by gender shows that women are significantly less sympathetic towards AI applications (M = 3.01, SD = 1.28) than men (M = 2.85, SD = 1.58). In contrast, there is no significant difference between women and men in perceiving AI as a personality (M = 4.21, SD = 1.48; M = 4.24, SD = 1.23).

3.6 Teaching experience and intended use

The connection between teachers' teaching experience and their openness to technology is the subject of controversial debate. The starting point for these discussions is very often Prenksy's presentation. He coined the term digital natives - a generation that, in contrast to digital immigrants, has already grown up with digital media and uses it intensively: "Today's students [...] represent the first generations to grow up with this new technology. They have spent their entire lives surrounded by and using computers, video games, digital music players, video cams, cell phones, and all the other toys and tools of the digital age" (Prensky, 2001, p. 23). The depiction of this dichotomy between digital natives and digital immigrants repeatedly found in the literature certainly does not appear to be accurate in this form (Brandhofer, 2015, p. 153). However, access to and use of technology is dependent on one's technology socialisation and experience (Flanagin & Waldeck, 2004; Gómez, 2020; Reidl et al., 2020; Suckfüll et al., 1999, p. 30). It is, therefore, worth taking a closer look at the dependence of AI acceptance on teachers' teaching experience.

The years of teaching experience of the teachers who participated in the survey were recorded and summarised in 10-year cohorts. Of the 465 teachers, 203 had 0 - 9 years of teaching experience, 108 had more than nine years, 84 had more than 19 years, 44 had more than 29 years, and 26 had more than 39 years. (see Figure 4)

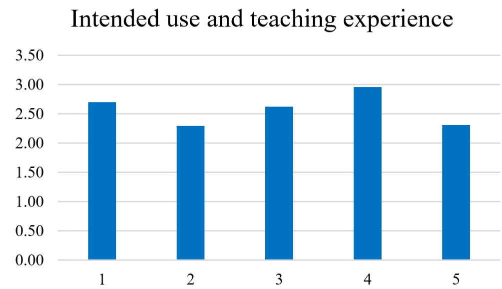

Figure 4 Mean values for intention to use teaching experience (1: 0-9 years, 2: 10-19 years, 3: 20-29 years, 4: 30-39 years, 5: more than 39 years

The group least inclined to integrate AI into their everyday lives are teachers with between 30 and 39 years of teaching experience (*M* = 2.95, *SD* = 1.31), followed by the group of people with 0 - 9 years of teaching experience (*M* = 2.71, *SD* = 1.35). Consequently, there needs to be a clear trend in the connection between intention to use and teaching experience. The situation is similar for the students who took part in the survey. The lowest intention to use is among students in their first semester (*M* = 3.24, *SD* = 1.25). A comparison of the participant groups shows that university lecturers are most likely to integrate AI into their everyday lives (*M* = 2.25, *SD* = 1.2), teachers at schools are less inclined to do so (*M* = 2.77, *SD* = 1.39), and students have the most significant reservations about it (*M* = 3.10, *SD* = 1.35). In summary, the intention to use AI applications is separate from the level of study progress or teaching experience.

3.7 Distortions due to AI applications

The survey results show that 10.2% of respondents do not believe, and 15.8% do not believe AI leads to injustice or systematic disadvantage (Brandhofer & Tengler, 2024). This result is surprising in the context of the discussion on biases in AI applications. Generative AI models can convey biases and false information to users, even without malicious intent (Adeoso et al., 2024; Haller et al., 2023; Horwath, 2022; Kidd & Birhane, 2023; Park & Hu, 2023; Sun et al., 2023). Colonial, discriminatory structures in AI applications depend not only on who owns the companies: "Discrimination and marginalisation are already part of the technical, material reality" (Geuter, 2024, p. 83).

Injustice and systematic disadvantage are most likely to concern students (*M* = 2.55, *SD* = 1.3), especially those in higher semesters. Among teachers, the groups of teachers at intermediate and higher vocational schools (*M* = 3.5, *SD* = 1.1) and vocational schools (*M* = 3.28, *SD* = 1.6) have the highest mean value. About teaching experience, the cohort of teachers with 30 - 40 years of teaching experience agrees least with the statement that AI leads to injustice or systematic disadvantage (*M* = 3.09, *SD* = 1.1). Men (*M* = 2.86, *SD* = 1.35) rated this item on data ethics and AI fairness lower than women (*M* = 2.60, *SD* = 1.36). Based on these results, however, we do not want to use a stereotypical representation of diversity.

3.8 The relationship between use, concerns and knowledge of AI applications

The question arises about how AI applications and the self-referential belief in AI applications are related. How often do teachers or students who claim to have the necessary knowledge to work with artificial intelligence use AI applications? A correlation matrix illustrates This relationship well (Table 2).

Table 2 Correlation matrix use of AI applications about self-referenced conviction

		I have the necessary knowledge to use AI.				
		Agree	Tend to agree	Partly/partly	Rather disagree	Disagree
How often do you use AI applications per week?	Not at all	33	61	64	45	57
	Once a week	83	139	76	33	6
	2-3 times per week	48	28	21	8	3
	More	34	17	25	4	2

Use once a week, and agree that one is more likely to have the necessary knowledge to use AI applications, which has the highest number of cases here. The results of the associated correlation analysis show a medium correlation between usage (inverted) and self-referenced conviction ($r_s = 0.297$, $p < 0.001$).

AI applications are also critical in connection with concerns about data ethics and legal standards. Are AI applications used despite these concerns? A correlation matrix is again used to illustrate the relationship (Table 3).

Table 3 Correlation matrix use of AI applications about data ethics and AI fairness

How often do you use AI applications per week?	I have concerns about compliance with data ethics and legal standards.				
	Agree	Tend to agree	Partly/partly	Rather disagree	Disagree
Not at all	6	8	43	85	116
Once a week	16	38	87	122	74
2-3 times per week	4	15	24	30	33
More	6	16	20	26	14

Infrequent use is closely related to data ethics and legal concerns; the field with the highest number of cases is that with use once a week, and partial concerns about data ethics and legal standards in AI applications, followed by the field on no use and significant concerns. According to the correlation analysis, there is a low correlation between use (inverted) and the item on data ethics and AI fairness ($r_s = 0.165$, $p < 0.001$).

4 Summary, evaluation and outlook

Based on the correlation analyses, the model for AI acceptance in education can be supported. Compared to the study by Scheuer (2020), the lower degree of perceived anthropomorphism stands out. Scheuer's study was based on two specific chatbots, while the underlying survey was dedicated to AI applications in general (Brandhofer & Tengler, 2024).

The survey results show that teachers and student teachers are generally optimistic about the opportunities offered by AI. They think that they can work more flexibly and efficiently with the help of AI applications and see AI in schools and universities as an opportunity rather than a risk. Despite positive attitudes towards AI applications, there are concerns regarding data ethics and legal standards, among other things.

What insights can be drawn from the collected data for school teacher training and further education? The study results make clear the complexity of the topic of artificial intelligence in schools. This includes the fact that they are rarely used despite a fundamentally positive attitude towards AI and the widespread assumption that people have the necessary knowledge to deal with AI applications. Low usage makes it more difficult for teachers to develop expertise in AI. This is also related to the time resources of teachers and student teachers. The statement by Watanabe et al. on higher education applies equally to teachers at schools: "However, it is questionable whether university actors without significant experience can make a sufficiently valid assessment of the extent to which a perceived threat of AI-driven data use can be controlled" (Watanabe et al., 2023, p. 274).

It also shows that formats for further education and training should consider the discourse on bias in AI, data protection and legal issues. It will be challenging to achieve the necessary level of discussion and reflection here with the help of self-study courses without the opportunity for exchange between the participants. In addition, the challenges of dealing with artificial intelligence vary greatly depending on the type of school. The approach to the topic will and must be different in an elementary school than, for example, in vocational secondary schools, and school-type-specific offers for further and continuing education are necessary. In addition to the application-oriented approach and training in prompt formulation, evaluating the output of generative AI is significant. Learning *with* AI is essential to educational measures, but learning *about* AI should be addressed. It should also be noted that the promotion of AI literacy affects all age cohorts of teachers and student teachers to the same extent.

Targeted and comprehensive promotion of expertise in AI is necessary to ensure the effective integration of artificial intelligence in the educational context, successfully overcome potential challenges, and introduce students to its competent use.

Conflicts of interest

The authors declare that they have no conflict of interest.

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