Teachers' trust and perceptions of AI in education: The role of culture and AI self-efficacy in six countries

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Abstract

AI-based educational technology (AI-EdTech) is increasingly adopted in K-12 education. Teachers play a critical role in this process as they are expected to use AI-EdTech in ways that support their teaching practice and students' learning outcomes. Teachers' willingness to meaningfully integrate these technologies into their everyday educational activities depends on their attitudes toward AI-EdTech. We surveyed 508 K-12 teachers in six countries across four continents (Brazil, Israel, Japan, Norway, Sweden, USA) about the perceived benefits of, concerns about, and trust in AI-EdTech. We examine demographic, geo-cultural, professional, and psychological factors that might influence teachers' attitudes. Our results showed that teachers with higher AI understanding and self-efficacy perceive more benefits, fewer concerns, and stronger trust. We also found geographic and cultural differences in teachers' attitudes, including their trust in AI-EdTech, but no demographic differences emerged based on their age, gender, or level of education. The findings provide a comprehensive, international account of factors influencing teachers' attitudes toward AI-EdTech. Efforts to raise teachers' understanding of, and trust in AI-EdTech, while considering their cultural values are encouraged to support its adoption in K-12 education.

Keywords: Education, Teachers, Attitudes, Trust, Culture, Survey

1 Introduction

Over the last decade, artificial intelligence-based educational technology (AI-EdTech) has been increasingly used in K-12 (kindergarten, primary and secondary) education across many countries (Holmes, Persson, Chounta, Wasson, & Dimitrova, 2022; Nazaretsky, Ariely, Cukurova, & Alexandron, 2022; Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). Its use has accelerated since 2019 across all school years (Crompton, Jones, & Burke, 2022) and evolved towards the end of 2022 with the rapid integration of generative AI technologies due to the sudden popularity of OpenAI's ChatGPT (Lim, Gunasekara, Pallant, Pallant, & Pechenkina, 2023). AI-EdTech can potentially improve students' learning outcomes, critical thinking, and problem-solving skills (Wu & Yang, 2022), for example, by providing more immediate feedback and personalized learning paths (Benotti, Martnez, & Schapachnik, 2017). AI-EdTech also promises benefits for teachers. According to a recent systematic review, these include improved planning (e.g., around students' needs), implementation (e.g., immediate feedback and teacher intervention), and assessment (e.g., through automated essay scoring) (Celik, Dindar, Muukkonen, & Järvelä, 2022). Such benefits have the potential to improve the conditions for student learning and ultimately lead to improved learning outcomes. However, our understanding of the impact of AI-EdTech on teaching and learning is in its infancy as there is not yet widespread adoption of AI-EdTech in schools.

A critical area for systematic investigation is teachers' perspectives on AI-EdTech because they are ultimately the ones who need to meaningfully integrate it into their routines in ways that improve student learning and support their everyday teaching practices (Kizilcec, 2023; Seufert, Guggemos, & Sailer, 2021). Although teachers are essential stakeholders for AI-EdTech, our scientific understanding of their attitudes towards this technology, and what individual and contextual factors influence their attitudes, is limited (e.g., Cukurova, Miao, & Brooker, 2023; Velander, Taiye, Otero, & Milrad, 2023). Cukurova and colleagues (2023) note that the "slow adoption of AIED systems in real-world settings might, in part, be attributable to the frequent neglect of a range of other factors associated with complex education systems" (p. 152).

Prior research has examined several factors influencing teachers' adoption of AI-EdTech in education. These include teachers' level of knowledge about AI (e.g., Velander et al., 2023), perceived self-efficacy, anxiety, perceived usefulness, perceived ease of use (e.g., Almaiah et al., 2022; Wang, Liu, & Tu, 2021), and trust in these technologies (e.g., Nazaretsky, Ariely, et al., 2022; Nazaretsky, Cukurova, & Alexandron, 2022). In addition, a teacher's decision to adopt a new technology, such as AI-EdTech, is influenced by their initial perceptions of the technology (Moore & Benbasat, 1991). In particular, as Agarwal and Prasad (1997) point out, individuals "will be less likely to experiment with new technologies if they perceive a significant risk associated with such exploration" (p.574). Yet, teachers' attitudes toward AI-EdTech have received limited research attention, especially at scale and across countries. Only recently have researchers established frameworks for assessing teachers' perceived benefits, concerns, and trust related to AI-EdTech (Al Darayseh, 2023; Choi, Jang, & Kim, 2023; Nazaretsky, Ariely, et al., 2022; Nazaretsky, Cukurova, & Alexandron, 2022). This has created a foundation for studying factors that influence teachers' adoption of AI-EdTech in schools around the world (Cukurova et al., 2023; Kizilcec, 2023).

Multi-national studies are important in this domain because individuals' attitudes towards technology adoption are known to differ considerably across countries (F. Huang, Teo, Sánchez-Prieto, García-Peñalvo, & Olmos-Migueláñez, 2019; Morrone, Tontoranelli, & Ranuzzi, 2009), and people's trust in automation can be influenced by cultural differences (Berkovsky, Taib, Hijikata, Braslavsku, & Knijnenburg, 2018; Chien, Sycara, Liu, & Kumru, 2016; H.-Y. Huang & Bashir, 2018). In their seminal review of culture in information systems research (a review of 82 articles), Leidner and Kayworth (Leidner & Kayworth, 2006) found that several dimensions of culture influence the adoption and use of information technology. Their analysis is grounded in Hofstede's model of cultural values (Hofstede, Hofstede, & Minkov, 2010), the most often used model to conceptualize and study culture. Their findings show that four cultural values, namely uncertainty avoidance, power distance, masculinity (vs. femininity), and collectivism (vs. individualism), are important predictors of technology adoption (see Background for details). Context is known to play an important role in assessments of trust (Hong, An, Akerkar, Camacho, & Jung, 2019; Klein et al., 2019), and to our knowledge, there is no prior research on the impact of culture on school teachers' attitudes, including their level of trust—an affective attitude (Jones, 1996)—toward AI-EdTech.

To improve our scientific understanding of factors that influence teachers' adoption of AI-EdTech, the present study investigates teachers' attitudes in terms of *perceived benefits, concerns,* and *trust* in AI-EdTech in the context of K-12 education in six countries (Brazil, Israel, Japan, Norway, Sweden, USA). We selected countries to represent distinct geographic areas (North Europe, East Asia, Middle East, North and South America) in which individuals' cultural values are expected to differ along several dimensions (e.g., uncertainty avoidance and power distance) based on prior work by Hofstede and colleagues (2010). We also note that these countries differ in terms of their overall 2022 readiness to utilize AI according to the Oxford Insights Government

AI Readiness Index (Rogerson, Hankins, Fuentes Nettel, & Rahim, 2022). Considering the importance of cross-cultural differences in people's attitudes about automation and ICT (information and communication technologies), this study aims to understand better how teachers' attitudes, including the perceived benefits, concerns, and trust in AI-EdTech vary across countries and cultural value dimensions. This study marks an important step towards understanding the teacher perspective and developing interventions to support teachers' effective adoption and use of AI in schools to realize its full potential. Our study addresses the following overarching research question:
RQ: To what extent are K-12 teachers' perceived benefits, concerns, and trust in AI-EdTech influenced by (a) demographic and professional characteristics, (b) AI self-efficacy and understanding, (c) cultural values, and (d) geographic location?

2 Background

2.1 Teachers' attitudes about adopting AI-EdTech in schools

Research conducted so far on teachers' attitudes towards adopting AI-EdTech in schools has come to mixed and inconsistent conclusions. For example, Al Darayesh (Al Darayseh, 2023) examined teachers' perceptions ($N = 83$) of the factors that influence the use of an AI application in science education in a Middle Eastern school context. Building on the Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989), the findings indicated high acceptance of AI-EdTech by science teachers and a positive association of acceptance with self-efficacy, ease of use, expected benefits, and behavioral intentions. The study did not find evidence that teachers' level of anxiety and stress about AI-EdTech influence their adoption. In another study, Chounta and colleagues (2022) surveyed teachers ($N = 140$) regarding their perceptions of AI as a tool to support teaching in Estonian schools. They found that teachers are concerned about the effort it would require them to learn how to appropriately use AI technologies and about potential trust issues that could arise (for more about teachers' trust, see Section 2.3). The teachers reported limited knowledge about AI, and how it could support them in everyday teaching practices. The researchers partly attributed teachers' concerns to the socio-cultural context of the study: the teachers perceived AI as a tool to assist them in dealing with multilingual content.

Cukurova and colleagues (2023) developed a new instrument to measure factors that influence teachers' adoption of AI-EdTech, and to predict teachers' engagement with adaptive learning platforms. The survey results ($N = 792$ teachers in the United Arab Emirates) showed that teachers' knowledge, confidence, and AI-EdTech product quality are important factors. Additionally, ensuring that the tool does not create more workload, increasing teachers' sense of ownership and trust, providing teachers with support mechanisms, and assuring that ethical issues are mitigated are all important factors influencing the adoption of AI in schools. Unlike traditional methods of predicting teachers' *perceived adoption* with survey responses as the dependent variable, they used engagement logs of teachers from the tool as a proxy of *actual adoption* and showed that the factors above could be used to effectively predict teachers' real-world adoption of AI-EdTech in schools (Cukurova et al., 2023).

In a survey of 714 vocational senior high school teachers in Taiwan, Chou and colleagues (2023) developed a survey measure of teachers' efficacy perceptions of AI-based teaching applications and examined variation based on teacher characteristics. They found significant differences in self-efficacy based on teachers' gender (male vs. female), job position (executive staff vs. teacher vs. teacher and administrator), seniority (in years), and experience in teaching with AI-EdTech (in years). Furthermore, a survey of 428 teachers in Turkey examined AI self-efficacy (Celik, 2023) using a newly developed scale based on the TPACK framework (Koehler & Mishra, 2009). The results indicated that teachers' technological and pedagogical knowledge is critical for integrating AI-EdTech in classroom practice.

Thus, while several studies have examined teachers' attitudes toward adopting AI-EdTech and its underlying factors, their findings are mixed and mostly specific to a single country's context. This raises questions about the generalizability of these findings and calls for large-scale, cross-cultural research on teachers' attitudes and factors that may influence their attitudes. The present research addresses this call by studying teachers' attitudes regarding their perceived benefits, concerns, and trust in AI-EdTech across countries. We also study previously overlooked factors, including various teacher characteristics and cultural values, which may influence their willingness to meaningfully adopt AI-EdTech and use it to promote students' academic success in K-12 education.

2.2 Trust in AI

Trust is a consequential affective attitude (Jones, 1996). It matters in both interpersonal relationships (Slovic, 1993) and people's relationships with technology (Mcknight, Carter, Thatcher, & Clay, 2011), including teacher's relationship with AI-EdTech. It is recognized as "a critical aspect of AI adoption and usage" (Lukyanenko, Maass, & Storey, 2022, p. 1994). In this study, we focus specifically on trust in AI-EdTech compared to trust in people and organizations such as schools. With the rise of AI, the issue of trust in AI has become especially important, and despite scholars' increased attention to the topic, evidence in this area remains fragmented, especially in K-12 education settings (Kizilcec, 2023). Lukyanenko and colleagues (2022) note, "trust in the broader systems [e.g., K-12 education], in which AI is embedded due to AI being a component of the system, has, so far, escaped much research" (p.2008). Consequently, in this study, when studying teachers' attitudes, we also examine their affective attitudes regarding their trust in AI-EdTech.

There are many definitions of trust and trust in AI, and there is a lack of consensus around a widely accepted definition (for an overview, see (Lukyanenko et al., 2022; Mcknight et al., 2011)). For this study, we adopt the following systems-based definition of trust in AI: "a human mental and physiological process that considers the properties of a specific AI-based system, a class of such systems or other systems in which it is embedded or with which it interacts, to control the extent and parameters of the interaction with these systems" (Lukyanenko et al., 2022, p. 12). This definition suggests that a teacher's trust in AI is not static but rather a dynamic process that evolves, which is in line with earlier work on trust and trust formation (e.g., Glikson & Woolley, 2020; Lumineau & Schilke, 2018).

How trust develops and is sustained is important in implementing a system, and culture can play a major role in this process (Yerdon, Marlowe, Volante, Li, & Hancock, 2017). Too much or too little trust in automation can lead to misuse and disuse of a system (Hancock et al., 2011). Trust in a specific technology reflects individuals' (here, teachers') beliefs about its favorable attributes. Trusting beliefs can be decomposed into three components according to Mcknight et al. (2011): (1) beliefs about functionality, i.e., "whether one expects a technology to have the capacity or the capability to complete a required task", (2) beliefs about helpfulness, i.e., "a feature of the technology itself", and (3) beliefs about reliability, i.e., "one expects technology to work consistently and predictably" (p.12).

2.3 Teachers' trust in AI-EdTech

The 2022 *European Commission Ethical Guidelines on the use of AI and data in teaching and learning* explicitly called out the promotion of excellence and trust in AI as a priority for the Commission (Commission, Directorate-General for Education, & Culture, 2022). However, few evidence-based research studies have examined teachers' trust in AI-EdTech thus far. One study proposed a survey instrument to measure teachers' trust in AI-EdTech and validated it among 132 high-school biology teachers in Israel (Nazaretsky, Cukurova, & Alexandron, 2022). Their instrument comprised eight subscales, including the perceived benefits of AI-EdTech and anxieties related to using AI-EdTech. This work extends our theoretical understanding of the human factors influencing the acceptance of AI-EdTech among K-12 teachers.

Another study examined teachers' perceptions of AI as a tool to support teaching in Estonian K-12 education, focusing on Fairness, Accountability, Transparency, and Ethics (Chounta et al., 2022). They specifically found that teachers have concerns about trusting AI tools. For example, some teachers in the study stated that they would not trust AI to carry out tasks without error, which echoes the phenomenon of *algorithm aversion* previously highlighted in AI-adoption research in other domains (Dietvorst, Simmons, & Massey, 2015). Teachers were critical of how AI could undermine human-to-human communication and obstruct social components of learning. Nazaretsky and colleagues (2022) suggested one way to overcome this challenge in a study that developed and evaluated a teacher professional development program (PDP) to increase teachers' trust in AI-EdTech in K-12 settings. The results showed that during the PDP, teachers gained important knowledge about AI-powered assessment, which helped forestall some of their misconceptions and biases related to the nature of AI-EdTech. By the end of the program, teachers expressed a higher willingness to use AI-EdTech in their classrooms and proposed innovative ways to integrate this tool into their pedagogy. They were also more open to data-driven decision making, which can reinforce their positive attitudes toward AI. This highlights the importance of improving an understanding of AI among teachers to develop trust and acceptance.

Self-efficacy beliefs can be a key determinant of trust among teachers and self-efficacy has been found to influence trust in AI in a teacher-focused study (Nazaretsky, Ariely, et al., 2022). Bandura (1977) defined self-efficacy as confidence in one's ability to perform a task or undertake an endeavor. Self-efficacy has been found to influence persistence tasks and interest expression (Evans, Luft, Czerniak, & Pea, 2014). The development of self-efficacy requires experiences overcoming obstacles through continuous effort (Usher & Pajares, 2008). Thus, prior experience can help build self-efficacy and foster trust, as shown in He et al.'s (X. He, Stapel, Wang, & Happee, 2022) study examining the link between trust and experience with driving automation. Experienced drivers tended to be less sensitive to risk and more trusting of automation.

Although this review of related work presents some initial progress towards understanding teachers' perspectives and trust in AI-Edtech as well as their influence on adoption in schools, it also highlights a lack of cross-cultural research on teachers' perceptions of, and trust in, AI-EdTech that compares attitudes in different parts of the world.

2.4 Cultural differences in technology adoption and trust in EdTech

Individual's cultural values differ across countries (Hofstede et al., 2010), which can influence people's responses to their environment, and how much they trust people and institutions (e.g., Doney, Cannon, & Mullen, 1998; Hofstede et al., 2010; Klein et al., 2019) as well as technology and automation (e.g., Berkovsky et al., 2018; Chien, Lewis, Hergeth, Semnani-Azad, & Sycara, 2015; H.-Y. Huang & Bashir, 2018; Yerdon et al., 2017). As highlighted by Chien and colleagues (2015), "cultural values and norms can greatly influence an individual's trust and reliance on the automation as well as the formation, dissolution and restoration of trust" (p.688).

The role of culture in teachers' attitudes, including their trust in AI-EdTech in educational settings, is relatively understudied in the broader literature on culture in education. Relevant research in other contexts has studied different types of information and communication technologies, including AI tools. For example, Chien et al. (2016) examined the effects of cultural characteristics (i.e., the dimensions of power distance, individualism, and uncertainty avoidance, and personality traits on reported trust in automation in Taiwanese, Turkish, and US samples. They found that uncertainty avoidance and individualism were significantly correlated with respondents' general trust in automation in the US and Turkish sample, but not in the Taiwanese sample. In another study, Berkovsky et al. (2018) examined cultural differences when using recommendation systems across four countries (France, Japan, Russia, and the US). Their experiments with 102 participants from these countries found cultural differences in preferences for information presentation and explanation based on nine constructs of trust (e.g., transparency and integrity). They used Hofstede's original scores for the masculinity dimension to interpret their results (Hofstede et al., 2010): a culture's masculinity score (e.g., high in Japan) was strongly correlated with participants' preference for human (vs. AI) presentation and personalized explanations because they had more trust in them. Finally, Yerdon and colleagues (2017) examined cultural differences in trust in the setting of automotive automation, specifically for autonomous driving. They found that a driver's expected communication style, which varied based on the cultural dimension of individualism/collectivism, significantly affected their level of trust. Together, these studies demonstrate the importance of cultural differences in people's trust in different technologies and forms of automation.

The present study employs Hofstede's theoretical model of national culture (Hofstede et al., 2010) to examine the possible influence of teachers' cultural values on their perceived benefits, concerns, and trust in AI-EdTech. Hofstede and colleagues (2010) define culture as "the collective programming of the mind which distinguishes the members of one group or category of people from another" (p.5). While our study is grounded in Hofstede's model of culture and its core dimensions (individualism/collectivism, masculinity/femininity, power distance, uncertainty avoidance, and long/short-term orientation), we do not assume homogeneity in cultural values within a nation. Instead, we use these cultural dimensions to examine teacher's individual cultural values and how they relate to their perceived benefits, concerns, and trust in AI-EdTech. We chose to adopt Hofstede's model since it can "explain human behaviors better than other measures, such as country and language" ((Li, 2022), p. 269). It has previously been used to study cultural differences in students' and teachers' attitudes towards technology use in educational settings (F. Huang et al., 2019; Tarhini, Hone, Liu, & Tarhini, 2017; Viberg & Grönlund, 2013), as well as trust in information systems, including AI technologies (Berkovsky et al., 2018), and automation across countries (Chien, Lewis, Sycara, Liu, & Kumru, 2018).

3 Methods

3.1 Context and Participants

We collected responses from school teachers in six countries. Table A1 provides a comprehensive overview of sample characteristics. The data collection process (described below) varied across countries to adhere to local research standards. We obtained approval from institutional or national ethics boards before data collection, and all respondents included in the analysis provided informed consent. Teachers' participation was voluntary, and data collection occurred between November 2022 and June 2023.

The Israeli sample was collected from middle and high school science, math, and computer science teachers. The survey was distributed among in-service teachers' professional development communities and teachers studying for a master's degree in science education. Teachers completed the survey using an online platform built on WordPress. The survey items for measuring teachers' perceived benefits, concerns, and trust in AI-EdTech were originally composed in Hebrew and validated by (Nazaretsky, Cukurova, & Alexandron, 2022). The culture-related items were first translated into Hebrew and validated by the Israeli research team and the five additional science education experts. The research received ethical approval from an Institutional Review Board (IRB) committee (code number 11862).

The Norwegian sample was collected at five upper secondary schools in Norway's east, south, and western parts. All selected schools are medium to large schools in terms of the number of students, spanning from about 300 to 1000. School principals were sent information about the study and they invited their teachers to participate in the survey. Principals either sent the researchers a list of the teacher's e-mail addresses and they were sent the survey link, or they distributed the link to the survey directly to their teachers. After a short introduction to the study, the researchers involved, and the right to withdraw, teachers provided consent for the data to be used for research and proceeded to the survey. The online survey was administered using the software SurveyXact, which allowed for anonymous participation. The researchers translated the survey instrument into Norwegian, and several rounds of editing were conducted. The agency reported and approved the study for privacy and ethical concerns in research at the University of Bergen.

The Swedish sample was collected from junior and senior upper secondary school teachers. The survey was distributed among in-service teachers through professional development communities and the schools' principles, as well as through a newsletter sent by the Swedish National Agency of Education in May 2023. The survey instrument was translated into Swedish and validated by the Swedish research team, the two additional experts and the two teachers who piloted the survey items. The survey was distributed through an online platform, Artologik Survey and Report. Ethical approval was obtained from the National Ethical Review Board (2023-00291-01) in March 2023.

The Brazilian sample was collected from secondary school teachers using social media channels, and through the mailing list of a research center focused on basic education school teachers in Brazil. In addition to sending the survey link to teachers' school email lists, the professional network of the Regional Center for Studies on the Development of the Information Society was approached. The survey was cross-translated to Portuguese, and teachers completed the survey online using the Qualtrics survey platform. The survey had a preamble section informing the teachers about the study, the purpose of the research, the team involved, and the right to withdraw at any time. Teachers who agreed to proceed were asked to consent to data collection and use for research purposes. The study protocol received ethics approval from the institutional ethics board (REC 1760: Trust in AI-based EdTech and Cultural Values) and the data protection registration (Z6364106/2023/01/153).

The US teacher sample was collected by asking a superintendent to distribute the survey among teachers in a school district located in Upstate New York. A short study description was provided along with the URL to Qualtrics survey. The description read "Research about AI in Classrooms (short survey): The Future of Learning Lab, as part of an international research effort to support teaching practices, is inviting high school science teachers to complete a 15-20min survey about their attitudes toward AI-based technology for teaching. The study will compare teachers' responses across [countries]." The institutional review board at Cornell University approved the study protocol.

The Japanese sample was collected from junior high and high school teachers in science, mathematics, and computer science. Using Microsoft Forms, the anonymous online survey was distributed to several junior high and high school teachers' networks in Japan, where the co-authors are based. All the original questionnaire items in English were translated into Japanese and validated by the Japanese research teams. The research received ethical approval from an IRB committee (code number 2022-24).

3.2 Measures

An anonymous online survey was distributed to K-12 teachers in different countries. The survey instrument was structured into four parts: teacher characteristics, AI self-efficacy and understanding, perceived benefits, concerns, and trust in AI-EdTech, and finally, cultural values. The complete questionnaire is available on OSF: https://osf.io/abe9u/?view_only=b691f9365c0b4272b9472df5e81518f0.

Teacher characteristics: Respondents were asked to indicate their gender identity, age group, highest level of education, primary teaching subject(s), and the number of years of experience in education, and specifically experience using EdTech tools in teaching. Table A1 shows the response options for all items with response distributions in each sample and overall.

AI Self-efficacy: Self-efficacy was measured using an index of two items: "How knowledgeable are you about AI applications' use in education?" (5-point scale from Not knowledgeable at all [1], Slightly knowledgeable, Moderately knowledgeable, Very knowledgeable, to Extremely knowledgeable [5]), and "How confident are you discussing AI applications in education with others?" (5-point scale from Not confident at all [1], Slightly confident, Moderately confident, Very confident, to Extremely confident [5]). Responses were averaged into an index with high internal reliability (see Cronbach's alpha in Table A2).

AI Understanding: We assessed teachers' understanding of AI by asking them to select from a set of options the ones they consider the closest description of AI. This item was inspired by previous surveys on public perceptions of AI (e.g., Cave, Coughlan, & Dihal, 2019). As there is not one correct description of AI, we provided five options that vary in how accurately they describe AI in the context of EdTech. The two options we deemed most accurate (coded as 1) were "an algorithm for making decisions based on big data" and "a relationship between concepts, problems, and methods for solving problems." The two options we deemed least accurate (coded as -1) were "autonomous robots" as in terminator-like science fiction and "automated tasks that repeat themselves" as in traditional software. One option we deemed moderately accurate (coded as 0.5): "a replica of human intelligence" as in a simulation of human intelligence by machines (Dong, Hou, Zhang, & Zhang, 2020). We convert responses into a score between -2 to 2.5 by adding up the coded values.

Perceived benefits of AI-EdTech: Benefits were measured using an index of seven statements adopted from (Nazaretsky, Cukurova, & Alexandron, 2022): e.g. "Artificial Intelligence can assist teachers with in-class management activities, such as identifying students who are off-task." Responses to the seven statements were rated on a 5-point Likert scale and averaged with high internal reliability (see Cronbach's alpha in Table A2). The response scale ranged from strongly disagree (1), disagree (2), neither agree nor disagree (3), agree (4), to strongly agree (5).

Perceived concerns of AI-EdTech: Concerns were measured using an index of 5-point Likert-scale responses to nine statements adopted from Nazaretsky, Cukurova, and Alexandron (2022): e.g. "AI algorithms do not understand social, emotional, and motivational factors that are very important in teaching." Responses to the nine statements were averaged into an index with high internal reliability (see Cronbach's alpha in Table A2).

Trust in AI-EdTech: Trust was measured using an index of 5-point Likert scale responses to nine statements adopted from (Nazaretsky, Cukurova, & Alexandron, 2022): e.g. "I fully trust using AI-based educational technology in my classroom." Responses to the nine statements were averaged into an index with high internal reliability (see Cronbach's alpha in Table A2).

Cultural Values (power distance, uncertainty avoidance, collectivism, long-term orientation, and masculinity): We use the Individual Cultural Values Scale (CVSCALE) (Yoo, Donthu, & Lenartowicz, 2011) to measure teachers' cultural values with 26 items. This instrument is based on Hofstede's (Hofstede et al., 2010) cultural categories, but instead of assessing culture at the national level, it operates at the individual level, and it is valid for both "student and non-student samples" (p. 205) in five countries (Yoo et al., 2011). Each cultural values dimension is an index of four to six statements rated on a 5-point Likert scale: strongly disagree (1), disagree (2), neither agree nor disagree (3), agree (4), strongly agree (5).

3.3 Analytic Approach

To answer our research question, we fit three multiple linear regression models, one for each outcome variable (benefits, concerns, trust), with teacher characteristics as predictors (demographic, professional, AI self-efficacy and understanding, and cultural values). To account for the geographical clustering in our data, we use country fixed effects instead of random effects (i.e. a mixed-effects model), because it guarantees statistical consistency and the key assumption that the predictors are uncorrelated with the random intercept does not hold (Bell, Fairbrother, & Jones, 2019). In particular, we checked the models for potential multicollinearity by computing the variance inflation factor (VIF) for each predictor variable: all VIF scores are below 3, except for the sample fixed effects. This indicates that all predictor variables are sufficiently uncorrelated (VIF scores below 10 indicate low levels of multicollinearity), and there is no need to apply variable selection (it would not significantly change our findings). The higher VIF scores for the sample fixed effects indicate that the predictor variables are correlated with the country fixed effect, which violates a central assumption of random effects models, and leads us to use a fixed effect model.

Table 1 shows the pooled regression results with heteroskedasticity-robust standard errors. We performed ten imputations with predictive mean matching over 50 iterations to impute a small amount of missing data (using the *mice* package in R (Van Buuren & Groothuis-Oudshoorn, 2011). The share of missing values was less than 7% of observations. Following best practices for analyzing multiply imputed data, we fit the same multiple linear regression model on each of the ten imputed datasets and pool the results. This method accounts for the uncertainty associated with imputing missing data directly in the calculation of standard errors and p-values (Van Buuren & Groothuis-Oudshoorn, 2011). The results are reproducible using the analysis script and de-identified data available on OSF: https://osf.io/abe9u/?view_only=b691f9365c0b4272b9472df5e81518f0.

4 Results

The samples collected across six countries cover a range of demographic characteristics, academic subjects, and levels of experience with teaching and technology (Table A1). The average level of perceived benefits, concerns, and trust in AI-EdTech is overall slightly above the neutral midpoint. The three outcome variables (benefits, concerns, and trust) are significantly correlated with each other; additionally, self-efficacy is positively correlated with perceived benefits, collectivism is positively correlated with concerns, and masculinity is negatively correlated with trust (see Table A2). We conducted a multiple linear regression analysis for each outcome variable and included all independent variables as sample fixed effects. Note that we include all predictors at once because there is no evidence of multicollinearity (i.e., correlations between predictors; all VIF scores ¡ 3) and thus no need to perform variable selection. The regression results, presented in Table 1, yield the following five main findings that are statistically significant while adjusting for all other factors.

First, the regression results show that both AI self-efficacy (i.e., teachers' beliefs in their ability to use and discuss AI-EdTech) and AI understanding (i.e., how well teachers understand AI in lay terms) are associated with their attitudes towards AI in education. We find that more AI self-efficacy and more AI understanding significantly predict more perceived benefits, trust, and fewer concerns.

Second, we find several individual cultural values significantly predict teacher attitudes, including their trust in AI-EdTech. In particular, higher uncertainty avoidance and higher long-term orientation are associated with more perceived benefits of, and higher trust in, AI-EdTech. In contrast, higher masculinity is associated with lower perceived benefits and more concerns regarding AI-EdTech in the context of K-12 education. Collectivism is also associated with increased concerns.

Third, we find that teachers with more experience in education have fewer concerns. However, beyond this association, we find that teacher's age, gender identity, level of education, and the subject they teach do not explain their attitudes toward AI-EdTech in teaching. The absence of attitudinal variation associated with sociodemographic and subject characteristics is remarkable.

Finally, we find country-level variation across samples in teachers' attitudes. Teachers perceive more benefits and fewer concerns about AI in education and trust it more in Brazil, Israel, and Japan than in Norway, Sweden, and the United States. Teachers in the Israeli sample also perceived slightly more concerns relative to the Brazilian sample.

5 Discussion and Conclusions

This study investigated several factors that may influence K-12 teachers' willingness to effectively adopt AI-EdTech: (a) their demographic and professional characteristics, (b) AI understanding and self-efficacy, (c) cultural values, and (d) geographic location. Our survey of teachers' perceived benefits, concerns, and trust in AI-EdTech across six geographically and culturally distinctive samples offers compelling new evidence

Table 1 Results for multiple regressions explaining perceived AI benefits, concerns, and trust with various teacher characteristics, including attitudes, cultural values, with sample location fixed effects. Standard errors in parentheses are heteroskedasticity robust.

	Benefits	**Concerns**	**Trust**
(Intercept)	2.47^{***} (0.43)	2.65^{***} (0.32)	2.06^{***} (0.33)
AI Self-Efficacy	0.18^{***} (0.04)	-0.13^{***} (0.03)	0.16^{***} (0.03)
AI Understanding	0.11^{*} (0.04)	-0.07^{*} (0.03)	0.10^{**} (0.03)
Experience in Education	0.01 (0.05)	-0.09^{*} (0.04)	-0.00 (0.04)
Teaching with Technology	0.03 (0.05)	0.08 (0.04)	0.02 (0.04)
Highest Edu.: Master	-0.13 (0.08)	0.03 (0.06)	-0.09 (0.07)
Highest Edu.: Doctorate	-0.04 (0.15)	-0.08 (0.12)	-0.15 (0.12)
Highest Edu.: Other	-0.22 (0.23)	0.06 (0.18)	-0.05 (0.19)
Subject: Biology	0.03 (0.10)	-0.15 (0.08)	0.04 (0.08)
Subject: Chemistry	0.05 (0.10)	-0.01 (0.08)	-0.03 (0.08)
Subject: CS	-0.12 (0.09)	0.02 (0.08)	-0.12 (0.08)
Subject: Math	0.06 (0.10)	-0.00 (0.08)	-0.01 (0.08)
Subject: Physics	-0.07 (0.10)	-0.02 (0.08)	-0.10 (0.08)
Subject: Other	0.08 (0.09)	0.02 (0.07)	-0.01 (0.07)
Age	0.00 (0.04)	0.01 (0.03)	0.01 (0.03)
Gender: F	0.06 (0.07)	-0.02 (0.06)	0.06 (0.06)
Gender: Non-binary	0.30 (0.60)	0.02 (0.61)	0.14 (0.60)
Uncertainty Avoidance	0.13^{*} (0.06)	0.05 (0.04)	0.14^{**} (0.04)
Masculinity	-0.10^{*} (0.05)	0.10^{**} (0.03)	-0.02 (0.04)
Collectivism	-0.03 (0.05)	0.10^{*} (0.04)	0.03 (0.04)
Power Distance	0.01 (0.07)	-0.05 (0.05)	0.05 (0.05)
Long-term Orientation	0.17^{*} (0.07)	0.02 (0.05)	0.12^{*} (0.06)
Sample: Israel	0.09 (0.14)	0.27^{*} (0.12)	0.18 (0.12)
Sample: Japan	-0.06 (0.15)	0.20 (0.13)	0.00 (0.13)
Sample: Norway	-0.47^{***} (0.14)	0.72^{***} (0.11)	-0.72^{***} (0.12)
Sample: Sweden	-0.30^{*} (0.14)	0.50^{***} (0.13)	-0.44^{***} (0.12)
Sample: USA	-0.52^{***} (0.15)	0.77^{***} (0.14)	-0.65^{***} (0.14)
Num. Observations	508	508	508
Num. Imputations	10	10	10
R^2 (adj.)	20% (16%)	28% (24%)	30% (26%)

Note: Statistical significance indicated by $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

that teachers' AI self-efficacy, AI understanding, cultural values, and geographic location influence their attitudes about AI-EdTech. Next, we discuss each finding and its implications for theory and practice.

5.1 Developing AI understanding and self-efficacy with professional development

The findings of this study show that teachers across six countries perceive more benefits and fewer concerns, and have more trust when they have a high level of knowledge and confidence in using and communicating about AI (AI self-efficacy). This finding echoes recent results from studies of teachers in specific national contexts (e.g., Cukurova et al., 2023). Moreover, we find that teachers with a better intuitive understanding of AI also perceived more benefits, fewer concerns, and had more trust. Remarkably, we did not find that teachers' age, gender, level of education, or their experience in using digital technology in education influence their attitudes toward AI-EdTech. Overall, this suggests that educating teachers at all stages about AI in general and AI-EdTech in particular, is important and should be considered either as a part of professional development (PD) or as part of the program curriculum. PD can equip teachers with relevant knowledge about AI-EdTech and raise their confidence and trust in using these technologies in their everyday educational practices. Teaching K-12 teachers about AI is a challenging and complex task and it is not yet prevalent in formal school settings (Casal-Otero et al., 2023). However, scholars have started exploring ways to implement PD programs, with positive results on teachers' increased understanding of, and trust in, AI-EdTech (e.g., Nazaretsky, Ariely, et al., 2022). Further, building on the results of a recent study by (Celik, 2023), we suggest that such programs should focus on providing teachers with technological and pedagogical knowledge about AI-EdTech to support effective adoption in K-12 settings and ultimately improve students' learning outcomes. Our results emphasize the importance of emerging AI literacy frameworks for teacher PD (Miao & Shiohira, 2022), ethical principles on using AI in K-12 settings (Adams, Pente, Lemermeyer, & Rockwell, 2023), and research on AI literacy (Casal-Otero et al., 2023). We encourage future research to expand on these findings by examining teacher attitudes and responses to PD in other grade levels, including primary- and secondary school settings.

5.2 Cultural differences in teachers' attitudes about AI-EdTech

Culture emerges at many different levels from geographical regions, nations, districts, schools, and classrooms. We found evidence of cultural differences in teachers' attitudes, which suggests that cultural values should be considered when integrating AI-EdTech in the K-12 setting. In particular, we found significant differences along four cultural dimensions: uncertainty avoidance; long- vs. short-term orientation; masculinity vs. femininity, and collectivism vs. individualism. This evidence indicates that Hofstede's model of culture (Hofstede et al., 2010) is relevant for considerations of the adoption and effective use of AI-EdTech among teachers. Our results echo some of the findings of a recent review of factors that contribute to the acceptance of AI (Kelly, Kaye, & Oviedo-Trespalacios, 2022); the review also finds that culture plays a role in users' acceptance/rejection of AI. However, the findings of the review article are not grounded in studies conducted in K-12 education, and they do not explain which exact cultural values are critical to consider for the effective adoption of AI-EdTech by teachers. Without this contextualized and specific knowledge, we are limited in our ability to develop culture-sensitive implementations that can facilitate the adoption and use of AI-EdTech by teachers (Van Boeijen & Zijlstra, 2020). Our study findings offer a more nuanced perspective that is grounded in a large sample of teachers across six countries that are diverse in terms of cultural values and readiness to harness AI, according to the AI-Readiness Index (Rogerson et al., 2022).

First, we found that teachers with a higher level of *uncertainty avoidance* perceive more benefits and have more trust in AI-EdTech (Table 3). The association between *uncertainty avoidance* and *trust* is in line with prior work that found the same relationship in the context of automation across the US, Taiwan, and Turkey (Chien et al., 2016). In K-12 education, it makes sense that teachers will rely more on AI-EdTech when they experience less uncertainty about different aspects of AI-EdTech. This can be achieved by providing teachers with careful instructions, guidance, and support regarding the transparency of AI algorithms and using AI-EdTech for teaching and learning. In our study, teachers reported a rather high level of uncertainty avoidance (i.e., above the midpoint on the 1-to-5 Likert scale) in all of the country samples (Table 1). In general, this indicates a level of uncertainty avoidance that is likely conducive to teachers' effective adoption of AI in schools across the sampled countries.

Second, we found that teachers with stronger *long-term orientation* perceive more benefits and have more trust in AI-EdTech (Table 3). A longer-term orientation was most pronounced among teachers in the Norwegian, Israeli, and Swedish samples, while the other teacher samples indicated a more short-term orientation, but still above the midpoint (Table 1). A long-term orientation is associated with persistence, perseverance, and adaptability (Hofstede et al., 2010), which are all helpful traits for technology adoption. Our finding suggests that it can help to orient teachers to the potential longer-term benefits of integrating AI-EdTech to realize the utility value of additional efforts and perhaps frustrations incurred in the short term. This may be realized through targeted PD, which could highlight the downstream benefits for teachers to adopt a long-term orientation.

Third, we found that teachers with higher *masculinity* scores perceived fewer benefits and more concerns regarding AI-EdTech in education. Notably, the average masculinity scores were below the midpoint (¡3 on the Likert scale) for all six country samples in this study. Still, the masculinity dimension can offer insights into how teachers from different cultures perceive and interact with AI in education, potentially impacting their perceived benefits, concerns, and trust in AI technologies. More masculine societies (e.g., Japan and the USA) might have higher expectations for AI's success and achievement possibilities in education and therefore more concerns if it does not meet these expectations due to the slow adoption of such tools. To better calibrate expectations, stakeholders such as teachers, school administrators, and policymakers could benefit from training about how AI works, and how it can complement their practices.

5.3 Limitations

This study has several limitations to consider when suggesting implications from our findings. First, we collected a convenience sample in each country that is not nationally representative, limiting the generalizability of the result compared to a more costly probability sample (Jager, Putnick, & Bornstein, 2017). To address this concern, we tried our best to reach a heterogeneous teacher sample in each country.

Second, we emphasize that our results represent a snapshot of teachers' attitudes towards AI-EdTech at a certain point in time, while AI, and its public perception, are highly dynamic. Thus, even without designated interventions such as teacher PD programs, teachers' attitudes are expected to change, particularly in response to significant events that capture widespread attention, such as the sudden popularity of

Open AI's ChatGPT. In this regard, we note that most of our data were collected after the release of ChatGPT, at the initial stages of its use.

Third, cross-cultural research, like the present study, compares samples that differ not only in their geographic location and culture but also in other, often unobservable characteristics. Further studies can build on this work to test the external validity of our results to the broader population of teachers (other grade levels, e.g., pre-school and primary school levels) in K-12 education in each country.

Fourth, while the translation of the survey instrument from English into Swedish, Japanese, Portuguese, Norwegian, and Japanese was performed by native speakers and doubled or triple-checked by domain experts, the translated surveys did not undergo formal evaluation. This is a common limitation in cross-cultural research involving survey instrument (J. He & van de Vijver, 2012).

Fifth, our regression model offers suggestive evidence of factors that matter for teacher attitudes, but it does not offer causal evidence. By adjusting for many characteristics simultaneously, we can reduce omitted variable biases for observed factors, but the presence of some factors (e.g., collectivism) might affect the observed evidence for other factors (e.g., masculinity). Understanding the interplay and interaction effects of various factors would require further analysis and greatly benefit from the application of qualitative research methods.

Finally, we caution against generalizing our result to other K-12 contexts without further research in other cultural contexts. To this end, we recommend collecting cultural measures that do not rely on Hofstede's original national scores (Hofstede et al., 2010), since cultural values are not static (Varnum & Grossmann, 2017) and measuring them at an individual level for the target population (i.e., teachers) as opposed to the national level may yield different results.

5.4 Broader implications and next steps

Overall, the results of this study have implications that transcend beyond simple correlations of various factors influencing teachers' perceived benefits, concerns, and trust in AI. Similar to recent calls from the literature (e.g., Cukurova et al., 2023; Kizilcec, 2023), they imply the need to encompass a broader spectrum of considerations at the teacher, classroom, school, and educational ecosystem levels when researching the adoption of AI-EdTech. Even at the teacher level, constructs like AI literacy would benefit from a broader perspective. Although often considered to be limited to technical knowledge acquisition, practical know-how of some AI applications, and well-versed straightforward ethical considerations, AI literacy would benefit from human-centered perspectives that involve considerations of human agency, the increasing need for lifelong learning, as well as a mindset that prioritizes cultural values and human intelligence. In this paper, we show that cultural values are significant predictors of teachers' perceived benefits, concerns, and trust in AI-Edtech. This means that cultural values and their wider implications should be part of the research and practice of AI literacy, teacher training, and PD efforts. Only by engaging with these broader considerations can we reach more human-centric approaches to AI-EdTech and potentially achieve more informed, ethical, and effective uses of AI technologies in education to accelerate student learning.

With the sudden explosion of generative AI technologies and the increasing number of teachers using AI beyond, we encourage future research to evaluate these aspects based on their actual usage in authentic settings. Such research will be vital for gaining a deeper understanding of the impact of AI-EdTech on teaching and learning and their adoption by educators across countries. Future research could investigate whether teachers' experience with EdTech leads to higher trust in AI, ultimately leading to more effective adoption and use of AIEdTech in K-12 education. Moreover, future studies might also examine trust and other attitudes towards using AI, based on the type of AI application, such as decision-making or generative AI. Also, the results of this study demonstrated that certain individual cultural values are influential for teachers' attitudes in AI-EdTech. To gain a deeper understanding of the possible influence of other cultural values and dimensions, we recommend qualitative research studies and applying other cultural models. Furthermore, for designers of AI-EdTech, we recommend considering the implementation of culture-sensitive design methods that have been used in other contexts (Van Boeijen & Zijlstra, 2020).

In summary, the results of this study offer a comprehensive, international account of not only teachers' overall positive attitudes towards AI-EdTech, but also, factors affecting these attitudes. While we did not find evidence that teachers' demographic characteristics affect their attitudes toward AI-EdTEch, we offer new evidence that efforts to raise teachers' understanding of and trust in AI-EdTech, while considering their cultural values, are necessary to support effective adoption of AI-EdTech in K-12 education.

Acknowledgments. We thank our study participants and everyone who has assisted us in translating and distributing the survey.

References

Adams, C., Pente, P., Lemermeyer, G., Rockwell, G. (2023). Ethical principles for artificial intelligence in k-12 education. *Computers and Education: Artificial Intelligence*, *4*, 100131,

Agarwal, R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision sciences*, *28*(3), 557–582,

Al Darayseh, A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Computers and Education: Artificial Intelligence*, *4*, 100132,

Almaiah, M.A., Alfaisal, R., Salloum, S.A., Hajjej, F., Shishakly, R., Lutfi, A., ... Al-Maroof, R.S. (2022). Measuring institutions' adoption of artificial intelligence applications in online learning environments: Integrating the innovation diffusion theory with technology adoption rate. *Electronics*, *11*(20), 3291, Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review*, *84*(2), 191,

Bell, A., Fairbrother, M., Jones, K. (2019). Fixed and random effects models: making an informed choice. *Quality & quantity*, *53*, 1051–1074,

Benotti, L., Martnez, M.C., Schapachnik, F. (2017). A tool for introducing computer science with automatic formative assessment. *IEEE transactions on learning technologies*, *11*(2), 179–192,

Berkovsky, S., Taib, R., Hijikata, Y., Braslavsku, P., Knijnenburg, B. (2018). A cross-cultural analysis of trust in recommender systems. *Proceedings of the 26th conference on user modeling, adaptation and personalization* (pp. 285–289).

Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., Barro, S. (2023). Ai literacy in k-12: a systematic literature review. *International Journal of STEM Education*, *10*(1), 29,

Cave, S., Coughlan, K., Dihal, K. (2019). " scary robots" examining public responses to ai. *Proceedings of the 2019 aaai/acm conference on ai, ethics, and society* (pp. 331–337).

Celik, I. (2023). Towards intelligent-tpack: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (ai)-based tools into education. *Computers in Human Behavior*, *138*, 107468,

Celik, I., Dindar, M., Muukkonen, H., Järvelä, S. (2022). The promises and challenges of artificial intelligence for teachers: A systematic review of research. *TechTrends*, *66*(4), 616–630,

Chien, S.-Y., Lewis, M., Hergeth, S., Semnani-Azad, Z., Sycara, K. (2015). Cross-country validation of a cultural scale in measuring trust in automation. *Proceedings of the human factors and ergonomics society annual meeting* (Vol. 59, pp. 686–690).

Chien, S.-Y., Lewis, M., Sycara, K., Liu, J.-S., Kumru, A. (2018). The effect of culture on trust in automation: reliability and workload. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, *8*(4), 1–31, Chien, S.-Y., Sycara, K., Liu, J.-S., Kumru, A. (2016). Relation between trust attitudes toward automation, hofstede's cultural dimensions, and big five personality traits. *Proceedings of the human factors and ergonomics society annual meeting* (Vol. 60, pp. 841–845).

Choi, S., Jang, Y., Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction*, *39*(4), 910–922,

Chou, C.-M., Shen, T.-C., Shen, T.-C., Shen, C.-H. (2023). The level of perceived efficacy from teachers to access ai-based teaching applications. *Research and Practice in Technology Enhanced Learning*, *18*, 021–021,

Chounta, I.-A., Bardone, E., Raudsep, A., Pedaste, M. (2022). Exploring teachers' perceptions of artificial intelligence as a tool to support their practice in estonian k-12 education. *International Journal of Artificial Intelligence in Education*, *32*(3), 725–755,

Commission, E., Directorate-General for Education, S., Youth, Culture. (2022). *Ethical guidelines on the use of artificial intelligence (ai) and data in teaching and learning for educators.* Publications Office of the European Union.

Crompton, H., Jones, M.V., Burke, D. (2022). Affordances and challenges of artificial intelligence in k-12 education: A systematic review. *Journal of Research on Technology in Education*, 1–21,

Cukurova, M., Miao, X., Brooker, R. (2023). Adoption of artificial intelligence in schools: Unveiling factors influencing teachers' engagement. *International conference on artificial intelligence in education* (pp. 151–163).

Davis, F.D., Bagozzi, R.P., Warshaw, P.R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982–1003,

Dietvorst, B.J., Simmons, J.P., Massey, C. (2015). Algorithm aversion: people erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114,

Doney, P.M., Cannon, J.P., Mullen, M.R. (1998). Understanding the influence of national culture on the development of trust. *Academy of management review*, *23*(3), 601–620, Dong, Y., Hou, J., Zhang, N., Zhang, M. (2020). Research on how human intelligence, consciousness, and cognitive computing affect the development of artificial intelligence. *Complexity*, *2020*, 1–10,

Evans, R., Luft, J., Czerniak, C., Pea, C. (2014). *The role of science teachers' beliefs in international classrooms: From teacher actions to student learning.* Springer.

Glikson, E., & Woolley, A.W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660,

Hancock, P.A., Billings, D.R., Schaefer, K.E., Chen, J.Y., De Visser, E.J., Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. *Human factors*, *53*(5), 517–527,

He, J., & van de Vijver, F. (2012). Bias and equivalence in cross-cultural research. *Online readings in psychology and culture*, *2*(2), 8,

He, X., Stapel, J., Wang, M., Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. *Transportation research part F: traffic psychology and behaviour*, *86*, 178–195,

Hofstede, G., Hofstede, G.J., Minkov, M. (2010). *Cultures and organizations: software of the mind: intercultural cooperation and its importance for survival.* McGraw-Hill.

Holmes, W., Persson, J., Chounta, I.-A., Wasson, B., Dimitrova, V. (2022). *Artificial intelligence and education: A critical view through the lens of human rights, democracy and the rule of law.* Council of Europe.

Hong, M., An, S., Akerkar, R., Camacho, D., Jung, J.J. (2019). Cross-cultural contextualisation for recommender systems. *Journal of Ambient Intelligence and Humanized Computing*, 1–12,

Huang, F., Teo, T., Sánchez-Prieto, J.C., García-Peñalvo, F.J., Olmos-Migueláñez, S. (2019). Cultural values and technology adoption: A model comparison with university teachers from china and spain. *Computers & Education*, *133*, 69–81, Huang, H.-Y., & Bashir, M. (2018). Users' trust in automation: a cultural perspective. *Advances in human factors in robots and unmanned systems: Proceedings of the ahfe 2017 international conference on human factors in robots and unmanned systems, july 17- 21, 2017, the westin bonaventure hotel, los angeles, california, usa 8* (pp. 282–289).

Jager, J., Putnick, D.L., Bornstein, M.H. (2017). Ii. more than just convenient: The scientific merits of homogeneous convenience samples. *Monographs of the Society for Research in Child Development*, *82*(2), 13–30,

Jones, K. (1996). Trust as an affective attitude. *Ethics*, *107*(1), 4–25,

Kelly, S., Kaye, S.-A., Oviedo-Trespalacios, O. (2022). What factors contribute to acceptance of artificial intelligence? a systematic review. *Telematics and Informatics*, 101925,

Kizilcec, R.F. (2023). To advance ai use in education, focus on understanding educators. *International Journal of Artificial Intelligence in Education*, 1–8,

Klein, H.A., Lin, M.-H., Miller, N.L., Militello, L.G., Lyons, J.B., Finkeldey, J.G. (2019). Trust across culture and context. *Journal of Cognitive Engineering and Decision Making*, *13*(1), 10–29,

Koehler, M., & Mishra, P. (2009). What is technological pedagogical content knowledge (tpack)? *Contemporary issues in technology and teacher education*, *9*(1), 60–70,

Leidner, D.E., & Kayworth, T. (2006). A review of culture in information systems research: Toward a theory of information technology culture conflict. *MIS quarterly*, 357–399,

Li, Y. (2022). Cross-cultural privacy differences. *Modern socio-technical perspectives on privacy* (pp. 267–292). Springer International Publishing Cham.

Lim, W.M., Gunasekara, A., Pallant, J.L., Pallant, J.I., Pechenkina, E. (2023). Generative ai and the future of education: Ragnarök or reformation? a paradoxical perspective from management educators. *The International Journal of Management Education*, *21*(2), 100790, Lukyanenko, R., Maass, W., Storey, V.C. (2022). Trust in artificial intelligence: From a foundational trust framework to emerging research opportunities. *Electronic Markets*, *32*(4), 1993–2020,

Lumineau, F., & Schilke, O. (2018). Trust development across levels of analysis: An embedded-agency perspective. *Journal of Trust Research*, *8*(2), 238–248,

Mcknight, D.H., Carter, M., Thatcher, J.B., Clay, P.F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on management information systems (TMIS)*, *2*(2), 1–25,

Miao, F., & Shiohira, K. (2022). *K-12 ai curricula. a mapping of government-endorsed ai curricula.* UNESCO. https://unesdoc. unesco. org/ark:/48223/pf0000380602.

Moore, G.C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, *2*(3), 192–222,

Morrone, A., Tontoranelli, N., Ranuzzi, G. (2009). *How good is trust?: Measuring trust and its role for the progress of societies.* OECD.

Nazaretsky, T., Ariely, M., Cukurova, M., Alexandron, G. (2022). Teachers' trust in ai-powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, *53*(4), 914–931,

Nazaretsky, T., Cukurova, M., Alexandron, G. (2022). An instrument for measuring teachers' trust in ai-based educational technology. *Lak22: 12th international learning analytics and knowledge conference* (pp. 56–66).

Rogerson, A., Hankins, E., Fuentes Nettel, P., Rahim, S. (2022). *Government ai readiness index 2022.* Oxford Insights.

Seufert, S., Guggemos, J., Sailer, M. (2021). Technology-related knowledge, skills, and attitudes of pre-and in-service teachers: The current situation and emerging trends. *Computers in Human Behavior*, *115*, 106552,

Slovic, P. (1993). Perceived risk, trust, and democracy. *Risk analysis*, *13*(6), 675–682,

Tarhini, A., Hone, K., Liu, X., Tarhini, T. (2017). Examining the moderating effect of individual-level cultural values on users' acceptance of e-learning in developing countries: a structural equation modeling of an extended technology acceptance model. *Interactive Learning Environments*, *25*(3), 306–328,

Usher, E.L., & Pajares, F. (2008). Sources of self-efficacy in school: Critical review of the literature and future directions. *Review of educational research*, *78*(4), 751–796,

Van Boeijen, A., & Zijlstra, I. (2020). *Culture sensitive design: A guide to culture in practice*. BIS Publishers.

Van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in r. *Journal of statistical software*, *45*, 1–67,

Varnum, M.E., & Grossmann, I. (2017). Cultural change: The how and the why. *Perspectives on Psychological Science*, *12*(6), 956–972,

Velander, J., Taiye, M.A., Otero, N., Milrad, M. (2023). Artificial intelligence in k-12 education: eliciting and reflecting on swedish teachers' understanding of ai and its implications for teaching & learning. *Education and Information Technologies*, 1–21,

Viberg, O., & Grönlund, Å. (2013). Cross-cultural analysis of users' attitudes toward the use of mobile devices in second and foreign language learning in higher education: A case from sweden and china. *Computers & Education*, *69*, 169–180,

Wang, Y., Liu, C., Tu, Y.-F. (2021). Factors affecting the adoption of ai-based applications in higher education. *Educational Technology & Society*, *24*(3), 116–129,

Wu, S.-Y., & Yang, K.-K. (2022). The effectiveness of teacher support for students' learning of artificial intelligence popular science activities. *Frontiers in Psychology*, *13*, 868623,

Yerdon, V.A., Marlowe, T.A., Volante, W.G., Li, S., Hancock, P.A. (2017). Investigating cross-cultural differences in trust levels of automotive automation. *Advances in cross-cultural decision making: Proceedings of the ahfe 2016 international conference on cross-cultural decision making (ccdm), july 27-31, 2016, walt disney world®, florida, usa* (pp. 183–194).

Yoo, B., Donthu, N., Lenartowicz, T. (2011). Measuring hofstede's five dimensions of cultural values at the individual level: Development and validation of cvscale. *Journal of international consumer marketing*, *23*(3-4), 193–210,

Zawacki-Richter, O., Marín, V.I., Bond, M., Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27,

Appendix A Supplementary Tables

Table A1 Descriptive statistics for each country's sample and the combined sample: percentages for categorical variables; means with standard deviations in parentheses for continuous variables.

	Brazil	Israel	Japan	Norway	Sweden	USA	Overall
Sample Size	41	99	87	102	111	68	508
Gender: % M/F/Non-binary	44/56/0	31/69/0	84/16/0	60/39/1	59/41/0	44/54/1	55/45/0
Age: % 20-30	10	4	9	9	6	4	7
Age: % 31-40	20	18	34	22	23	29	24
Age: % 41-50	22	36	32	36	31	35	33
Age: % 51-60	44	30	22	27	29	26	29
Age: % 61+	5	11	2	6	12	4	7
Highest Edu.: % Bachelor	17	15	53	34	68	3	36
Highest Edu.: % Master	68	66	41	63	22	90	55
Highest Edu.: % Doctorate	12	19	6	2	3	6	7
Highest Edu.: % Other	2	0	0	1	7	1	2
Subject: % Biology	5	18	26	7	16	24	17
Subject: % Chemistry	10	55	28	4	16	22	23
Subject: % Mathematics	29	18	45	10	5	4	17
Subject: % Physics	10	10	29	9	25	13	17
Subject: % CS	7	17	31	4	37	6	19
Subject: % Other	59	27	23	76	74	31	50
Experience in Educ.: % 0-5yrs	22	18	7	24	10	7	14
Experience in Educ.: % 6-10yrs	10	23	18	19	21	21	19
Experience in Educ.: % 11-20yrs	29	23	41	35	35	32	33
Experience in Educ.: % 21+yrs	39	35	33	23	34	40	33
Teaching w/ Technology: % 0-5yrs	37	27	44	25	10	10	24
Teaching w/ Technology: % 6-10yrs	37	41	24	19	31	22	29
Teaching w/ Technology: % 11-20yrs	17	23	22	48	44	40	34
Teaching w/ Technology: % 21+yrs	10	8	10	9	15	28	13
AI Understanding M (SD)	0.90 (0.85)	0.98 (0.73)	0.44 (0.90)	0.91 (0.76)	0.91 (0.75)	0.98 (0.87)	0.85 (0.82)
AI Self-efficacy M (SD)	2.46 (0.74)	1.89 (0.88)	1.73 (0.71)	2.51 (0.94)	2.42 (0.89)	2.01 (1.02)	2.17 (0.93)
AI Benefits M (SD)	4.02 (0.56)	3.97 (0.72)	3.61 (0.60)	3.56 (0.82)	3.77 (0.65)	3.43 (0.84)	3.71 (0.74)
AI Concerns M (SD)	2.91 (0.74)	3.14 (0.68)	3.06 (0.46)	3.68 (0.54)	3.33 (0.58)	3.66 (0.58)	3.33 (0.64)
AI Trust M (SD)	3.69 (0.64)	3.71 (0.60)	3.35 (0.47)	2.98 (0.69)	3.21 (0.59)	2.93 (0.69)	3.29 (0.68)
Power Distance M (SD)	1.68 (0.61)	1.73 (0.54)	1.88 (0.61)	1.60 (0.75)	1.54 (0.52)	1.59 (0.53)	1.66 (0.61)
Uncertainty Avoidance M (SD)	3.93 (0.58)	3.39 (0.70)	3.30 (0.48)	3.70 (0.75)	3.65 (0.66)	3.91 (0.59)	3.61 (0.68)
Collectivism M (SD)	3.19 (0.77)	3.04 (0.75)	2.63 (0.56)	3.39 (0.82)	2.87 (0.73)	2.79 (0.69)	2.98 (0.77)
Long-term Orientation M (SD)	3.97 (0.61)	4.06 (0.51)	3.63 (0.43)	4.10 (0.63)	4.07 (0.46)	3.95 (0.51)	3.97 (0.55)
Masculinity M (SD)	1.95 (0.97)	1.89 (0.90)	2.11 (0.77)	2.05 (1.12)	1.63 (0.72)	1.71 (0.74)	1.88 (0.90)

Table A2 Cronbach's alpha measure of internal consistency for each construct and Pearson correlation coefficients between constructs.

Construct	α	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. AI Benefits	0.850	-0.33***	0.62***	0.22***	-0.04	0.08	0.01	0.13	-0.18**	0.14*
2. AI Concerns	0.764		-0.50***	-0.14*	0.00	0.18**	0.21***	0.16**	0.15*	-0.04
3. AI Trust	0.806			0.14*	0.10	0.07	0.07	0.10	-0.03	0.10
4. AI Self-Efficacy	0.850				-0.07	-0.04	0.04	0.04	-0.19***	0.13
5. Power Distance	0.755					0.09	0.18	-0.08	0.43***	-0.13
6. Uncertainty Avoidance	0.717						0.22***	0.32***	0.01	-0.01
7. Collectivism	0.803							0.33***	0.17**	0.05
8. Long-term orientation	0.718								0.03	0.00
9. Masculinity	0.806									-0.09
10. AI Understanding	—									

Note: Statistical significance with multiple-testing adjustment indicated by $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.