Computers in Human Behavior 138 (2023) 107468

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education

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ARTICLE INFO

Keywords:
Artificial intelligence
Teacher education
Technology integration
TPACK

ABSTRACT

The affordances of artificial intelligence (AI) have not been totally utilized in education. To effectively integrate AI into education, teachers' AI-specific technological and pedagogical knowledge is important. Furthermore, due to novel ethical issues caused by AI, teachers also must have the knowledge to assess AI-based decisions. None of the previous studies so far explored teacher knowledge to pedagogically and ethically use AI-based tools. Considering this gap, we first developed a scale to measure the knowledge for instructional AI use based on the technological, pedagogical, and content knowledge (TPACK) framework. We extended TPACK with ethical aspects. Secondly, we built a model to investigate the interplay of TPACK components and ethics. The results indicated that as long as teachers have more knowledge to interact with AI-based tools, they will have a better understanding of the pedagogical contributions of AI. Further, technological knowledge (TK) allows teachers to better assess decisions of AI. However, only TK is not sufficient educational integration of AI-based tools. For teachers to deploy AI in education efficiently, TK is meaningful when it is combined with pedagogical knowledge (PK), reflected in technological pedagogical knowledge (TPK). Given pedagogical and technological affordances of AI-based tools, the current study suggests the Intelligent-TPACK framework.

1. Introduction

As an emerging computer science field, artificial intelligence (AI) appeared to have a transforming impact on business and health (Lin et al., 2021). The profound impact of AI is also present in education through AI-based tools such as intelligent tutoring and automated grading systems (Montebello, 2018; Wang & Zhao, 2020). However, the potential of artificial intelligence has not yet been fully harnessed in education (Luckin et al., 2022). Thus, AI use in instructional settings lags more behind than other sectors such as business (Luckin & Cukurova, 2019). One reason is that the role of teachers in the educational integration of AI-based tools so far has been ignored (Seufert et al., 2021).

AI-based tools offer novel pedagogical opportunities for learning and teaching purposes. As a promising opportunity, for example, AI-based tools have the potential to foster a learner-centred approach (Luan et al., 2020). This approach occurs with personalized learning experiences provided by AI-based tools (Hwang et al., 2020; Shum & Luckin, 2019). Accordingly, it is possible to identify the cognitive and emotional needs of learners with the help of AI (Chen et al., 2021). In response to these needs, learners are provided with personalized support (Mislevy et al., 2020). The support is also offered timely, and thus, learners might be more satisfied with on-time feedback (Zawacki-Richter et al., 2019). As a result, whereas their learning performance might increase, the rate of dropout decreases (Papamitsiou & Economides, 2014). Meanwhile, teachers have the advantage to monitor students' learning progress (Wang & Zhao, 2020). Also, some AI-based tools such as teacher dashboards can send real-time alerting (or notifications) about learners (Keuning & van Geel, 2021; van Leeuwen et al., 2021). This notification enables teachers to meet the student's needs simultaneously (Keuning & van Geel, 2021). From the teachers' side, AI can facilitate the effective formative and summative assessment of students' complex knowledge (Chen et al., 2021). Previous research has also shown that AI-based tools help teachers evaluate the teaching process, and facilitate lesson planning and implementation (Celik et al., 2022; Zawacki-Richter et al., 2019).

1.1. Teacher knowledge for AI-based instruction

As seen from the opportunities, AI has also dramatically transformed the implementation of instructional pedagogy (Luckin et al., 2022). For

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https://doi.org/10.1016/j.chb.2022.107468
Received 9 May 2022; Received in revised form 23 August 2022; Accepted 25 August 2022
Available online 29 August 2022
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teachers to totally exploit the opportunities of AI in education, they must know the pedagogical contributions of AI-based tools (Xu, 2020). AI technology can be deployed for effective teaching when teachers have sufficient pedagogical knowledge to utilize AI-based tools (Cavalcanti et al., 2021). For instance, the more teachers recognize the utilities of AI-based tools, the more they use such tools to foster learner motivation and engagement (Wang et al., 2021). Similarly, teachers with more knowledge about AI can better select appropriate AI-based tools for teaching purposes (Edwards et al., 2018). Hence, teachers' knowledge of AI enables them to use AI-based tools for personalized learning and timely feedback (Popenici & Kerr, 2017). Therefore, it is important to understand their knowledge on integrating AI-based tools in education. In fact, the role of technological and pedagogical knowledge is vital in the successful educational integration of any technology (Mishra & Koehler, 2006).

It is not assumed that AI will replace teachers in the future (Hrastinski et al., 2019). This is because the interaction of the teacher with students is irreplaceable in learning progress and students' individual development (Cheng & Tsai, 2019). However, learning and teaching environments will be surrounded by AI and its sub-fields due to their rapid advancement (Ng et al., 2021; Xu, 2020). Hence, AI will transform the teacher's professional knowledge for AI-based instruction (Seufert et al., 2021). In this point of view, the knowledge to technologically and pedagogically utilize AI-based systems is crucial for the teaching profession. The technological, pedagogical, and content knowledge (TPACK) framework could explain the necessary knowledge for teachers to integrate AI-based tools in education. TPACK refers to teachers' professional knowledge to effectively use technology for instructional purposes (Mishra & Koehler, 2006). TPACK is regarded as a flexible framework for a variety of pedagogical approaches and technological tools (Mishra et al., 2010; Valtonen et al., 2017). We presume that the TPACK framework, when aligned with the technological and pedagogical contributions of AI, will provide a robust framework for better understanding teacher knowledge for AI-based instruction.

Despite the opportunities of AI-based technologies for teaching and learning, they have also ethical issues. For instance, AI-based tools may make decisions with systematic and repeatable errors (Sao Pedro et al., 2013; Shin, 2020). These errors cause discriminating against students from various races and cultures, violating the inclusiveness of education (De Cremer & De Schutter, 2021; Dietvorst et al., 2018). Specifically, some AI-based applications for language learning can fail to recognize different gender voices (Akgun & Greenhow, 2021). Likewise, the outputs of automated scoring systems sometimes emerge concerns in terms of fairness (Almusharraf & Alotaibi, 2022, pp. 1–17). Further, it is sometimes challenging for educators to understand the justifications underlying the decisions of AI-based tools. This may be due to the black-box nature of AI-based decisions (Castelvecchi, 2016; Dörr & Hollnbuchner, 2017). Ethical concerns about AI-based tools may also arise from uncertainty on developers of the relevant AI software (Shin & Park, 2019). Therefore, it is a controversial issue when teachers or students are provided with less information on the responsible organization for the AI-based technology.

The ethical issues require all stakeholders in education to consider and evaluate AI-based decisions (Buckingham, 2022). Hence, we argue that teachers must have the knowledge to understand, justify and evaluate results by AI-based tools. This knowledge of ethical assessments is critically important for teachers to create an inclusive future generation (Holmes et al., 2019, pp. 1–35; Luckin et al., 2022). In addition to teachers' technological and pedagogical knowledge, their ethical assessments play an important role in effective AI integration.

1.2. The aim of the study

Despite the important role of teachers (Luckin et al., 2022; Seufert et al., 2021), little is known about the teacher knowledge to utilize AI-based tools in education (Kim et al., 2021). Therefore, there is a dearth of research on measuring teachers' professional knowledge for AI-based instruction. Further, ethical considerations and evaluations on AI have yet to be investigated from the teacher's perspective. Thus, there is less understanding of how teachers interpret and evaluate AI-based decisions. Lastly, there is limited empirical evidence explaining how teachers' instructional skills to use AI are associated with their ethical assessment. In light of these gaps, the purpose of the research is to reveal teachers' knowledge to use AI-based tools for effective teaching based on TPACK. Assessing the decisions by AI-based tools requires different knowledge component from pedagogical knowledge (Buckingham, 2022; Holmes et al., 2021). For example, teacher assessment of transparency and fairness is not similar to understanding personalized feedback opportunities. We addressed ethical assessment as a distinct knowledge component to provide a comprehensible and explicit perspective. In the current study, TPACK was extended with ethical assessments of AI-based tools. In other words, we attempted to identify ethical knowledge that teachers should have for ethical integration of AI-based tools.

The current study has the potential to make some contributions. AI-based technologies are also regarded as intelligent machines. Teachers must know not only to use but also to interact with intelligent machines (Guggemos & Seufert, 2021). Previous research that investigated teachers' TPACK skills has so far focused on the usage of a certain type of technology (Koh & Divaharan, 2013; Lee & Tsai, 2010). Unlike previous studies, this study deals with the knowledge and skills both for using and interacting with AI-based technologies. There is a growing body of research on teachers' acceptance of AI-based technologies such as chatbots and automated exam scoring (Chocarro et al., 2021; Choi et al., 2022). However, the acceptance concept is widely related to the usage of AI. Apart from the acceptance of AI systems, we emphasize the integration of AI-based technologies into education. It is worth noting that teachers without solid technological knowledge fail to benefit from pedagogical opportunities (Koehler & Mishra, 2009). The reason is that they do not perceive technological tools as easy to use (Joo et al., 2018).

Pedagogical knowledge is vital for the effective deployment of AI-based technologies. This is because AI has transformed the pedagogical knowledge that teachers must have (Seufert et al., 2021). Previous research provided a limited understanding of some skills for the pedagogical use of AI such as monitoring and timely intervention (Choi et al., 2022; Du & Gao, 2022). To the best of our knowledge, this is the first study to present a holistic view of relevant knowledge from AI-specific technological and pedagogical perspectives.

Ethics is somehow ignored in the teachers' technology integration process. With the exception of a few studies (Smakman et al., 2021; Yurdakul et al., 2012; Yurdakul & Coklar, 2014), the ethical aspect in TPACK has not been tackled with technology use. However, in these studies, ethical issues that stem from particularly AI are not considered. The current study responds to these issues by highlighting AI-specific ethical challenges.

To achieve research aims, two successive studies were conducted in this study. In stage 1, a data collection tool, namely the Intelligent-TPACK scale, was developed. Afterward, the interplay of Intelligent-TPACK components was investigated through structural equation modeling.

1.3. Theoretical underpinning

1.3.1. Technological pedagogical and content knowledge (TPACK) framework

The TPACK framework is grounded on pedagogical content knowledge (PCK) as proposed by Shulman (1986, 1987). PCK is defined as the understanding of how certain features of subject matter are planned, adjusted, and transformed to strengthen student learning (Shulman, 1986). In other words, PCK is a combined form of content knowledge (CK) and pedagogy knowledge (PK), and it consists of the appropriate methods and strategies to teach a particular content.

Mishra and Koehler (2006) extended PCK by incorporating technological knowledge (TK) to better understand teachers' knowledge for effective technology integration. The extension process yielded technological content knowledge (TCK), technological pedagogical knowledge (TPK), and technological pedagogical content knowledge (TPACK). The knowledge components of the TPACK framework are illustrated in Fig. 1. Since TPACK is a flexible and broad framework (Mishra et al., 2010) several researchers adopted TPACK for different technological tools and pedagogical methods. For instance, Lee and Tsai (2010) determined knowledge to use web technologies in the scope of TPACK. Further, Valtonen et al. (2017) adopted TPACK for teaching twenty-first-century skills such as critical thinking and collaboration. The current study addresses the knowledge and skills to use AI-based tools. Hence, we focused on TK-related knowledge components, namely, TK, TCK, TPK, and TPACK.

TK is described as an understanding of the affordances and challenges of technology, and the skills to utilize technology (Mishra & Koehler, 2006). TK also covers an interest to follow emerging technologies. Teachers with higher TK are capable of applying technological tools to their professional and daily life. Further, they could easily comprehend to what extent technology can support or hinder the accomplishment of a task (Koehler & Mishra, 2009). Next, TCK refers to an understanding of the relations between content knowledge and technology, and how technology and content impact and restrict each other. TCK includes knowledge about the particular technologies utilized within the content field (e.g., mathematics and geography) (Mishra & Koehler, 2006). TCK also reflects how a particular technology can contribute to teachers' content-specific knowledge (Koehler & Mishra, 2009). For instance, a science teacher can search an updated subject matter using a chatbot. Similarly, professional development courses can be conducted on online platforms with a virtual tutoring system. Meanwhile, TPK is the knowledge about the nature of teaching and learning by deploying technology. TPK covers the knowledge regarding the advantages and drawbacks of numerous technologies for specific pedagogical approaches (Mishra et al., 2010; Mishra & Koehler, 2006). Lastly, TPACK consists of a combined form of knowledge and skills of the other fundamental components. TPACK is the understanding of using a suitable technological tool to teach a particular content by implementing effective pedagogical strategies. In other words, teachers with greater TPACK competency are capable of using technologies to perform content-specific pedagogical methods (Mishra & Koehler, 2006).

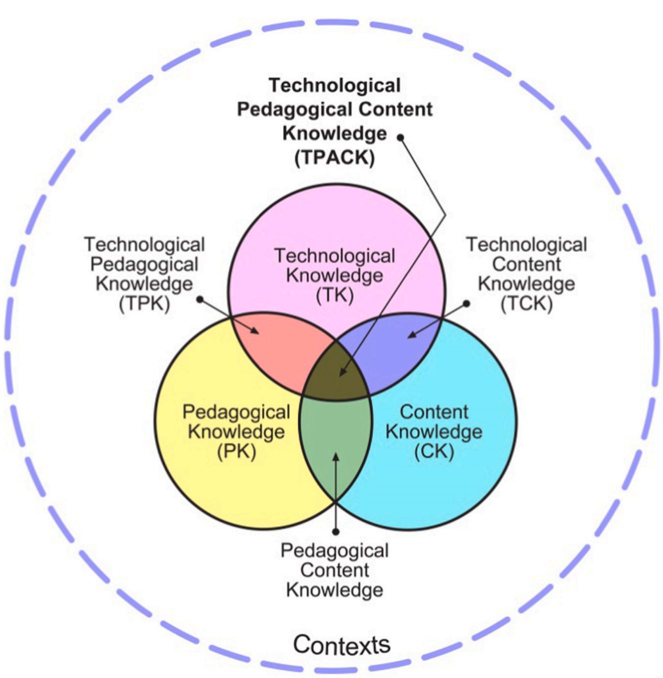

Fig. 1. Tpack framework (tpack.org).

1.4. Artificial intelligence and ethical considerations

AI is a technical term, meaning that learning to execute a task related to humans by reasoning and interacting with the environment (Russel & Norvig, 2010). In other words, the technological tools powered by AI can capture data from the environment, and process; ultimately, producing adaptive and environment-specific outputs. AI is a general concept with a variety of analytical methods. The most prominent methods are machine learning, natural language processing, and deep learning (Zawacki-Richter et al., 2019).

In educational environments, AI is embedded in several tools for various purposes. The current study targets four AI-based tools: Chatbots, intelligent tutoring systems, dashboards, and automated assessment systems. The main reason for this is that such tools are the most prevalent AI-based technologies in K-12 education (Akgun & Greenhow, 2021; Celik et al., 2022; Chen et al., 2022). Chatbots function as conversational or virtual agents to learners and teachers. Educators are able to start a conversation with chatbots through voice or text inputs (Luo et al., 2019). Teachers can utilize to get help from chatbots for maintaining learners' motivation (Huang et al., 2022). Also, chatbots can send notifications to teachers about students' learning progress (Chocarro et al., 2021). Intelligent tutoring systems are also interchangeably used with adaptive learning systems and personalized learning platforms. In these systems or platforms, students are provided with learning content based on their needs (Pai et al., 2021). Intelligent tutoring systems reduce teachers' workload, and, thus, give those more time during the instruction (Mohamed & Lamia, 2018). AI-enhanced dashboards enable teachers to monitor student knowledge construction, cognitive and emotional engagements (Verbert et al., 2013). Such indicators are represented through visualizations helping teachers to orchestrate and support learning progress (Pardo et al., 2018). Automated assessment systems recognize and automatically score responses from students. These tools are also known as automated grading systems. For automation, natural language processing and automated speech recognition are generally used as AI subfields (Ahn & Lee, 2016). For instance, in foreign language learning, these systems help teachers to assess students writing and speaking in the exams and assignments (Wang & Zhao, 2020).

Despite the advantages of AI-based tools, ethical issues raise serious concerns about the implementation of AI in education (Castelvecchi, 2016; Shin, 2020). As aforementioned, AI-based technologies have their own reasoning process to accomplish a task. For reasoning, AI creates algorithms based on previous data (or training data). As the data have bias, the output of the AI algorithms will more likely become biased. As a result of this, AI might increase existing inequality gaps among learner subpopulations (e.g., gender, race, and socio-economic status) (Holmes et al., 2021; Shin, 2020). Responsible or explainable AI involves several ethical assessments and considerations from multiple stakeholders (e.g., designer, developer, and end-users). Given the frequently raised ethical issues of AI-based tools in previous studies (Shin & Park, 2019; Shin, 2020), the current study tackles teachers' ethical assessments with four aspects: transparency, inclusiveness, fairness, and accountability. These aspects are mainly based on end-user experience (Shin & Park, 2019). Further, four ethical aspects might apply to AI-based tools targeted in the current study (Cerratto Pargman et al., 2021; Holmes et al., 2021). *Transparency* refers to the information about how AI-based tools make a decision and underlying the reasoning behind the decisions (Ananny & Crawford, 2018). There might be sometimes insufficient information on the possible consequences of the AI system. For instance, an early warning notification from a dashboard might be unreasonable or pedagogically meaningless. Teachers must justify the decision of AI-based tools. *Accountability* in the explainable AI context is defined as the responsibility of AI designers and developers (Diakopoulos, 2016).

In other words, the team of designers and developers is responsible for the educational consequences of AI systems. From the teacher's perspective, the accountability consideration requires teachers to understand who the responsible people developing the AI-based technologies. *Fairness* is defined as an indicator of the absence of algorithmic bias. For ensuring fairness, AI-based tools should avoid building discriminatory or unfair consequences (Yang & Stoyanovich, 2017). Specifically, AI-based tools should be used in ways that promote equity between different groups of students rather than discriminating against any subgroup of students. Teachers should have knowledge about how the AI systems consider equity among learners. *Inclusiveness* is an aspect of the accessibility of AI-based tools. Accordingly, efforts in inclusiveness allow AI-based technology to become accessible to all targeted learners, with special consideration given to identifying and enabling access for potentially excluded or vulnerable groups. Teachers should assess the accessibility of AI-based tools in terms of different subgroups.

2. Stage 1 – The development of the Intelligent-TPACK scale

This stage addressed the validity and reliability procedure along with data analysis and participants. After these, the results were presented on the relationships of the Intelligent-TPACK scale items with the TPACK framework.

2.1. Validity and reliability procedure

The validation procedure was initiated with a detailed literature review to create an item pool. In this regard, we reviewed the studies on the pedagogical premises of AI-based tools and recent TPACK scales. For teachers to benefit from AI-based tools in the instruction, the relevant skills and knowledge are determined based on TPACK. To measure necessary knowledge and skills, the sample items were adapted from existing TPACK scales (Jang & Tsai, 2013; Sang et al., 2016; Schmid et al., 2020; Valtonen et al., 2017). Different from these scales, pedagogical opportunities of AI-based tools such as timely feedback and personalized learning were reflected in the items. We also utilized several data collection instruments about teachers' use of AI-based tools (e.g., Nazaretsky et al., 2022; Sohn & Kwon, 2020). As a result of the literature review, the initial draft of 37 items was generated. The descriptions of Intelligent-TPACK factors are as follows:

- *Intelligent-TK* tackles the knowledge to interact with AI-based tools and to use fundamental functionalities of AI-based tools. This component aims to measure teachers' familiarization level with the technical capacities of AI-based tools.
- *Intelligent-TPK* addresses the knowledge for pedagogical affordances of AI-based tools such as personal and timely feedback, and monitoring students' learning. Also, Intelligent-TPK measures teachers' understanding of alerting (or notification) and interpretation of messages from AI-based tools.
- *Intelligent-TCK* focuses on the knowledge of field-specific AI-based tools. It measures to what extent teachers use AI-based tools to update their content knowledge. This component also tackles teachers' understanding of particular technologies which are more suitable for addressing subject-matter learning in their field.
- *Intelligent-TPACK* is regarded as the core knowledge domain. It measures teachers' professional knowledge to select and use suitable AI-based tools (e.g., intelligent tutoring systems) for performing a teaching strategy (e.g., monitoring and timely feedback) to accomplish the instructional goals in a particular domain.
- *Ethics* measures the teacher's assessment concerning the decision on AI-based tools. The assessment is based on transparency, fairness, accountability, and inclusiveness.

Next, three experts in educational psychology, computer science, and educational technology reviewed the first version. The computer scientist had an experience of more than five years in the development of AI and machine learning algorithms. The educational technologist published several papers on the pedagogical use of emerging technologies such as AI. The educational psychologist had expertise in scale development and psychometric properties. Based on their suggestions and reviews, 25 items were rephrased and eight items were removed from the draft. We employed construct validity analysis on the final draft of the scale with remained 29 items. For this, exploratory factor analysis (EFA) was conducted to reveal latent factors underlying the items (Field, 2009). The options in a 7-point Likert type ranged from "1: strongly disagree" to "7: strongly agree" (Likert, 1932). We performed a principal component analysis in the EFA process. The cut-off for factor loadings is defined as 0.40, due to suggestions in the literature (see Ferguson & Takane, 1989). The EFA through the principal component analysis enabled us to recognize any item which has similar loadings within different factors. Since we aimed to develop a brand new scale with five factors, we selected appropriate items from the item pool by conducting EFA. This is also the common approach among other TPACK scale development studies (e.g., Jang & Tsai, 2013; Valtonen et al., 2014). In the current study, the EFA was performed with SPSS 24.

After the EFA, confirmatory factor analysis (CFA) was carried out to understand how measured TPACK factors support the theoretical framework (Harrington, 2009). The structural equation modeling (SEM) through the maximum likelihood technique was utilized to apply CFA. To meet the normality assumptions of CFA, we checked the skewness and kurtosis coefficients. The followings were used to interpret the goodness-of-fit of CFA results with the TPACK framework: Chi-square ($\chi 2$), the ratio of chi-square to the degree of freedom ($\chi 2/df$; Tavakol et al., 2011), Normed Fit Index (NFI; Bentler, 1990) and Comparative Fit Index (CFI; Bentler, 1990), root mean square error of approximation (RMSEA; Browne & Cudeck, 1993), Tucker–Lewis Index (TLI; Tucker & Lewis, 1973). Acceptable and good fit indices for criterion references are as follows (Hu & Bentler, 1999; Tanaka & Huba, 1985): $\chi 2/df \leq$ 4–5 (acceptable), ≤ 3 (good); $0.06 < RMSEA < 0.08$ (acceptable), ≤ 0.05 (good); $0.90 < NFI < 0.94$ (acceptable), ≥ 0.95 (good); $CFI \geq 0.95$ (acceptable), ≥ 0.97 (good); $0.90 < TLI < 0.94$ (acceptable); ≥ 0.95 (good); $0.85 < AGFI$ and $GFI < 0.89$ (acceptable), ≥ 0.90 (good). We used IBM Amos 22.0 in the application of CFA.

To ensure the reliability of the scale, item-total correlation and internal consistency were calculated. Item-total correlation is described as the association of each scale item with the total score of the scale. A positive and high correlation indicates that the items are an indicator of a similar construct (Koc & Barut, 2016). The cut-off value for the correlation is regarded as 0.30 (Pallant, 2007). The internal consistency level of the scale is computed with Cronbach's (1990) alpha consistency coefficient. The alpha is sufficient to be 0.70 and above for ensuring internal consistency (DeVellis & Thorpe, 2021).

2.2. Participants and data collection procedure

Seven hundred teachers in a large city in Turkey were asked to fill in the Intelligent-TPACK scale. Four hundred thirty-nine teachers voluntarily filled out the Intelligent-TPACK scale. The ages of teachers range from 29 to 38 years old. The data from eleven teachers with uncompleted surveys were excluded from the analysis. Hence, the final set of data comprised 428 teachers of whom 258 (60%) female and 170 (40%) male. With the selecting case function of SPSS, the number of participants was randomly split into two subsamples. We used the first group for the EFA and the second group for the CFA.

In Turkey, the Ministry of Education created an interactive platform entitled EBA for online distance education during the COVID-19 pandemic. All teachers working at primary, secondary, and high schools in Turkey utilized and interacted with the platform. We collected data from teachers with experience in using the EBA platform. The EBA included AI-based tools such as a dashboard and virtual tutoring system powered by AI (e.g., machine learning algorithms and natural language processing) (MEB, 2020). In the process of online education during the pandemic, a chatbot started to serve as a conversational agent in the EBA (Cbot, 2022). The system offers some opportunities such as personalized learning and adaptive feedback with the help of AI. The EBA dashboard also provides teachers with several visualizations to monitor student engagement. The Intelligent-TPACK scale covered the items related to pedagogical affordances of the EBA (e.g., monitoring, personalization, and adaptive feedback).

Self-reported data were gathered through an online survey. Although educators interact with AI-based technologies in daily life, the majority of them are unaware that these technologies benefit from AI (Luckin & Cukurova, 2019). Therefore, at the beginning of the survey, we presented a short and functional description of AI-based tools with some examples of educational use to help teachers' understanding (Please see Appendix).

3. Results

Prior to performing EFA, we first checked if the data is suitable to reveal factors. To measure the adequacy of the sample the Kaiser-Meyer-Olkin (KMO) was calculated as 0.955, which is greater than the suggested threshold of 0.60 (Pallant, 2007). We found out the Barlett sphericity test (10642.334, $p < 0.001$) was significant, meaning that the data set indicates the factorability feature.

Principal component analysis through the varimax rotation method was applied to explore the factor structure of the Intelligent-TPACK scale. The decision on the number of factors was based on the Kaiser-Guttman criterion (Eigenvalue >1) and theoretical considerations (Goretzko et al., 2021). After initial analysis, we observed a five-factor structure considering the eigenvalue higher than 1. However, one of the TPK items with a factor loading of less than 0.40 was removed from the scale. Similarly, one item in TCK was extracted due to its close factor loading in TPK. After removing two items, the EFA procedure was carried out iteratively. As a result of the EFA, the final version of the Intelligent-TPACK scale was found to include 27 items with five factors. Moreover, the scale items explained 69.41% of the total variance. The explored factors with the relevant items and the results of EFA are shown in Table 1. According to Table 1, the factor loadings vary between 0.499 and 0.824, implying that all items were robust to measure relevant factors (Hair et al., 2010).

Before CFA, we had checked the necessary assumptions for maximum likelihood. For the normality of the data, skewness and kurtosis coefficients were observed in the acceptable range from -1 to $+1$ (Skewness: -0.558, Kurtosis: -0.760). Further, the number of participants ($N = 214$) was regarded as sufficient to employ CFA (Kline, 2005). After checking the assumptions, a CFA was conducted with five latent variables with 27 items. The new values obtained from the analysis are: ($\chi2/df$) = 3.13 $p < 0.001$, RMSEA = 0.058, NFI = 0.917, CFI = 0.942, AGFI = 0.875, TLI = 0.933. According to the RMSEA and AGFI indices, the model has a good fit and acceptable fit. The NFI, CFI, and TLI values were found to be in the range of an acceptable fit (Bentler, 1990). The RMSEA value was also noticeably lower than the threshold of 0.1 for a good fit (Browne & Cudeck, 1993).

With regard to the reliability of the intelligent-TPACK scale, item-total correlations and internal consistency coefficient were calculated. As seen in Table 1, all scale items were positively and significantly related to the total score of the scale. The Cronbach's alphas of all factors (TK = 0.856, TCK = 0.868, TPK = 0.858, TPACK = 0.895, and ETHICS = 0.864) were discovered to be above the threshold value of 0.70, and, thus items were internally consistent within their factors.

4. Stage2 - model development and testing

In this stage, we aimed at developing a model explaining the interplay of TPACK components and ethical assessments to use AI-based tools in teaching. To achieve this aim, we collected a different data set

Table 1
EFA results of intelligent TPACK scale.

Factor/item	Factor Loading	item-total r	Mean (SD)
Intelligent TK Eigen value: 3.15; Variance Explained:17.99%			
TK1: I know how to interact with AI-based tools in daily life.	0.655	0.529**	2.56 (1.06)
TK2: I know how to execute some tasks with AI-based tools.	0.687	0.580**	2.97 (1.16)
TK3: I know how to initialize a task for AI-based technologies by text or speech.	0.699	0.540**	3.44 (1.08)
TK4: I have sufficient knowledge to use AI-based tools.	0.614	0.574**	2.83 (1.06)
TK5: I am familiar with AI-based tools and their technical capacities.	0.499	0.604**	3.70 (0.93)
Intelligent TPK Eigen value: 4.73; Variance Explained:14.39%			
TPK1: I can understand the pedagogical contribution of AI-based tools to my teaching field.	0.645	0.714**	3.48 (0.90)
TPK2: I can evaluate the usefulness of feedback from AI-based tools for teaching and learning.	0.733	0.748**	3.62 (0.89)
TPK3: I can select AI-based tools for students to apply their knowledge.	0.766	0.769**	3.64 (0.87)
TPK4: I know how to use AI-based tools to monitor students' learning.	0.674	0.743**	3.31 (0.94)
TPK5: I can interpret messages from AI-based tools to give real-time feedback.	0.740	0.594**	3.80 (0.85)
TPK6: I can understand alerting (or notification) from AI-based tools to scaffold students' learning.	0.824	0.605**	3.76 (0.84)
TPK7: I have the knowledge to select AI-based tools to sustain students' motivation.	0.757	0.606**	3.52 (0.87)
Intelligent TCK Eigen value:2.83; Variance Explained:9.88%			
TCK1: I can use AI-based tools to search for educational material in my teaching field.	0.657	0.588**	3.41 (0.97)
TCK2: I am aware of various AI-based tools which are used by professionals in my teaching field.	0.719	0.620**	3.33 (0.87)
TCK3: I can use AI-based tools to better understand the contents of my teaching field.	0.711	0.559**	3.23 (0.97)
TCK4: I know how to utilize my field-specific AI-based tools (e.g., intelligent tutor for Math).	0.745	0.564**	3.30 (0.92)
Intelligent TPACK Eigen value: 4.10 Variance Explained:19.70%			
TPACK1: In teaching my field, I know how to use different AI-based tools for adaptive feedback.	0.669	0.752**	3.45 (0.88)
TPACK2: In teaching my field, I know how to use different AI-based tools for personalized learning.	0.705	0.722**	3.48 (0.89)
TPACK3: In teaching my field, I know how to use different AI-based tools for real-time feedback.	0.765	0.754**	3.40 (0.95)
TPACK4: I can teach a subject using AI-based tools with diverse teaching strategies.	0.678	0.564**	3.07 (1.07)
TPACK5: I can teach lessons that appropriately combine my teaching content, AI-based tools, and teaching strategies.	0.727	0.694**	3.55 (0.93)
TPACK6: I can take a leadership role among my colleagues in the integration of AI-based tools into our teaching field.	0.669	0.531**	3.62 (0.84)
TPACK7: I can select various AI-based tools to monitor students' learning in my teaching process.	0.705	0.548**	3.73 (0.87)
Ethics Eigen value: 2.78 Variance Explained: 7.42%			
ETHICS1: I can assess to what extent AI-based tools consider individual differences (e.g., race and gender) of all students in my teaching.	0.710	0.697**	3.54 (0.87)

(*continued on next page*)

Table 1 (*continued*)

Factor/item	Factor Loading	item-total r	Mean (SD)
ETHICS2: I can evaluate to what extent AI-based tools behave fair to all students in my teaching.	0.731	0.700**	3.41 (0.92)
ETHICS3: I can understand the justification of any decision made by an AI-based tool.	0.679	0.662**	3.31 (0.98)
ETHICS4: I can understand who the responsible developers are in the design and decision of AI-based tools.	0.668	0.626**	3.64 (0.83)

**: $p < 0.01$.

through the valid and reliable form of the Intelligent-TPACK scale. The research model with the hypotheses is illustrated in Fig. 2. The hypotheses explaining the relationships based on previous literature are detailed below. After giving information on participants and the data collection procedure, empirical results are provided.

4.1. Hypothesis development procedure

For teachers to interact with AI-based tools, they must know the basic technical functions of these tools (Guggemos & Seufert, 2021; Seufert et al., 2021). In fact, the knowledge for effective AI-based instruction requires technical knowledge to use or interact with AI-based tools (Luckin et al., 2022). The teacher's technological knowledge is positively related to successful technology integration in the classrooms (Dogan et al., 2021; Koh et al., 2013). Technological knowledge is regarded as a good indicator to understand the pedagogical potential of relevant technology (Koehler & Mishra, 2009; Schmid et al., 2020). Further, the more teachers have knowledge in any certain technology, the more they are aware of pedagogical affordances (Celik et al., 2014; Mishra & Koehler, 2006; Sahin et al., 2013). Huang et al. (2022) maintained that teachers who are more familiar with chatbots in daily life can create chatbots for pedagogical purposes such as feedback. Similarly, more technological knowledge in AI-based tools may lead to an increase in teachers' usage for field-specific purposes (Guggemos & Seufert, 2021). For instance, teachers who are capable of using intelligent tutoring systems are more likely to better select field-specific intelligent tools. Also, teachers might rely on their technological knowledge to ethically evaluate any decision from a particular technological tool (Akgun & Greenhow, 2021; Daugherty & Wilson, 2018). We argue that experience and familiarization with AI-based tools may be crucial in understanding how AI-based tools ethically make a decision. Thus, we hypothesize the followings:

H1a. Intelligent-TK positively influences Intelligent-TPK.

H1b. Intelligent-TK positively influences Intelligent-TCK.

H1c. Intelligent-TK positively influences ETHICS.

H1d. Intelligent-TK positively influences Intelligent-TPACK.

Recognizing the benefits of automated essay scoring applications was reported to positively influence teachers' use of these AI-based applications (Wang et al., 2021). Similarly, Chocarro et al. (2021) empirically evidenced that teachers' understanding of chatbot utilities served to increase their possibility of usage. The more use of AI-based tools might contribute to the teacher's professional knowledge in the integration of these tools. Further, Du and Gao (2022) conducted a study with teachers in the English as a Foreign Language (EFL) context. As EFL teachers notice the effectiveness of AI-based tools, they will become more knowledgeable about using them in the instructional process. Considering this, we hypothesize the following:

H2. Intelligent-TPK positively influences Intelligent-TPACK.

As long as teachers search for field-specific content through AI-based tools, they become familiar with these tools (Luckin et al., 2022). Further, as teachers share information about field-specific AI-based tools with their colleagues, they can also learn how to use these apps in their field (Smutny & Schreiberova, 2020). A STEM field teacher, for instance, is more likely to better integrate AI-based tools in education if they know about how AI-based technologies will change the content knowledge.

H3. Intelligent-TCK positively influences Intelligent-TPACK.

Previous research suggests that teachers' ethical evaluations of AI-based decisions are closely associated with their pedagogical use of AI-based tools. For instance, Kabakcı-Yurdakul et al. (2012) addressed ethical competencies as core knowledge of TPACK. In another study based on TPACK, Kabakcı-Yudakul and Coklar (2014) found positive relationships between preservice teachers' ethical competencies and their technology integration knowledge. Teachers' interaction with AI-based tools could result in a better evaluation of AI-based tools' decisions (Akgun & Greenhow, 2021). Therefore, increased ethical evaluation might be an antecedent of the pedagogical use of AI-based tools in teaching (Nazaretsky et al., 2022). For instance, a skillful teacher at assessing the justification of decisions by AI-based tools can effectively utilize AI-based tools for instructional purposes. Based on this, we

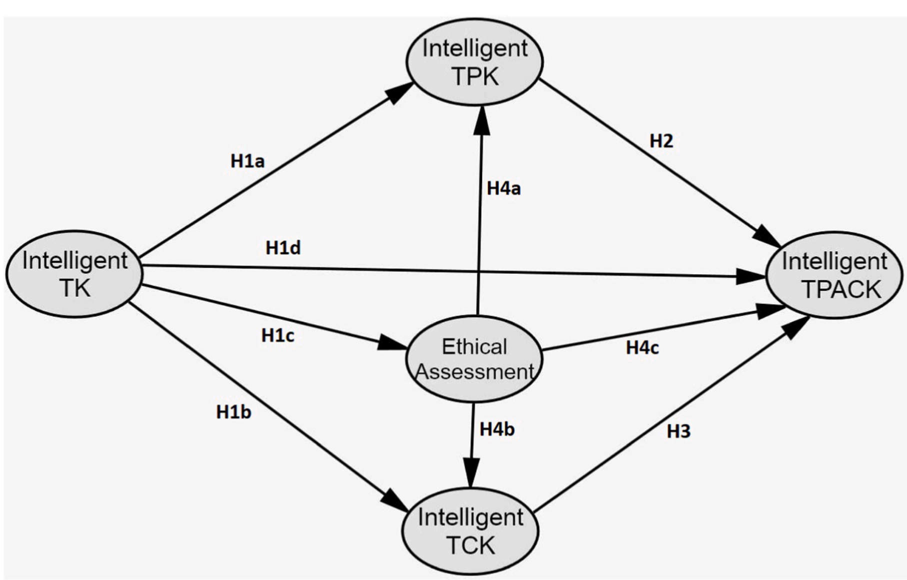

Fig. 2. Hypothesized research model.

assume the followings:

H4a. ETHICS positively influences Intelligent-TPK.

H4b. ETHICS positively influences Intelligent-TCK.

H4c. ETHICS positively influences Intelligent-TPACK.

4.2. Participants and data collection procedure

A new set of data was collected from teachers to test the hypothesized research model. Four hundred teachers were sampled in a different city from the first data set gathered. We used the valid and reliable form of Intelligent-TPACK scale (Please see Appendix). We sent the online survey link to the participants. Two hundred forty-one teachers answered the survey. We removed the data from twelve teachers since they have not completed the data collection tool. In the end, the data set consisted of 219 teachers ($n_{females} = 101$; $n_{males} = 118$; $M_{age} = 37.4$; $SD_{age} = 5.43$; $M_{experience} = 7.4$; $SD_{experience} = 3.28$) from K-12 levels ($f_{high\ school} = 92$; $f_{middle\ school} = 76$; $f_{primary\ school} = 51$) working at public and private schools ($f_{public} = 128$; $f_{private} = 91$). Similar to stage 1, another SEM analysis was conducted to estimate the interplays in the research model. The hypotheses were tested to delineate the predictor relationships among Intelligent-TPACK components (TK, TCK, TPK, and TPACK), and ethics. We also checked ($\chi2/df$), RMSEA, NFI, AGFI, and TLI for the results.

4.3. Results

SEM analysis initially yielded both significant and insignificant relationships among the TPACK components (TK, TCK, TPK, and TPACK) and ethics (Initial fit values: $\chi2/df = 2.87$; GFI = 0.851; AGFI = 0.908; CFI = 0.935; TLI = 0.948; NFI = 0.895; RMSEA = 0.063). We then deleted insignificant relationships, and found the research model to be robust with acceptable and good fit indices: $\chi2/df = 1.37$; GFI = 0.893; AGFI = 0.955; CFI = 0.980; TLI = 0.993; NFI = 0.919; RMSEA = 0.037 (Hu & Bentler, 1999; Tanaka & Huba, 1985). As illustrated in Fig. 3, TK was found to have a positive effect on TPK ($\beta = 0.44$; H1a accepted) and TCK ($\beta = 0.30$; H1b accepted). TK was positively associated with ethics ($\beta = 0.34$) but not with TPACK. Hence, H1c was accepted and H1d rejected. Further, the research model indicated that ethics was found to have a positive effect on TPK ($\beta = 0.48$; H4a accepted), TCK ($\beta = 0.64$; H4b accepted) and TPACK ($\beta = 0.41$; H4c accepted). We also revealed that both TPK ($\beta = 0.38$) and TCK ($\beta = 0.14$) were positively related to TPACK, supporting H2 and H3. TK combined with ethics to account for 64% of TCK, and 57% of TPK variance. As a whole, TPACK was explained at 69% with the combined effects of the TPK, TCK, and ethics.

5. Discussion

The affordances of AI in education have not been totally utilized (Luckin et al., 2016). To effectively integrate AI into education, teachers' AI-specific technological and pedagogical knowledge is regarded as vital (Seufert et al., 2021). Furthermore, due to novel ethical issues caused by Al, teachers also must have the knowledge to assess AI-based decisions. None of the previous studies so far explored teacher knowledge to pedagogically and ethically use of AI-based tools. Considering this gap, we first developed a scale to measure the knowledge for instructional AI use based on the TPACK framework. We extended TPACK with ethical aspects. Secondly, we built a model to investigate the interplay of TPACK components and ethics. Kim et al. (2021) conducted a study to identify teacher competencies to teach AI technologies based on the TPACK framework. Their study suggested important results and conceptualized necessary teacher knowledge and skills for *effective teaching of AI.* Different from Kim et al. (2021), the current study specifically focuses on teachers' professional knowledge for *effective teaching through AI.*

5.1. The scale development

The scale development process was launched by creating an item pool. In the item phrasing stage, we focused on the knowledge not only for use but also for interacting with AI-based tools. Moreover, the scale items also covered knowledge and skills to understand and interpret the alerting from AI systems. Intelligent technologies should be regarded as a partner rather than a tool (Guggemos & Seufert, 2021). Indeed, this is the basic difference between AI-based systems and conventional technologies (Davenport & Kirby, 2016). In Wilson et al.'s (2021) study, teachers perceived automated scoring applications as a partner helping them evaluate student writing. Therefore, Guggemos and Seufert (2021) suggest that teachers might need more knowledge to interact and collaborate with AI technologies. Consistent with this, we attempted to measure the skills associated with interaction and understanding of AI in the integration process.

We received views of experts from different fields such as computer

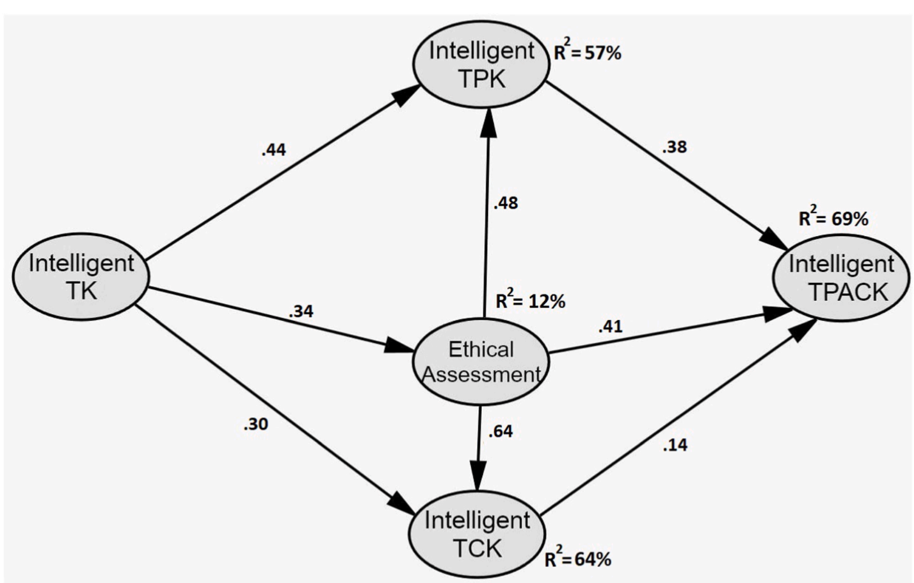

Fig. 3. Research model with standardized estimates.

science and educational technology. Following their comments and suggestions, some items were rephrased and removed from the scale. The final form of the scale was administered to teachers with experience of AI-based tools, chatbots, and predictive analytical dashboards. The data from teachers were analyzed through EFA, yielding a five-factor structure. As a result of EFA, the explained variance of the scale was revealed to be 69% of the total variance. According to Kline (1994), the explained variance varying from 40% to 60% is regarded as sufficient in the social sciences. Hence, the scale was acceptable in terms of explained variance. Previous studies on the TPACK scale development explored different cumulative variances. For instance, a five-factor solution accounted for 59% of the explained total variance in a study (Kabakci Yurdakul et al., 2012). The scale with eight factors explained 79% of the variance (Sang et al., 2016). It is assumed that the differences in variance are due to the number of factors in the scales.

Acceptable and good model fits from CFA enable us to understand measured TPACK factors verified by the theoretical framework (Harrington, 2009). That is, TPACK is a robust and valid framework to measure teacher knowledge for AI-based instruction. Researchers utilized the TPACK framework to explore professional knowledge for the educational integration of several technologies such as interactive whiteboards (Jang & Tsai, 2012) and second life (Kontkanen et al., 2015). Valtonen et al. (2017) focused on PK and PK-related components of TPACK to measure teachers' twenty-first-century skills, suggesting an updated version of TPACK. Here, we particularly addressed TK and other components including TK (TPK, TCK, and TPACK). The current study also extended TPACK with the component of ethical knowledge for assessing the decisions of AI-based tools. Therefore, we offer an updated and extended TPACK framework, namely Intelligent-TPACK (see Fig. 4). The intelligent-TPACK can shed light on the knowledge and skills to use intelligent technologies ethically and pedagogically.

5.2. The interplay of the TPACK and ethics

The SEM analysis yielded a positive relationship between TK and TPK (H1a). That is, as long as teachers have more knowledge to interact with AI-based tools, they will have a better understanding of the pedagogical contributions of AI. Similarly, it is more possible for a teacher to evaluate the usefulness of AI as they are more familiar with AI-based technologies. Supporting this, Wilson et al. (2021) reported that teachers with more knowledge on the basic functions of an automated scoring system could better recognize its pedagogical potential in the teaching process. Also, teachers' fundamental and technical skills to use AI-based

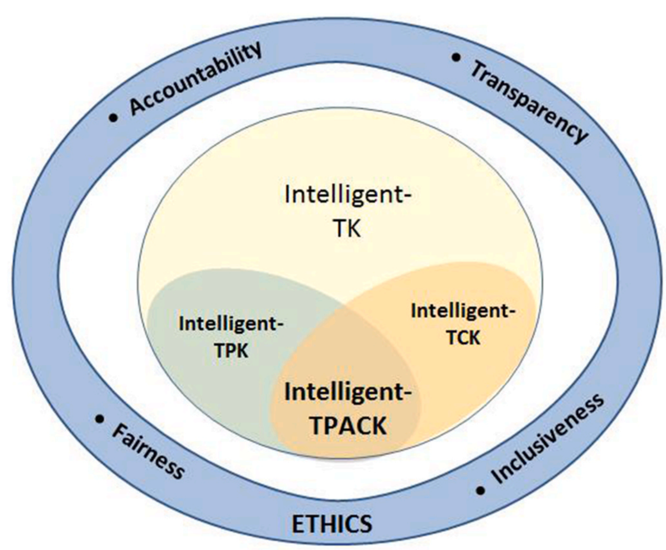

Fig. 4. Intelligent-TPACK Framework and its components.

tools enabled them to utilize such tools for monitoring and feedback (Holstein et al., 2018). We found that teachers' TK contributed to their TCK (H1b). In other words, teachers' familiarization with AI systems can lead to more knowledge in field-specific AI-based tools. For instance, teacher collaboration and support contributed to being aware of AI technologies (Chiu & Chai, 2020). In this way, teachers could have a chance to notice frequently utilized AI-driven intelligent tools in their subject. Our findings also imply that more knowledgeable teachers in AI can better anticipate how AI-based technologies will change subject matter.

Contrary to our hypothesis, TK was associated with ethics (H1c) but not with TPACK (H1d). That means, TK allows teachers to better assess decisions of AI. However, only TK is not sufficient educational integration of AI-based tools. The interaction with AI systems could lead to an increase in teachers' ethical assessment skills. More knowledge in AI enables teachers to critically approach AI-based tools. Individuals with less knowledge to use AI can over-trust AI systems (Glikson & Woolley, 2020). Our results can be explained by the powerful role of PK in technology integration. Indeed, effective technology integration is accomplished when teachers exploit technologies in a way activating pedagogical knowledge (Tondeur et al., 2021). Expanding this, our research model indicated that for teachers to deploy AI in education efficiently, TK is meaningful when it is combined with PK, reflected in TPK.

We also found TPK as a positive and strong predictor of TPACK (H2). Accordingly, teachers' better understanding of how AI changes pedagogy will most probably increase the use of AI systems in their teaching. For instance, teachers with more knowledge in adaptive feedback might want to use this strategy in their instruction. However, it is challenging for teachers to provide all students with personalized feedback due to time limitations (Beardsley et al., 2021). Our result implies that if teachers know that it is possible to give personalized feedback through AI systems, they can utilize AI in their instruction. Supporting this, Sánchez-Prieto et al. (2020) have reported that teachers will use more AI-driven assessment tools in their instruction when they are aware of the usefulness of AI-based tools.

The research model revealed that TCK is positively associated with TPACK (H3). This result shows as teacher knowledge of field-specific AI-based tools increases, the utilization of AI will more likely be promoted. In other words, teachers engage with AI systems specific to their field, they can also learn how to use them for teaching purposes. For instance, teachers have opportunities to interact with emerging technologies such as AI-based tools in professional development programs. It was reported that when teachers gain knowledge of field-specific technologies in professional development programs, they better integrate such technologies into education (Kiray et al., 2018).

The teacher's ethical assessment was positively related to TPK (H4a) and TCK (H4b). We also found out ethics contributed to the increase in TPACK (H4c). The ethical assessment is not regarded as a main component of TPACK; however, it is as effective as TPK in influencing TPACK. This finding indicated that the more teachers recognize ethical issues in AI such as fairness, the more they become knowledgeable about the integration of AI-based tools in education. Ethical assessment requires some technical and pedagogical knowledge from teachers (Kabakci Yurdakul & Çoklar, 2014). To understand if any notification is educationally meaningful and reasonable, teachers use both technology and pedagogy knowledge. Hence, such evaluations on AI can foster their TPACK.

5.3. Theoretical implications and the significance of the study

Previous research on ethical issues of AI has been mostly focused on the development aspect of AI technology (e.g., Diakopoulos, 2016). However, end users' perceptions and assessments are crucial for ethical AI deployment in educational settings (Buckingham, 2022; Holmes et al., 2021). Teachers are regarded as important end-users for the ethical integration of AI (Luckin et al., 2022). Therefore, the educational integration process of AI should include teachers' ethical assessments. However, no previous studies have so far determined ethical assessments in terms of the teacher's professional knowledge. One of the key contributions of the current study is the extension of TPACK with the knowledge of ethical assessments.

In this study, an updated TPACK framework was developed, Intelligent-TPACK, which also incorporated teacher ethical knowledge on AI-based tools. The core component of this framework highlights the teacher's knowledge for effective AI-based teaching. In the literature, little is known about the role of teachers' AI-based ethical assessment in effective AI-based teaching. This study thus attempts to fill a noteworthy gap by addressing the associations of TPACK components with the ethical assessment.

The research model suggests some practical implications for professional development. Namely, professional development programs prioritize technological knowledge for raising ethical awareness of AI-based tools. On the other hand, it is crucial to train teachers about the pedagogical affordances of AI-based tools, when it is aimed to foster their knowledge for effective AI integration. The results of this study can also shed light on the teacher education context. The educational technology courses might be designed for promoting pre-service teachers' ethical assessment and their knowledge of educational AI use. Considering the results of the current study, it is suggested that for pre-service teachers to better understand the ethical concerns of AI, they should know what AI is and how it works. In this context, several AI-based applications (e.g., Chatbots) with relevant AI sub-field (e.g., natural language processing) might be introduced. As pre-service teachers gain knowledge of the way AI works (e.g., learning from training data sets), they may better comprehend the ethical issues of AI-based decisions such as transparency and accountability. For the integration process, pedagogical affordances (e.g., personalized and timely feedback) of AI-based tools could be emphasized. Hence, they will have technological pedagogical knowledge; ultimately they are more likely to use AI-based tools in their teaching profession. It is also important that field-specific AI-based tools (e.g., Chatbot for language learning) could be demonstrated. Thus, as also seen in the result of the current study, technological content knowledge might be promoted. Then, it is expected for an English teacher will likely know how to utilize a field-specific AI-based tool.

This is the first study to develop an instrument for measuring teacher professional knowledge from a robust theoretical perspective, TPACK. Researchers can utilize the Intelligent-TPACK scale to better understand AI-based instructions by tackling other variables. For instance, a study might be conducted to what extent the components of Intelligent-TPACK predict the quality of teachers' use of AI-based tools.

6. Limitations and future directions

The first limitation is related to the self-reported data. The data in this study were gathered through a validated scale to measure the teacher's knowledge to integrate AI-based tools in education. Although the validity and reliability of the self-reported scale were ensured, a multiple-data modality is still needed. Future studies can combine qualitative data through interviews or video with self-reported data to measure the knowledge of AI-based instructions from multiple perspectives. Sample size can be regarded as the second limitation. Although the number of participants meets the assumption to test the validity and reliability, it would be useful for future studies to collect data from a larger sample size. The participants consisted of in-service teachers from public and private schools. However, it is also important for future research to recruit pre-service teachers. In the present study, we focused on four AI-based tools in the course study due to their prevalence in educational settings. However, this is considered the third limitation of the current study. Hence, future studies can extend the diversity of AI based-tools such as educational robots. The current study recruited teachers with experience in using the EBA platform, and, thus, we assume that the teachers filling out the Intelligent-TPACK scale have used AI-based tools. Future studies can utilize the relevant scale after teachers' actual use of certain AI-based tools such as intelligent tutoring systems.

7. Conclusion

AI-based tools are becoming widespread in the K-12 context. However, little is known about teachers' knowledge and skills to integrate AI-based tools. There is a dearth of research investigating the integration of AI in education from a robust theoretical perspective. Based on the TPACK framework, we developed a valid and reliable measurement tool. Teachers' TK is important to assess the outcome of AI-based systems. However, TK is not sufficient to effectively use AI-based systems in education. Therefore, teachers should know the pedagogical affordances of AI. Teachers' ethical knowledge to utilize AI is crucial. The orchestrator role of teachers is emphasized in AI-based instruction (Dillenbourg, 2013; Holstein et al., 2019). We conclude that the orchestrator role requires a teacher's not only technical but also pedagogical and ethical knowledge and skills. TPACK might be considered a robust framework to shed light on the skills for AI-based instruction. The current study offers an updated framework on teacher knowledge to ethically integrate AI-based tools, namely, Intelligent-TPACK.

CRediT authorship contribution statement

Ismail Celik: Conceptualization, Methodology, Investigation, Formal analysis, Writing – original draft, Writing – review & editing.

Data availability

Data will be made available on request.

Appendix

Artificial intelligence (AI) is a broad branch of computer science. The aim of AI is to create smart technological tools by simulating human intelligence. Many technological applications benefit from AI and its sub-fields. We selected four AI-based tools in the current study: Chatbots, intelligent tutoring systems, dashboards, and automated assessment systems.

- Chatbot: Teachers can utilize chatbots to get help or notifications on student learning through voice or text inputs.
- Intelligent tutoring systems: Teachers can understand students' readiness. Students are provided with learning goals based on their needs.
- AI-enhanced dashboards: Teachers are enabled to monitor student knowledge construction and engagements through visualizations.
- Automated assessment systems: Teachers can use automated assessment systems for automatically scoring responses from students or plagiarism checks.

Please consider these four AI-based tools when you fill out the survey items. You might be familiar with these tools from the EBA system and daily life.

Intelligent – TPACK Scale

Intelligent TK
- I know how to interact with AI-based tools in daily life.
- I know how to execute some tasks with AI-based tools.
- I know how to initialize a task for AI-based technologies by text or speech.
- I have sufficient knowledge to use AI-based tools.
- I am familiar with AI-based tools and their technical capacities.

Intelligent TPK
- I can understand the pedagogical contribution of AI-based tools to my teaching field.
- I can evaluate the usefulness of feedback from AI-based tools for teaching and learning.
- I can select AI-based tools for students to apply their knowledge.
- I know how to use AI-based tools to monitor students' learning.
- I can interpret messages from AI-based tools to give real-time feedback.
- I can understand alerting (or notification) from AI-based tools to scaffold students' learning.
- I have the knowledge to select AI-based tools to sustain students' motivation.

Intelligent TCK
- I can use AI-based tools to search for educational material in my teaching field.
- I am aware of various AI-based tools which are used by professionals in my teaching field.
- I can use AI-based tools to better understand the contents of my teaching field.
- I know how to utilize my field-specific AI-based tools (e.g., intelligent tutor for Math).

Intelligent TPACK
- In teaching my field, I know how to use different AI-based tools for adaptive feedback.
- In teaching my field, I know how to use different AI-based tools for personalized learning.
- In teaching my field, I know how to use different AI-based tools for real-time feedback.
- I can teach a subject using AI-based tools with diverse teaching strategies.
- I can teach lessons that appropriately combine my teaching content, AI-based tools, and teaching strategies.
- I can take a leadership role among my colleagues in the integration of AI-based tools into our teaching field.
- I can select various AI-based tools to monitor students' learning in my teaching process.

Ethics
- I can assess to what extent AI-based tools consider individual differences (e.g., race and gender) of all students in my teaching.
- I can evaluate to what extent AI-based tools behave fair to all students in my teaching.
- I can understand the justification of any decision made by an AI-based tool.
- I can understand who the responsible developers are in the design and decision of AI-based tools.

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