Instrument Validation for Measuring Teachers' Practice and Trust in AI-Based Educational Technology

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Abstract

Objective. The aim of this study is to validate a unified survey combining the intelligent-Technological Pedagogical Content Knowledge (i-TPACK) scale and the Trust in AI-based Technology in Education (TRAIT-Ed) scale and develop a brief version of the combined 52-item scale. The survey was administered to K–12 teachers (N=121) before and after a two-day professional development workshop on artificial intelligence (AI) integration. The unified instrument is designed to capture both teachers' instructional competence (i-TPACK) and trust in adopting AI-based educational technologies (TRAIT-Ed) and examines changes in teachers' confidence, competence, and trust in using AI-based educational tools. This approach offers a more holistic view of AI adoption in education.

Method. Confirmatory Factor Analysis (CFA) was conducted to evaluate the internal structure of the unified instrument. The Weighted Least Squares Mean Variance (WLSMV) estimator was used given the ordinal nature of the data (likert-type scale). Model fit was assessed using common fit indices including chi-square ($\chi 2$), comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Skewness and Kurtosis values were used to assess univariate normality. Internal consistency was assessed using Cronbach's alpha (α) and McDonald's Omega (ω) coefficients. Convergent validity was assessed by examining Pearson correlations between composite scores on the i-TPACK and Trust subscales.

Results. For the original combined instrument, overall, the internal structure of the factor solution consisting of eight latent variables, including, five i-TPACK factors: Technological Pedagogical Content Knowledge (TPACK), Technological Knowledge (TK), Technological Content Knowledge (TCK), Technological Pedagogical Knowledge (TPK), Ethics; and three Trust factors: Working alongside AI to improve pedagogy (Pedagogy), Perceived Benefits of AI in an educational setting (Benefit), Reasons for not trusting AI diagnosis (Barrier), demonstrated appropriate model fit except for the SRMR index, based on post-survey data: χ^2=1930.160 (p-value=0.000), df=1,246.000, χ^2/df=1.55, RMSEA=0.079 (90% CI=0.072-0.086), SRMR=0.107, and CFI=0.975, TLI=0.974. All item factor loadings (λ) were significant ($p<0.001$), supporting convergent validity. Twenty-one items were removed for reasons including low variability, cross-loadings, relatively weak loading and multicollinearity. An improved fit was achieved with a reduced 31-item version of the unified scale demonstrating good fit: χ^2=518.056 (p-value=0.000), df=413.000, χ^2/df=1.25, RMSEA= 0.054 (90% CI=0.038-0.068), SRMR=0.052, and CFI=0.993, TLI=0.992.

Significance of results. Overall, findings support the validity and reliability of a unified and brief version of a refined 31-item instrument. The final version of the i-TPACK-Trust instrument offers a holistic approach to measuring teachers' trust and competence for AI integration in K-12 education. Insights from data collected using the final instrument can guide the design of professional development training programs for teachers and AI-based Educational Technology designers on improving practice and trust in AI-based EdTech.

Keywords: professional development, k-12 teachers, AI-based EdTech, confirmatory factor analysis (3 to 10 keywords)

Introduction

A background on the gradual evolution of Education from 1.0 to 5.0 and use of contemporary technologies is previously outlined by Ahmad et al. (2023). Education 5.0 recognizes that 21st-century skills such as critical thinking, creativity, and problem-solving cannot be developed through passive learning or traditional rote memorization (Lin et al., 2022). The practical implementation of Education 5.0 in schools leverages the use of artificial intelligence to support instructors in curriculum design, real-time classroom orchestration, and data-driven decision-making (Lin et al., 2022). Efforts to align the Education 4.0 framework strategically to match with Industry 4.0 framework, addressing needs relevant to the workforce has been described in Chakraborty et al. (2023). Specifically, an integrated alignment model linking Education 4.0 to Industry 4.0 demands has identified core competencies including decision-making, entrepreneurial thinking, efficiency orientation, problem-solving, conflict resolution, and analytical skills (Chakraborty et al., 2023). The framework strategically incorporates competencies such as mathematics, modeling, artificial intelligence, simulation, machine learning, IoT, deep learning, big data, neural networks, and cloud technologies into the learning experience (Chakraborty et al., 2023). Successful implementation of AI-based educational technology (AI-EdTech) requires more than technological infrastructure; it demands that educators develop new competencies and place trust in these systems. The TPACK (Technological Pedagogical Content Knowledge) framework has been extended to create the Intelligent-TPACK (i-TPACK) framework, which specifically addresses the unique challenges of integrating AI-based tools into teaching.

The increased prevalence of artificial intelligence (AI) in education has created a need not only to understand its mechanisms and applications (Kim & Kwon, 2023) but also to develop comprehensive frameworks that can guide teachers' development of pedagogical competencies and strategies that promote student learning in different subject areas. Developing such capacities involves constructing connections among content, pedagogy, and technology as well as fostering teachers' trust to use AI-powered educational technology (AI-EdTech) (Kim et al., 2021). Kim et al. (2021) noted that the Technological Pedagogical Content Knowledge (TPACK) framework is widely used to identify teachers' integration of technology into their teaching methods. It provides the language needed to conceptualize and explain the teacher capacity and knowledge required to incorporate technology into instruction. The decision to adopt and use a new AI-based educational technology (EdTech) is fundamentally an act of trust (Hosmer, 1995; Viberg et al., 2025). Trust is a necessary condition for any type of cooperative behavior (Davis & Whinston, 1962) and a critical aspect of AI adoption and usage (Viberg et al., 2025). Examining both teachers' knowledge and their willingness to accept and trust AI-based technology in their practice may help identify factors that contribute to successful adoption and use of EdTech.

The transformation of educational technologies with the emergence of artificial intelligence requires the adaptation of the TPACK framework to account for AI-driven digital technologies, which raise new challenges and require new forms of knowledge and strategies. Celik (2023) argued that new AI-based educational technology (EdTech) introduces pedagogical, ethical, and practical concerns that the conventional TPACK framework is not able to explain. AI is embedded in several educational tools, including chatbots, intelligent tutoring systems, dashboards, and automated assessment systems. These new AI-based technological tools learn from data and make autonomous decisions.

The Intelligent Technological Pedagogical Content Knowledge (i-TPACK) scale (Celik, 2023) and the Trust in AI-Based Technology in Education (TRAIT-Ed) scale (Nazaretsky et al., 2022) were developed independently to measure teachers' knowledge of factors that might influence AI-tool adoption. The general aim was to address the unique challenges of AI-powered EdTech tools due to their focus on computer systems capable of accomplishing tasks traditionally associated with human capabilities (Celik, 2023; Nazaretsky et al., 2022). However, these two scales have several limitations that pertain to their restricted original validation samples, fuzzy boundaries between constructs in the case of i-TPACK, and TRAIT-Ed's limited validation rigor, as it was validated via exploratory factor analysis (EFA). Moreover, little research has examined the psychometric properties or theoretical alignment of the two related constructs of i-TPACK and trust in a unified measure.

Celik (2023) conducted exploratory factor analysis (EFA) to reveal latent factors underlying the items and confirmatory factor analysis (CFA) to understand how measured TPACK factors support the TPACK theoretical framework. Structural equation modeling (SEM) through the maximum likelihood technique was utilized to apply CFA with five latent variables and 27 items. The NFI, CFI, and TLI values were found to be within the range of acceptable fit, and internal consistency reliability (Cronbach's α) ranged from 0.82 to 0.91 across subscales. The RMSEA value was also found to be lower than the threshold of 0.10 for a good fit. The values obtained from the analysis include: $\chi^2/df = 3.13$, $p < .001$; RMSEA = 0.058; NFI = 0.917; CFI = 0.942; AGFI = 0.875; TLI = 0.933. However, convergent and discriminant validity were not established through a comprehensive psychometric evaluation. Another limitation was the data collection procedures, as the instrument was developed and validated outside of the United States, in Turkey, within a single national context, which raises questions about its applicability to U.S. K-12 settings.

The goal of the current study was to validate a unified survey combining the intelligent-Technological Pedagogical Content Knowledge (i-TPACK) scale and the Trust in AI-based Technology in Education (TRAIT-Ed) scale and develop a brief version of the combined 52-item scale. To evaluate the internal structure, we hypothesized that the eight-factor structure of the unified iTPACK-TRAIT-Ed scale would have good fit indices and evidence of internal consistency (Hypothesis 1). To establish preliminary convergent validity evidence, we hypothesized that scores on the trust instrument would be positively correlated with scores of TPACK, TK, TPK, TCK (Hypothesis 2). Cohen's (1988) guidelines for interpreting effect size were used to assess for convergent validity such that a correlation above .50 would be interpreted as evidence of convergent validity.

Nazaretsky et al. (2021) developed and validated the Trust in AI-Based Technology in Education (TRAIT-Ed) scale to address the need for measures of teacher trust in AI-EdTech. Nazaretsky et al. (2021) noted that there was no previously established instrument for measuring educators' perceptions of AI-based EdTech and the impact of these perceptions on their willingness to adopt these tools for teaching and practice. The development process included collecting qualitative research data to identify trust dimensions and iterative improvement through expert review and pilot testing. The instrument was administered to 132 high school science teachers. To explore the factorial structure of the collected data, all 25 Likert items were subjected to exploratory factor analysis (EFA) using the principal axis factoring method with oblique rotation. The internal consistency of the selected seven-factor model was measured using Cronbach's α. The resulting values, ranging from 0.62 to 0.85, indicated adequate internal consistency reliability.

The results showed that eight factors influence teachers' trust in adopting AI-based EdTech: Perceived Benefits of AI-Based EdTech; AI-Based EdTech's Lack of Human Characteristics; AI-Based EdTech's Perceived Lack of Transparency; Anxieties Related to Using AI-Based EdTech; Self-Efficacy in Using AI-Based EdTech; Required Shift in Pedagogy to Adopt AI-Based EdTech; Preferred Means to Increase Trust in AI-Based EdTech; and AI-Based EdTech vs. Human Advice/Recommendation. The instrument provides a valuable measure of teachers' trust in AI-based EdTech. However, the instrument has several limitations, including a validation population that was limited to high school science teachers. Moreover, the internal validity of the instrument was not examined using confirmatory factor analysis (CFA), which could provide more insight into the distribution of teachers' responses. Nazaretsky et al. (2025) extended the TRAIT-Ed framework to measure students' trust perceptions in AI-EdTech. Using EFA and CFA on responses from 665 higher education STEM students, four critical factors shaping AI-EdTech adoption were identified: Perceived Usefulness, Perceived Obstacles, Perceived Trust, and Perceived Readiness.

Literature Review

The purpose of this literature review is to synthesize studies on the Intelligent Technological Pedagogical Content Knowledge (i-TPACK) and the Trust in AI-Based Educational Technology (TRAIT-Ed) scales in order to establish theoretical foundations and synergies for the integration and validation of a unified measure for K-12 teachers in the context of professional development.

Intelligent-TPACK

The Technological Pedagogical Content Knowledge (TPACK) framework is rooted in Shulman's (1986) pedagogical content knowledge (PCK) model. Shulman conceptualized the integration of content and pedagogical knowledge as a necessary requirement for effective instruction. TPACK was developed in response to the absence of a robust theory to guide the integration of technology in education (Rosenberg & Koehler, 2015). Brantley-Dias and Ertmer (2013) argued that when TPACK was introduced, it was intended to provide a new means to discuss the tools teachers use in the service of teaching and learning and the specific knowledge they need to be successful. It has become a popular framework for explaining and examining the types of knowledge needed to achieve effective technology integration (Brantley-Dias & Ertmer, 2013). Brantley-Dias and Ertmer (2013) reported that TPACK has been conceptualized in four main ways: (a) as a new definition of technology integration; (b) as the integration of content, pedagogical, and technological knowledge; (c) as the knowledge base needed for effective technology integration; and (d) as a distinct body of knowledge. The TPACK theoretical framework is intended to provide a common language and simple labels that can be easily recognized for discussion of technology integration and instructional technological tools.

TPACK suggests a holistic view of the entire knowledge base teachers need for effective technology application in their classrooms (Mishra & Koehler, 2006). TPACK as knowledge refers to something teachers possess, such as concepts, rules, and procedures (Willermark, 2018). Mishra and Koehler (2006) explain that TPACK is about teachers incorporating technological knowledge into the structure of pedagogical content knowledge and the surrounding context. In the context of English language learning, TPACK highlights knowledge of the application of technologies used in learning environments (Technological Knowledge, TK), knowledge of practices, procedures, or methods necessary for teaching and learning, including educational theories and assessment (Pedagogical Knowledge, PK), and knowledge of the subject matter, including language proficiency, language awareness, and knowledge of culture (Content Knowledge, CK) (Bostancıoğlu & Handley, 2018). Niess (2013) suggested that these domains exist in a dynamic relationship in which each domain of TPACK is in continuous and evolving interaction with the others.

Equally important to the model are the intersections among these bodies of knowledge, including knowledge of subject matter representation with technology, such as how technology can be used to represent language, content, and culture in different ways (Technological Content Knowledge, TCK); knowledge of the application of teaching approaches and general pedagogical strategies applied to the use of technology (Technological Pedagogical Knowledge, TPK); knowledge of teaching methods, general pedagogical strategies, and lesson planning to make the subject matter more understandable to learners (Pedagogical Content Knowledge, PCK); and knowledge of using various technologies to implement teaching methods for different designated subject content and to communicate relevant information to students and peers (Technological Pedagogical Content Knowledge, TPCK) (Bostancıoğlu & Handley, 2018). Koehler et al. (2014) suggest that TPACK is a form of professional knowledge that goes beyond knowledge of content, pedagogy, and technology taken individually.

Celik (2023) developed a valid and reliable measurement tool, the Intelligent-TPACK (i-TPACK) scale, based on the TPACK framework, to assess teachers' technological knowledge, AI-based instruction, and teacher knowledge for ethical integration of AI-based tools. The Intelligent-TPACK scale explains teachers' knowledge of interactions with and use of AI-based tools (Intelligent-TK); pedagogical affordances such as personalized and timely feedback and monitoring students' learning (Intelligent-TPK); knowledge of field-specific AI-based tools and their appropriateness for addressing subject-matter learning (Intelligent-TCK); teachers' professional knowledge to select and use suitable AI-based tools (e.g., intelligent tutoring systems) to perform a teaching strategy (e.g., monitoring and timely feedback) to accomplish instructional goals in a particular domain (Intelligent-TPACK); and teachers' assessment concerning decisions about using AI-based tools (Ethics).

Celik's (2023) study indicates that Technological Pedagogical Knowledge (TPK), the combination of technological knowledge (TK) and pedagogical knowledge (PK), is a significant predictor of teachers' AI-specific pedagogical knowledge. Other studies, such as An et al. (2023), refined the AI-TPACK framework to account for the potential for AI to function independently as an educator or collaborator. An et al. (2023) proposed an AI-TPACK model that distinguishes between the knowledge required for human teachers and that applicable to AI machine teachers, distinguishing between TPK and TPCK as distinct dimensions. This conceptualization accounts for the new emerging systems that not only support teachers but also function autonomously as pedagogical agents. An et al.'s (2025) AI-TPACK scale was developed for secondary English teachers in China.

Trust in AI in Education

Evidence from the literature underlines the critical role that human factors such as trust play in technology adoption. Nazaretsky et al. (2022) argue that the issue of trust is even more complex in the case of artificial intelligence (AI)-powered tools due to practitioners' lack of knowledge about AI, AI-specific misconceptions, myths, and fears, including mass unemployment and privacy violations. The decision and willingness of a teacher to adopt a new technology create a state of vulnerability because it might not function as expected or create challenges with negative consequences for the teacher's performance and relationship with students (Viberg et al., 2025). Teachers' trust in AI-EdTech is intertwined with perceived benefits and concerns about AI-EdTech.

Well-established theories such as the theory of academic resistance, resistance to organizational change theory, and the technology acceptance model (TAM) address the issue of teachers' perceptions and attitudes towards using technology and resistance to change. However, none of these theories focuses on the specific features of AI-based tools (Nazaretsky et al., 2022). Viberg et al. (2025) noted that few evidence-based studies have examined teachers' trust in AI-EdTech. Classic definitions frame trust as the willingness to accept vulnerability to another entity (Hosmer, 1995). Nazaretsky et al. (2022) defined teachers' trust toward the use and adoption of AI-EdTech as a multidimensional construct that encompasses attitudinal aspects, including teachers' beliefs, fears, anxieties, knowledge, and evaluations of AI-EdTech capabilities and limitations, as well as behavioral intentions.

Nazaretsky et al.'s (2022) study indicates that presenting teachers with explanations of how AI makes decisions and how AI can complement and enhance teachers, rather than replace them, can improve trust in AI-EdTech. This definition of trust aligns with Mayer et al.'s (1995) integrative model of organizational trust. Mayer et al. (1995) argue that although conditions leading to trust have been discussed repeatedly in the literature, three characteristics of a trustee emerge: ability, benevolence, and integrity. Applying Mayer et al.'s (1995) model to the context of technology, these three characteristics have been interpreted as the functionality of the technology, its helpfulness, and its reliability (Viberg et al., 2025), and they have been examined in the context of benefits and concerns.

AI-EdTech creates a unique challenge to trust due to several factors, including privacy concerns, the AI "black box" problem, and transparency. Felzmann et al. (2019) explained that the core concerns linked to AI are connected to automated decision-making processes—decisions that are delegated to a machine or system. There are clear indications of active resistance to using AI-based educational technology in schools due to negative connotations (Nazaretsky et al., 2021). The increased interest in AI has resulted in the proliferation of AI tools for K–12, along with confusion (Casal-Otero et al., 2023). Many teachers perceive AI to be less helpful in assisting them in understanding how students learn and to be less prestigious compared to neuroscience and educational psychology due to "lacking adherence to scientific methods" (Nazaretsky et al., 2021). Research has shown that people quickly lose trust in automated recommendation systems after seeing that they make mistakes (Dietvorst et al., 2015). This phenomenon, where teachers hold AI-EdTech to error-free standards, is referred to as algorithm aversion. It has also been shown that teachers expect AI output to be fully consistent with their beliefs and opinions. Such differences between AI-EdTech output and teachers' opinions are likely to reduce trust in AI-EdTech (Nazaretsky et al., 2021). These tendencies can further lead to teachers' resistance to AI-EdTech and failure to recognize its functionality and relevance.

Research Questions

Not much research has examined the psychometric integration of i-TPACK and Trust. This study was guided by the following questions: (1) What are the psychometric features of a unified i-TPACK–Trust measure for K–12 teachers in professional development settings? (2) To what extent does the unified instrument demonstrate validity and internal consistency?

Methods

Data

This validation study used data collected at a professional development workshop on AI in education from middle and high school teachers in the Mid-Atlantic region of the United States of America (N=121). The study was reviewed and approved by the institutional Review Board. Survey data was collected through the REDCap (Research Electronic Data Capture) platform. REDCap is a secure, web-based software platform designed to support data capture for research studies, providing 1) an intuitive interface for validated data capture; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for seamless data downloads to common statistical packages; and 4) procedures for data integration and interoperability with external sources. After excluding incomplete responses, the analytic sample included 110 teachers at pre-test and 88 at post-test. The majority identified as female, and the modal age range between 50 and 59 years (table 1).

Professional Development Intervention

The professional development (PD) intervention consisted of a two-day, in-person workshop hosted at a university located in the Mid-Atlantic Region of the United States of America in July 2025.

Recruitment and Participants

Participants were recruited using an open-enrollment strategy intended to maximize access across diverse educational roles and contexts. Recruitment channels included email outreach through school and district partnerships, professional email lists, word-of-mouth referrals, and social media outreach on Facebook and LinkedIn. Additional statewide visibility was achieved through support from the State Department of Education, which distributed workshop registration information to all State public school teachers via a monthly newsletter. Participation incentives included free registration, professional development certificates, and complimentary lunch provided on both days of the workshop. The workshop was open to K–12 educators across all grade levels and subject areas, as well as non-classroom educational professionals such as technology integration specialists, assistant principals, and other school administrators. No prerequisite knowledge of artificial intelligence (AI) was required. Attendance ranged from approximately 150 to 200 participants per day, with slightly lower attendance observed on the second day. Participation in the research component was voluntary; therefore, not all workshop attendees completed the pre- and post-intervention surveys used for analysis.

Structure and Schedule

The workshop was delivered over two consecutive days, with programming running from 10:00 a.m. to 3:00 p.m. each day, for a total of 10 hours of professional development. Each day consisted of four one-hour sessions, with a scheduled lunch break at 12:00 p.m. Sessions were delivered sequentially in a large auditorium. While no formal breakout rooms were used, sessions incorporated structured pauses and informal opportunities for discussion and collaborative activity among participants. All sessions were facilitated in a whole-group format. Participants primarily collaborated in small, self-selected groups with nearby peers, facilitating informal discussion and shared problem-solving within the large-group setting.

Content and Pedagogical Focus

Workshop content was designed to introduce participants to practical and pedagogically relevant applications of AI in K–12 educational settings. Instruction emphasized instructional use cases rather than technical development, focusing on how AI tools can support teachers' existing professional responsibilities. Core topics included prompt engineering for instructional design, AI-assisted creation of teaching materials, and classroom-relevant applications of generative AI tools. Participants were introduced to a range of AI tools commonly used in educational contexts, including ChatGPT, Gemini, Magic School, Brisk, Playlab, Notebook LM, Genially, and Synthesia. These tools were presented as examples of broader categories of AI-supported instructional technologies, such as lesson planning assistants, assessment generators, accessibility tools, and content creation platforms. The workshop also included a teacher-led tool-sharing "show-and-tell" session, during which participants volunteered to demonstrate AI tools they currently use or have explored in their professional practice. This session emphasized peer-to-peer learning and positioned teachers as contributors to collective professional knowledge. Ethical and policy considerations were explicitly addressed through both instructional sessions and panel discussions. A dedicated session titled School AI Policy with Instructional Innovation Specialists featured administrators and instructional innovation specialists from multiple school divisions, which included various counties. Panel discussions focused on ethical and practical considerations related to AI adoption, including student data privacy, algorithmic bias, equity implications, and district-level processes for evaluating AI tools for classroom and large-scale adoption.

Learning Activities

Session formats included lectures, hands-on workshops, panel discussions, and "show-and-tell" style presentations. Hands-on learning was a central component of the intervention. During interactive sessions, participants engaged in guided activities focused on applying prompt engineering techniques to generate instructional artifacts relevant to their professional roles. Activities included creating lesson plans, project-based learning modules, assessments, rubrics, tests, and individualized education program (IEP) support using AI tools demonstrated during the workshop. Collectively, the professional development intervention was designed to enhance participants' confidence, competence, and critical awareness related to AI integration in education, while providing structured opportunities to explore pedagogical affordances, ethical considerations, and trust-related concerns associated with AI-based educational technologies.

Analysis

Incomplete responses were excluded from analysis. Items 128, 129, 1210-1216 in the Trust measure were re-coded and renamed as 128R, 129R, 1210R-1216R to match the valence of all the other items measuring trust. The numbering of items was modified from the original survey since both instruments were merged and administered as one instrument in a single-seating to participating teachers. Analyses were conducted in Mplus 8.10 and R 4.4.1. Data screening evaluated missingness and the shape of item distributions. All items met recommended thresholds of univariate skewness (< 3) and kurtosis (< 7) (table 2). The most common estimation procedure in CFA is maximum likelihood (ML), which carries with it the assumption of multivariate normality (MVN). When normality is violated, it is recommended to use the Robust Maximum Likelihood (MLR) estimator, which adjusts the standard errors and chi-square tests for non-normality. MLR is robust to both moderate and severe deviations from normality. However, for ordinal data, for example, from likert scale responses, instead of the MLR estimator, the Weighted Least Squares Mean Variance (WLSMV) estimator is more suitable (Muthen et al., 1997). The WLSMV estimator is also particularly useful for data that is not normally distributed. For the present study, CFA analysis was conducted using the WLSMV estimator.

CFA models were estimated for: (a) the unified eight-factor model, (b) the five-factor i-TPACK model, and (c) the three-factor TRAIT-Ed model, using post-survey data as the primary basis for validation. Model fit was evaluated using χ^2, df, χ^2/df, RMSEA, CFI, TLI, and SRMR. Values of $\chi^2/df \leq 2$, RMSEA < .08 (Awang, 2012), CFI ≥ .90, TLI ≥ .90 (Hu & Bentler, 1999), and SRMR < .08 were interpreted as evidence of acceptable fit. Modification indices were inspected to identify potential cross-loadings and correlated residuals. Internal consistency was assessed using Cronbach's alpha (Cronbach, 1951) and McDonald's omega (Bittencourt et al., 2021). Convergent validity was examined via correlations between the trust subscales and i-TPACK subscales and assessed through the average variance extracted (AVE) (Henseler et al., 2015). Measure of sampling adequacy (MSA) was also assessed using the Kaiser-Meyer-Olkin (KMO) statistic (Kaiser, 1970; Kaiser & Rice, 1974). Items with KMO values above 0.5 at 95% confidence interval were considered of good quality (Lorenzo-Seva & Ferrando, 2021).

A list of items for removal from the final unified instrument was created based on low variability (SD < 0.50), cross-loading and multicollinearity (Modification Index > 10), and weak loading (< 0.70). The item factor loading cut-off value employed in the current analysis was < 0.3 (Costello & Osborne, 2005). These cut-points were used as general guidelines. Interpretation focused on comparing the indicators, alignment to theory and number of indicators per latent factor, to help decide which items to keep or remove, while also considering how item removal affected overall model fit. To ensure accurate measurement, at least three items were retained for each subscale.

Research Design

The current study constituted a pre- then post- quasi-experimental design with professional development intervention. Data was aggregated for analysis to protect participant confidentiality.

Surveys were administered to help inform refinement of teacher training materials and guide future scale-up efforts to ensure equitable AI integration in diverse K–12 settings. Participants completed a survey that included demographic (table 1) and professional background items. Demographic items included gender and age. Professional background items included years of teaching experience, school district, school type, school name, grades taught, and main subject area taught.

Measures

The present study leveraged survey items from two previously developed instruments: (1) a scale measuring teachers' trust in AI-based Educational Technology (EdTech) developed by Nazaretsky et. al. (2022), and (2) a validated Intelligent-TPACK scale developed by Celik (Celik, 2023).

Intelligent-TPACK Scale

The Intelligent-TPACK (i-TPACK) scale is a revised extension of the Technological, Pedagogical, and Content Knowledge (TPACK) framework designed to measure teachers' knowledge for instructional AI use incorporating ethical dimensions (Celik 2023). The 27-item i-TPACK scale includes five dimensions including, intelligent-TK, intelligent-TPK, intelligent-TCK, intelligent-TPACK and Ethics. The Intelligent-TK sub-scale comprises 5 items measuring teachers' familiarization level with the technical capacities of AI-based tools. Intelligent-TPK sub-scale comprises 7 items measuring knowledge for pedagogical affordances of AI-based tools such as personal and timely feedback, and monitoring students' learning. Intelligent-TCK sub-scale comprises 4 items measuring to what extent teachers use AI-based tools to update their content knowledge. Intelligent-TPACK sub-scale comprises 7 items measuring teachers' professional knowledge to select and use suitable AI-based tools for performing a teaching strategy (e.g., monitoring and timely feedback) to accomplish the instructional goals in a particular domain. Ethics sub-scale comprises 4 items measuring teachers' assessment concerning the decision on AI-based tools. The ethics assessment is based on transparency, fairness, accountability, and inclusiveness. Responses are based on a 5-point, Likert-type scale ranging from 1 (Strongly Disagree), 2 (Disagree), 3 (Neither Agree Nor Disagree), 4 (Agree), to 5 (Strongly Agree). For the current study, item-level aggregate scores were used for analysis.

Trust in AI-based Technology in Education Scale

The Trust in AI-based Technology in Education (TRAIT-Ed) scale is an instrument previously developed by Nazaretsky et al. (2022) to measure teachers' trust in AI-based Educational Technology (EdTech). The 25-item TRAIT-Ed scale consists of three dimensions including, Perceived benefits of AI in an educational setting comprising 8 items; Reasons for not trusting AI diagnosis comprising 8 items; Working alongside AI to improve pedagogy comprising 9 items. Responses are based on a 5-point, Likert-type scale ranging from 1 (Strongly Disagree), 2 (Disagree), 3 (Neither Agree Nor Disagree), 4 (Agree), to 5 (Strongly Agree).

Results

Model Fit

The 52-item unified eight-factor model showed mixed fit: χ^2 = 1930.160 (p-value = 0.000), df = 1,246.000, χ^2/df = 1.55, RMSEA = 0.079 (90% CI = 0.072 - 0.086), SRMR = 0.107, and CFI = 0.975, TLI = 0.974 (table 6). While the SRMR value exceeded the recommended cut-off, the remaining indices including the CFI and TLI were well above the 0.90. The five-factor i-TPACK model demonstrated the following fit indices: χ^2 = 426.629 (p-value = 0.000), df = 314.000, χ^2/df = 1.36, RMSEA = 0.064 (90% CI = 0.048 - 0.079), SRMR = .046, and CFI = 0.996, TLI = 0.995. The values indicate a good model fit and align with previous studies (Celik, 2023). The three-factor Trust model demonstrated mixed fit: χ^2 = 1,139.927 (p-value = 0.000), df = 272.000, χ^2/df = 4.191, RMSEA = 0.192 (90% CI = 0.180-0.203), SRMR = .137, and CFI = 0.974, TLI = 0.972. Although RMSEA and SRMR values were slightly higher than ideal, and that the χ^2/df ratio was elevated, CFI and TLI met conventional thresholds, and all items loaded significantly on their intended factors. The final 31-item seven-factor model demonstrated good model fit: χ^2 = 518.056 (p-value = 0.000), df = 413.000, χ^2/df = 1.25, RMSEA = 0.054 (90% CI = 0.038 - 0.068), SRMR = 0.052, and CFI = 0.993, TLI = 0.992 (figure 1).

Factor Loadings and Reliability

All items in the 52-item unified model had standardized factor loadings above .40 (table 3), supporting item-level contributions. Internal consistency for each subscale was excellent: TPK (.95, .95), TK (.92, .93), TCK (.91, .92), TPACK (.97, .97), Ethics (.94, .94), Barrier (.90, .90), Pedagogy (.90, .90), and Benefit (.92, .92) for Cronbach's alpha and omega, respectively (table 4).

Convergent Validity

Trust-related dimension Perceived Benefits of Using AI demonstrated good correlations ($r > 0.5$), Working Alongside AI to Improve Pedagogy demonstrated moderate correlations ($r = .28$ to $r = .34$), while Reasons for not trusting AI diagnosis factor was weakly correlated with i-TPACK factors; TK, TPK, TCK, and TPACK providing partial support for convergent validity (Table 5). This result suggests that the Reasons for not trusting AI diagnosis factor represents a distinct psychological construct and was therefore removed such that this subscale was no longer part of the unified survey.

Convergent validity of the refined unified i-TPACK–TRAIT-Ed instrument was evaluated using Average Variance Extracted (AVE) and composite reliability (McDonald's ω). As shown in Table 8, all constructs demonstrated AVE values well above the recommended threshold of .50 (Fornell & Larcker, 1981), ranging from .832 to .945, indicating that a substantial proportion of variance in the observed indicators was accounted for by their respective latent constructs. Composite reliability estimates were uniformly high (ω = .915–.960), exceeding the recommended minimum of .70 (Raykov, 1997), and providing additional evidence of internal consistency.

Model Modification

To refine the internal structure of the 52-item unified i-TPACK–TRAIT-Ed instrument, items were removed sequentially based on psychometric criteria including low variability, suboptimal sampling adequacy, weak factor loadings, cross-loadings, high residual correlations, and severe multicollinearity. A summary of removed items and the corresponding rationale is presented in Table 7, and the complete list of items is provided in Appendix A. Specifically, two items (tk2, a116) were removed due to low variability ($SD < 0.50$). Several i-TPACK items (tck2, tpack5) and Trust items (a1319, a1318) demonstrated substantial cross-loadings ($MI > 10$), while others (tpk3, tpack2, tpack3, tpack5) exhibited high residual correlations ($r = .76–.89$), suggesting item redundancy. A number of Trust items (a1324, a1325, a1320) were removed due to severe multicollinearity and weak incremental contribution (MI up to 410.25). Additionally, a115 was excluded due to poor sampling adequacy ($MSA = 0.36$). The trust factor measuring “Reasons for Not Trusting AI diagnosis” consisting of items a128, a129, a1210 to 1216 was removed entirely from the final instrument because of low correlation with all other items: TPK, $r = 0.159$; TK, $r = 0.128$; TCK, $r = 0.046$; TPACK, $r = 0.128$; Ethics, $r = 0.319$ and low measure of sampling adequacy (MSA).

Discussion

The TCK items reflect strong confidence in integrating AI. Low variability implies that respondents feel similarly prepared to connect AI tools with content. Similarly, TK items show strong agreement and minimal dispersion, with most responses concentrated between *Agree* and *Strongly Agree* (figure 2). These distributions indicate widespread familiarity with AI technologies themselves, suggesting that baseline technological competence is high across the sample. Items within TPACK demonstrated high overall endorsement but also greater variability than TK or TCK alone. As shown in previous studies, this result suggests that integrating AI simultaneously across technological, pedagogical, and content domains is perceived as more complex than mastering a single domain independently. The TPK construct shows a pattern similar to TPACK. Respondents generally report confidence in using AI to support instructional strategies, though the variability suggests uneven comfort in adapting pedagogy around AI-enhanced teaching practices. Items within the Ethics construct exhibit medians clustered around *Agree (4)* and relatively narrow interquartile ranges. The distributions suggest high consensus among respondents regarding ethical awareness and responsibility when engaging with AI-based educational technologies. The limited presence of lower-end outliers indicates that ethical considerations are harmonized across the sample. Items within the trust sub-scale *Working Alongside AI to improve pedagogy* showed high medians (between 4 to 5). While most respondents endorse pedagogical practices that involve collaborating with AI, there is wider spread and occasional lower outliers suggesting variability in how confidently educators perceive AI as a pedagogical accompaniment. This pattern may reflect differences attributable to reasons including classroom experience, access to AI tools, or instructional autonomy. Distributions for items within the trust subscale *Perceived Benefits of using AI* are highly right-skewed. The tight clustering at the upper end of the scale indicates strong agreement that AI provides instructional value. Items within the Reasons for NOT Trusting AI Diagnosis show medians around 3 to 4 and broad interquartile ranges. Several items exhibit extended whiskers and multiple outliers, indicating greater heterogeneity in skepticism toward trusting AI diagnosis. These distributions suggest that distrust is not uniform; rather, concerns vary in intensity. These differences could be linked to factors including the subject taught or even the age range of the participants.

Research Question 1: The first research question was to investigate whether a unified i-TPACK/TRAIT-Ed instrument could adequately model teachers' AI competence and trust within a single eight-factor framework. The CFA results indicate that, in its current form, the unified measure does not demonstrate optimal global model fit. Model fit indices RMSEA and SRMR values, suggests that the constructs do not currently exist as a single stable structure. Inspection of modification indices indicated multicollinearity, low sampling adequacy, high residual correlation, and weak loading for select items, pointing to conceptual overlap and possible redundancy.

Research Question 2: The second research question focused on the degree to which the unified 52-item instrument demonstrates validity and internal consistency. Reliability estimates for all eight subscales were excellent, indicating that items within each subscale function consistently. However, evidence of structural validity differed across the two separate instruments. The i-TPACK model showed acceptable fit and strong loadings, providing support for its use as a measure of AI-related pedagogical competence in the U.S. K-12 professional development contexts. These findings replicate and extend prior work conducted in other national settings (Celik, 2023). By contrast, the TRAIT-Ed model exhibited poor fit in the current sample, despite adequate reliability. This suggests that the original three-factor structure may not capture the full complexity of teachers' trust in AI-EdTech. Convergent validity was only partially supported. While perceived benefits and pedagogy-related trust showed moderate associations with i-TPACK factors, barrier-related trust concerns emerged as more independent. Following model modification, a modified 31-item instrument indicating appropriate model fit measuring i-TPACK and Trust was created for use in subsequent studies.

Implications

Findings underscore the complementary but distinct roles of AI pedagogical competence and trust in supporting meaningful AI integration in K–12 classrooms. While the strong psychometric performance of the i-TPACK scale suggests that teachers' technological, pedagogical, and ethical AI-related knowledge can be reliably measured and developed, the weaker structure of the trust model indicates that trust in AI remains a complex and evolving construct. Trust-related concerns, particularly perceived barriers and diagnostic skepticism, appear to operate differently than pedagogical competence. This aligns with theoretical perspectives that AI adoption is not solely a technical or pedagogical process, but also a social, psychological, and ethical decision-making process (Hosmer, 1995; Mayer et al., 1995; Nazaretsky et al., 2022; Viberg et al., 2025). Even highly competent teachers may hesitate to fully integrate AI tools if transparency, reliability, and professional autonomy are perceived as threatened (Dietvorst et al., 2015; Felzmann et al., 2019; Nazaretsky et al., 2021).

Practically, results highlight that professional development should address both skill development and trust formation. Technical competence alone is insufficient without addressing teacher concerns about algorithmic transparency, instructional autonomy, and student data privacy. Opportunities for reflection, dialogue, and sensemaking around ethical use, data governance, and human–AI role boundaries appear critical, as training focused solely on tool proficiency may increase perceived competence without meaningfully influencing adoption behavior. For EdTech developers, findings emphasize the importance of designing AI tools that support explainability and human-involved decision-making. For school leaders, the results reinforce the need for clear AI use policies, ethical guidelines, and sustained teacher support. While educators may feel well-prepared and ethically grounded in their use of AI, unresolved trust concerns may continue to shape how, and whether, AI is integrated into high-stakes educational decisions.

Finally, the unified i-TPACK–Trust instrument provides a tool to examine instructional competence and trust in AI simultaneously rather than in isolation. Prior studies have typically assessed either teacher knowledge frameworks or attitudes toward AI adoption independently, limiting insight into how these constructs interact in practice. By integrating i-TPACK and TRAIT-Ed within a single validated model, this study offers a more holistic lens for conceptualizing AI adoption as a sociotechnical process in which pedagogical capability and trust co-evolve but may develop at different rates. The refined 31-item scale provides a parsimonious yet theoretically grounded tool for capturing these relationships.

Conclusion

Findings confirm that AI competence and trust represent distinct but interdependent dimensions of AI adoption. Sustained AI integration depends not only on technical and pedagogical skill, but equally on trust in the reliability, transparency, and ethical alignment of AI-based systems.

For Educators and Instructional Designers: These findings underscore that professional development initiatives must address both skill development and trust formation simultaneously. The strong psychometric performance of the i-TPACK scale demonstrates that teachers' technological, pedagogical, and ethical AI-related knowledge can be reliably measured and developed. Educators benefit from opportunities for reflection, dialogue, and sensemaking around ethical use, data governance, and human-AI role boundaries. Training focused solely on tool proficiency may increase perceived competence without meaningfully influencing adoption behavior, that is, trust.

For STEM Bridge Instructors and K-12 to Engineering Pathway Programs: This unified instrument provides a practical framework for assessing and developing teacher readiness across the K-12 and can be extended to higher education assessment. STEM bridge instructors connecting K-12 pathways to 4-year engineering programs can leverage the refined 31-item i-TPACK-TRAIT-Ed scale to evaluate both the computational thinking competencies and trust dispositions of students and teachers transitioning into advanced technical coursework. By understanding how pedagogical capability and trust co-evolve at different rates, bridge program administrators can design targeted interventions that build confidence in AI-assisted problem-solving while maintaining the human-centered design principles essential to engineering education. Additionally, the identification of distinct trust factors, particularly perceived barriers and diagnostic skepticism, suggests that bridge instructors should explicitly teach students how AI tools complement rather than replace human engineering judgment.

For EdTech Developers and School Leaders: For EdTech developers, findings emphasize the importance of designing AI tools that support explainability and human-involved decision-making. For school leaders, the results reinforce the need for clear AI use policies, ethical guidelines, and sustained teacher support. While educators may feel well-prepared and ethically grounded in their use of AI, unresolved trust concerns may continue to shape how, and whether, AI is integrated into high-stakes educational decisions.

Methodological and Research Implications

The unified i-TPACK-TRAIT-Ed instrument provides a tool to examine instructional competence and trust in AI simultaneously rather than in isolation. Prior studies have typically assessed either teacher knowledge frameworks or attitudes toward AI adoption independently, limiting insight into how these constructs interact in practice. By integrating i-TPACK and TRAIT-Ed within a single validated model, this study offers a more holistic lens for conceptualizing AI adoption as a sociotechnical process in which pedagogical capability and trust co-evolve but may develop at different rates.

Limitations and Future Directions

In the current study, several limitations should be considered. First, the sample size, limited statistical power for complex modeling. Second, participants were drawn from a single geographic region within a voluntary professional development context, introducing potential self-selection bias. Finally, the TRAIT-Ed scale has not yet undergone extensive CFA-based validation across diverse K-12 populations.

Future studies can prioritize large-scale, multi-site validation of the new unified instrument across diverse K-12 and higher education settings, including specialized STEM contexts and engineering bridge programs. Longitudinal designs may clarify how trust evolves with sustained classroom AI use and how student outcomes vary as a function of teacher competence and trust profiles. Future work can explore measurement invariance across disciplines, grade levels, and gender, as well as investigate the instrument's utility in non-English-speaking contexts and culturally diverse educational systems.

Appendix

Appendix A: i-TPACK and Trust Survey Instrument Descriptions and Status

Construct / Subscale	Item	Item Statement	Status
Intelligent Technological Knowledge (i-TK)	tk1	I know how to interact with AI-based tools in daily life.	Retained
	tk2	I know how to execute some tasks with AI-based tools.	Removed
	tk3	I know how to initialize a task for AI-based technologies by text or speech.	Retained
	tk4	I have sufficient knowledge to use AI-based tools.	Retained
	tk5	I am familiar with AI-based tools and their technical capacities.	Retained
Intelligent Technological Pedagogical Knowledge (i-TPK)	tpk1	I can understand the pedagogical contribution of AI-based tools to my teaching field.	Retained
	tpk2	I can evaluate the usefulness of feedback from AI-based tools for teaching and learning.	Retained
	tpk3	I can select AI-based tools for students to apply their knowledge.	Removed
	tpk4	I know how to use AI-based tools to monitor students' learning.	Retained
	tpk5	I can interpret messages from AI-based tools to give real-time feedback.	Retained
	tpk6	I can understand alerting (or notification) from AI-based tools to scaffold students' learning.	Retained
	tpk7	I have the knowledge to select AI-based tools to sustain students' motivation.	Retained

Construct / Subscale	Item	Item Statement	Status
Intelligent Technological Content Knowledge (i-TCK)	tck1	I can use AI-based tools to search for educational material in my teaching field.	Retained
	tck2	I am aware of various AI-based tools which are used by professionals in my teaching field.	Removed
	tck3	I can use AI-based tools to better understand the contents of my teaching field.	Retained
	tck4	I know how to utilize my field-specific AI-based tools (e.g., intelligent tutor for Math).	Retained
Intelligent Technological Pedagogical Content Knowledge (i-TPACK)	tpack1	In teaching my field, I know how to use different AI-based tools for adaptive feedback.	Retained
	tpack2	In teaching my field, I know how to use different AI-based tools for personalized learning.	Removed
	tpack3	In teaching my field, I know how to use different AI-based tools for real-time feedback.	Removed
	tpack4	I can teach a subject using AI-based tools with diverse teaching strategies.	Retained
	tpack5	I can teach lessons that appropriately combine my teaching content, AI-based tools, and teaching strategies.	Removed
	tpack6	I can take a leadership role among my colleagues in the integration of AI-based tools into our teaching field.	Retained
	tpack7	I can select various AI-based tools to monitor students' learning in my teaching process.	Retained

Construct / Subscale	Item	Item Statement	Status
AI Ethics Awareness	eth1	I can assess to what extent AI-based tools consider individual differences (e.g., race and gender) of all students in my teaching.	Retained
	eth2	I can evaluate to what extent AI-based tools behave fairly toward all students in my teaching.	Retained
	eth3	I can understand the justification of any decision made by an AI-based tool.	Retained
	eth4	I can understand who the responsible developers are in the design and decision of AI-based tools.	Retained
Perceived Benefits of AI	a111	Artificial Intelligence can assist in formative assessment of complex tasks and suggest personalized feedback in real time.	Retained
	a112	Artificial Intelligence can assist in assigning individualized learning paths for students' self-learning.	Retained
	a113	Artificial Intelligence can assist in creating intelligent agents that serve as learning pals or teaching assistants.	Retained
	a114	Artificial Intelligence can assist in diagnosing students' difficulties to support personalized tasks.	Retained
	a115	Artificial Intelligence can assist teachers with in-class management activities.	Removed
	a116	Artificial Intelligence can assist teachers in planning lessons and activities before class.	Retained
	a117	Artificial Intelligence can improve teacher professional training using simulations or avatars.	Retained
Trust and Intended Use of AI	a1317	I fully trust using AI-based personalized learning tools in my classroom.	Retained

Construct / Subscale	Item	Item Statement	Status
	a1318	I believe I will be successful in using AI-based tools for personalization in my classroom.	Removed
	a1319	I will use AI-based tools for personalization in my class when available.	Removed
	a1320	Using AI-based tools for personalization will require significant pedagogical change.	Removed
	a1321	As AI-based tools become more prevalent, they will gain my full trust.	Retained
	a1322	The more I know how an AI-based tool makes decisions, the more I will trust it.	Retained
	a1323	The more data available to an AI-based tool, the more I will trust its insights.	Retained
	a1324	I trust AI recommendations as much as those from fellow teachers.	Removed
	a1325	I trust AI recommendations as much as those from experts.	Removed
Reasons for Not Trusting AI (Reverse-coded)	a128R	Discrepancies between AI diagnosis and teacher opinion.	Removed
	a129R	AI developers lack educational experience.	Removed
	a1210R	AI does not understand social, emotional, and motivational factors.	Removed
	a1211R	Teachers' intuition is superior to computer judgment.	Removed
	a1212R	AI does not know students' history outside the system.	Removed
	a1213R	Lack of transparency in AI decision-making.	Removed
	a1214R	AI removes autonomy and control from teachers.	Removed
	a1215R	Increased AI use will reduce the need for teachers.	Removed

Construct / Subscale	Item	Item Statement	Status
	a1216R	Use of AI raises privacy risks for teachers and learners.	Removed

Appendix B: List of Acronyms

AGFI – Adjusted Goodness-of-Fit Index

AI – Artificial Intelligence

AI-EdTech – Artificial Intelligence–Based Educational Technology

AVE – Average Variance Extracted

CFA – Confirmatory Factor Analysis

CFI – Comparative Fit Index

CK – Content Knowledge

df – Degrees of Freedom

EFA – Exploratory Factor Analysis

IEP – Individualized Education Program

i-TPACK – Intelligent Technological Pedagogical Content Knowledge

K–12 – Kindergarten through 12th Grade

KMO – Kaiser-Meyer-Olkin Measure of Sampling Adequacy

λ (Lambda) – Factor Loading

ML – Maximum Likelihood

MLR – Robust Maximum Likelihood

MSA – Measure of Sampling Adequacy

MVN – Multivariate Normality

NFI – Normed Fit Index

PCK – Pedagogical Content Knowledge

PD – Professional Development

PK – Pedagogical Knowledge

RMSEA – Root Mean Square Error of Approximation

SD – Standard Deviation

SEM – Structural Equation Modeling

SRMR – Standardized Root Mean Square Residual

Std_Loading (STDYX) – Standardized Factor Loading

TAM – Technology Acceptance Model

TK – Technological Knowledge

TCK – Technological Content Knowledge

TLI – Tucker–Lewis Index

TPACK – Technological Pedagogical Content Knowledge

TPK – Technological Pedagogical Knowledge

TRAIT-Ed – Trust in AI-Based Technology in Education

WLSMV – Weighted Least Squares Mean and Variance Adjusted Estimator

Figures

Figure 1: Diagram of Refined 31-Item CFA Factor Structure

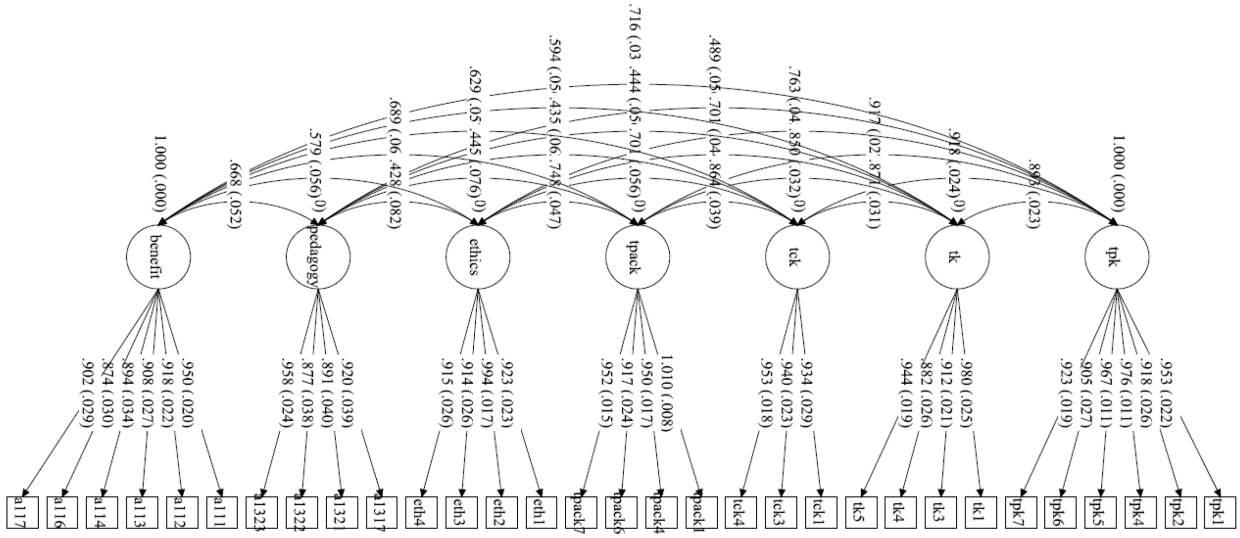
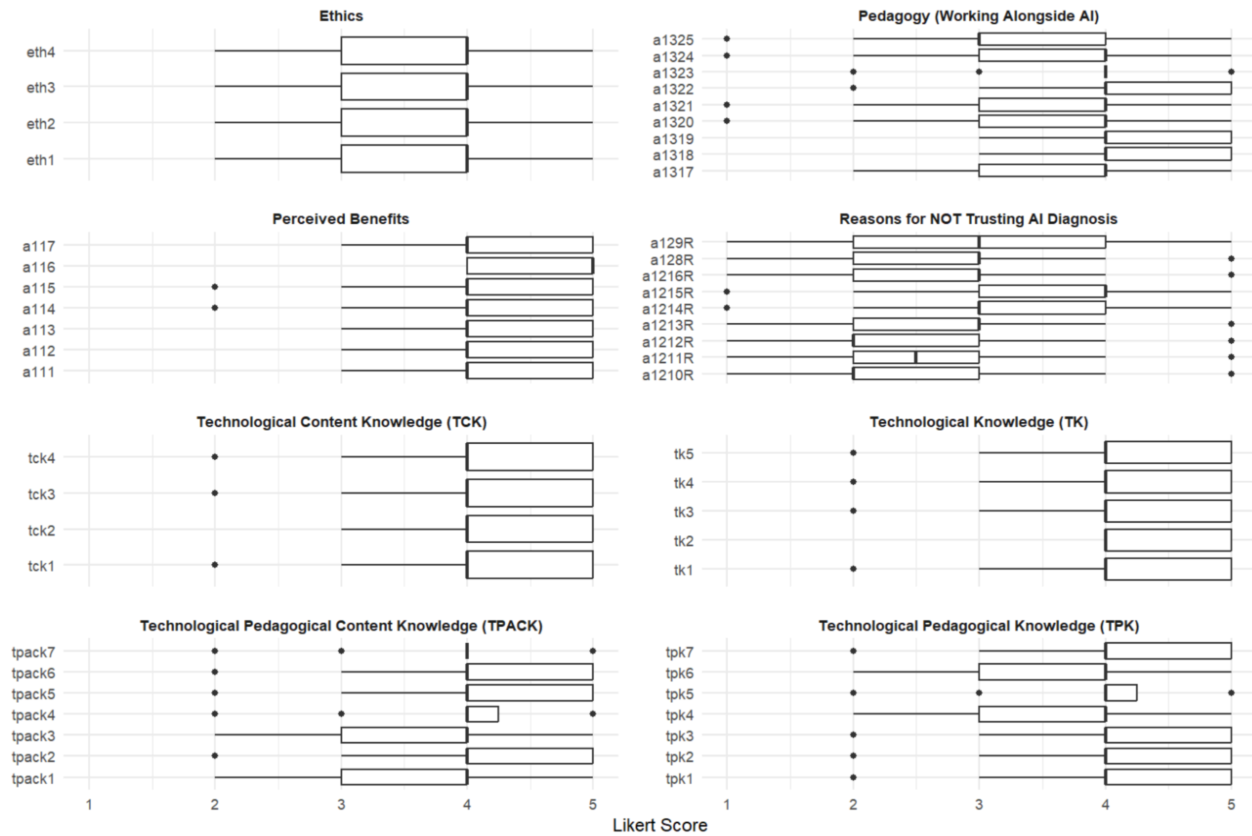


Figure 2: Post-survey aggregate score distribution across constructs



Tables

Table 1: Demographic Variables

Variables	n		%	
	Pre	Post	Pre	Post
Gender				
Male	13	12	11.8	13.6
Female	96	75	87.3	85.2
Nonbinary/Nongender	-	-	-	
Choose not to disclose	1	1	0.9	1.1
Age				
18-29	8	6	7.3	6.8
30-39	25	21	22.7	23.9
40-49	24	20	21.8	22.7
50-59	38	26	34.5	29.5
60-69	15	14	13.6	15.9
70+	-	-	-	-
Choose not to disclose	-	1	-	1.1

Table 2: Descriptive Statistics

	Descriptive Statistics						
Item	**n**	**mean**	**sd**	**min**	**max**	**skew**	**kurtosis**
tk1	88	4.25	0.61	2	5	-0.49	0.85
tk3	88	4.26	0.63	2	5	-0.53	0.57
tk4	88	4.11	0.73	2	5	-0.69	0.58
tk5	88	4.18	0.62	2	5	-0.42	0.74
tpk1	88	4.26	0.62	2	5	-0.51	0.79
tpk2	88	4.12	0.71	2	5	-0.56	0.33
tpk4	88	3.86	0.82	2	5	-0.25	-0.60
tpk5	88	4.02	0.74	2	5	-0.54	0.20
tpk6	88	3.86	0.78	2	5	-0.20	-0.50
tpk7	88	4.10	0.71	2	5	-0.52	0.23
tck1	88	4.38	0.59	2	5	-0.66	1.18
tck3	88	4.30	0.66	2	5	-0.63	0.31
tck4	88	4.14	0.73	2	5	-0.39	-0.52
tpack1	88	3.90	0.80	2	5	-0.21	-0.66
tpack4	88	4.05	0.71	2	5	-0.44	0.14
tpack6	88	3.99	0.89	2	5	-0.65	-0.27
tpack7	88	3.98	0.77	2	5	-0.55	0.12
eth1	88	3.84	0.76	2	5	-0.21	-0.38
eth2	88	3.82	0.74	2	5	-0.05	-0.55
eth3	88	3.78	0.89	2	5	-0.44	-0.50
eth4	88	3.68	0.90	2	5	-0.27	-0.72
a111	88	4.38	0.61	3	5	-0.41	-0.72
a112	88	4.36	0.63	3	5	-0.44	-0.72
a113	88	4.41	0.56	3	5	-0.23	-0.93
a114	88	4.34	0.64	2	5	-0.69	0.61
a116	88	4.57	0.50	4	5	-0.27	-1.95
a117	88	4.33	0.66	3	5	-0.45	-0.77
a1317	88	3.75	0.81	2	5	-0.18	-0.52
a1321	88	3.82	0.85	1	5	-0.53	0.29
a1322	88	4.11	0.69	2	5	-0.57	0.61
a1323	88	4.01	0.72	2	5	-0.38	-0.05

Note. Full descriptive statistics for all items is available as supplementary data upon request. Only the first 20 of 52 items are shown for brevity.

Table 3: Standardized Factor Loadings for the Eight-Factor CFA Model (WLSMV)

Factor	Item	Estimate	SE	z	p	Std_Loading
TPK	tpk1	0.943	0.024	39.450	0	0.943
	tpk2	0.916	0.029	32.010	0	0.916
	tpk3	0.882	0.026	33.940	0	0.882
	tpk4	0.974	0.011	85.370	0	0.974
	tpk5	0.972	0.011	85.920	0	0.972
	tpk6	0.896	0.028	31.660	0	0.896
	tpk7	0.928	0.018	50.760	0	0.928
TK	tk1	0.962	0.026	37.090	0	0.962
	tk2	0.961	0.020	48.560	0	0.961
	tk3	0.899	0.022	40.280	0	0.899
	tk4	0.883	0.026	33.370	0	0.883
	tk5	0.945	0.019	49.820	0	0.945
TCK	tck1	0.975	0.020	49.570	0	0.975
	tck2	0.781	0.036	21.850	0	0.781
	tck3	0.975	0.015	66.940	0	0.975
	tck4	0.964	0.020	47.300	0	0.964
TPACK	tpack1	1.010	0.005	198.530	0	1.010
	tpack2	0.978	0.008	127.000	0	0.978
	tpack3	0.984	0.007	131.460	0	0.984
	tpack4	0.988	0.006	173.050	0	0.988
	tpack5	0.982	0.008	116.340	0	0.982
	tpack6	0.923	0.023	40.050	0	0.923
	tpack7	0.955	0.015	63.470	0	0.955
Ethics	eth1	0.926	0.024	38.600	0	0.926
	eth2	0.990	0.017	57.730	0	0.990
	eth3	0.921	0.028	33.460	0	0.921
	eth4	0.910	0.028	32.490	0	0.910
Barrier	a128R	0.657	0.063	10.460	0	0.657
	a129R	0.764	0.050	15.230	0	0.764
	a1210R	0.821	0.040	20.430	0	0.821
	a1211R	0.771	0.050	15.430	0	0.771
	a1212R	0.824	0.032	26.110	0	0.824
	a1213R	0.798	0.042	19.190	0	0.798
	a1214R	0.897	0.047	18.890	0	0.897
	a1215R	0.664	0.074	9.010	0	0.664
	a1216R	0.701	0.058	12.110	0	0.701
Pedagogy	a1317	0.876	0.035	24.960	0	0.876
	a1318	0.946	0.035	27.070	0	0.946
	a1319	0.851	0.043	19.980	0	0.851
	a1320	0.734	0.043	17.150	0	0.734
	a1321	0.851	0.036	23.540	0	0.851
	a1322	0.836	0.042	20.030	0	0.836
	a1323	0.923	0.023	40.870	0	0.923

	a1324	0.931	0.023	40.790	0	0.931
	a1325	0.962	0.022	44.520	0	0.962
Benefit	a111	0.984	0.012	84.930	0	0.984
	a112	0.957	0.012	80.940	0	0.957
	a113	0.901	0.029	31.020	0	0.901
	a114	0.880	0.033	26.520	0	0.880
	a115	0.751	0.054	14.000	0	0.751
	a116	0.883	0.029	30.800	0	0.883
	a117	0.902	0.031	29.040	0	0.902

Note. Standardized loadings are STDYX-equivalent. CFA estimated using WLSMV with ordinal indicators.

Table 4: Correlations Among Composite Factor Scores

Factor	TPK	TK	TCK	TPACK	Ethics	Barrier	Pedagogy	Benefit
TPK	1.00	0.84	0.79	0.88	0.67	0.16	0.43	0.62
TK	0.84	1.00	0.75	0.79	0.59	0.14	0.34	0.52
TCK	0.79	0.75	1.00	0.76	0.54	0.07	0.37	0.53
TPACK	0.88	0.79	0.76	1.00	0.66	0.14	0.38	0.57
Ethics	0.67	0.59	0.54	0.66	1.00	0.29	0.43	0.50
Barrier	0.16	0.14	0.07	0.14	0.29	1.00	0.28	0.17
Pedagogy	0.43	0.34	0.37	0.38	0.43	0.28	1.00	0.60
Benefit	0.62	0.52	0.53	0.57	0.50	0.17	0.60	1.00

Note. Values represent Pearson correlations based on composite mean scores for each factor.

Table 5: Inter-item Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1												
2	0.71	1											
3	0.778	0.744	1										
4	0.782	0.58	0.627	1									
5	0.793	0.678	0.729	0.792	1								
6	0.771	0.652	0.706	0.646	0.691	1							
7	0.697	0.621	0.694	0.569	0.579	0.794	1						
8	0.599	0.687	0.647	0.539	0.654	0.666	0.685	1					
9	0.712	0.62	0.711	0.619	0.71	0.71	0.723	0.718	1				
10	0.747	0.608	0.671	0.628	0.694	0.741	0.716	0.708	0.837	1			
11	0.654	0.503	0.634	0.552	0.629	0.677	0.68	0.602	0.839	0.784	1		
12	0.76	0.611	0.628	0.638	0.69	0.751	0.727	0.727	0.734	0.779	0.692	1	
13	0.689	0.564	0.622	0.561	0.597	0.735	0.598	0.569	0.627	0.659	0.587	0.643	1
14	0.46	0.573	0.366	0.44	0.474	0.476	0.358	0.485	0.476	0.501	0.423	0.495	0.694
15	0.723	0.564	0.634	0.591	0.625	0.709	0.679	0.613	0.667	0.709	0.637	0.69	0.854
16	0.721	0.59	0.667	0.593	0.659	0.661	0.678	0.601	0.704	0.694	0.744	0.681	0.756
17	0.709	0.599	0.64	0.683	0.688	0.706	0.71	0.709	0.853	0.814	0.752	0.783	0.636
18	0.674	0.656	0.599	0.706	0.678	0.667	0.664	0.643	0.737	0.751	0.637	0.773	0.622
19	0.66	0.585	0.638	0.689	0.666	0.704	0.675	0.736	0.835	0.845	0.769	0.709	0.628
20	0.715	0.61	0.561	0.718	0.664	0.683	0.652	0.674	0.762	0.762	0.679	0.742	0.642
21	0.737	0.618	0.595	0.694	0.664	0.642	0.617	0.677	0.719	0.803	0.6	0.744	0.632
22	0.597	0.59	0.616	0.6	0.611	0.634	0.604	0.612	0.754	0.696	0.63	0.637	0.639
23	0.596	0.54	0.552	0.572	0.612	0.665	0.614	0.726	0.794	0.782	0.723	0.715	0.595
24	0.559	0.447	0.543	0.53	0.506	0.584	0.617	0.501	0.577	0.6	0.491	0.5	0.416
25	0.588	0.452	0.571	0.55	0.53	0.614	0.64	0.519	0.645	0.681	0.56	0.519	0.474
26	0.481	0.378	0.447	0.46	0.449	0.461	0.554	0.467	0.558	0.564	0.49	0.489	0.395
27	0.458	0.307	0.447	0.419	0.455	0.502	0.494	0.455	0.562	0.61	0.495	0.444	0.461
28	0.338	0.393	0.287	0.262	0.347	0.318	0.418	0.332	0.331	0.336	0.313	0.386	0.27
29	0.435	0.513	0.315	0.383	0.41	0.424	0.419	0.414	0.468	0.484	0.415	0.487	0.431

	1	2	3	4	5	6	7	8	9	10	11	12	13
30	0.313	0.454	0.231	0.218	0.301	0.397	0.329	0.309	0.369	0.355	0.314	0.37	0.384
31	0.271	0.298	0.268	0.3	0.36	0.295	0.4	0.412	0.399	0.33	0.314	0.303	0.199
32	0.199	0.308	0.174	0.144	0.261	0.245	0.362	0.324	0.36	0.297	0.31	0.278	0.182
33	0.261	0.347	0.195	0.203	0.277	0.256	0.302	0.269	0.253	0.289	0.159	0.329	0.233
34	0.307	0.477	0.296	0.346	0.384	0.331	0.426	0.397	0.354	0.366	0.271	0.379	0.286
35	0.091	0.125	0.044	0.007	0.103	0.118	0.25	0.114	0.182	0.195	0.135	0.139	0
36	0.067	0.04	-0.01	-0.004	0.083	0.096	0.205	0.081	0.172	0.181	0.125	0.107	0.002
37	0.422	0.546	0.337	0.288	0.365	0.56	0.553	0.428	0.561	0.537	0.544	0.518	0.431
38	0.419	0.547	0.307	0.333	0.361	0.494	0.465	0.419	0.499	0.499	0.504	0.43	0.401
39	0.403	0.507	0.472	0.333	0.415	0.453	0.42	0.435	0.549	0.475	0.553	0.442	0.467
40	0.367	0.491	0.372	0.234	0.394	0.441	0.487	0.344	0.505	0.466	0.464	0.426	0.355
41	0.328	0.462	0.429	0.238	0.316	0.347	0.43	0.446	0.467	0.369	0.436	0.288	0.286
42	0.321	0.55	0.361	0.262	0.333	0.41	0.35	0.395	0.446	0.369	0.351	0.385	0.399
43	0.423	0.529	0.426	0.399	0.418	0.496	0.455	0.338	0.577	0.48	0.496	0.37	0.417
44	0.026	0.02	0.074	-0.004	0.063	0.076	0.075	0.011	0.103	0.083	0.025	0.061	-0.035
45	0.133	0.11	0.046	0.119	0.179	0.132	0.065	0.086	0.046	0.1	0.062	0.196	0.02
46	0.172	0.059	0.156	0.104	0.138	0.123	0.132	0.049	0.136	0.156	0.129	0.15	0.059
47	0.121	0.089	0.088	0.075	0.174	0.131	0.139	0.143	0.127	0.167	0.102	0.189	0.062
48	0.12	0.059	0.068	0.039	0.062	0.091	0.178	0.107	0.101	0.056	0.041	0.065	-0.051
49	0.113	-0.04	0.077	0.058	0.063	0.173	0.13	0.029	0.066	0.008	0.04	0.04	0.135
50	0.173	0.174	0.162	0.092	0.083	0.224	0.174	0.13	0.154	0.151	0.102	0.181	0.168
51	0.238	0.184	0.148	0.124	0.094	0.242	0.258	0.12	0.135	0.172	0.156	0.231	0.238
52	0.03	-0.024	0	-0.02	0.003	0.068	0.028	-0.002	-0.002	0.021	0.025	-0.01	0.029

	14	15	16	17	18	19	20	21	22	23	24	25	26
14	1												
15	0.619	1											
16	0.587	0.77	1										
17	0.53	0.683	0.75	1									
18	0.539	0.638	0.706	0.883	1								

	14	15	16	17	18	19	20	21	22	23	24	25	26
19	0.516	0.615	0.696	0.928	0.834	1							
20	0.557	0.654	0.698	0.856	0.87	0.846	1						
21	0.497	0.666	0.668	0.814	0.843	0.799	0.909	1					
22	0.515	0.589	0.621	0.802	0.787	0.815	0.71	0.696	1				
23	0.499	0.618	0.617	0.867	0.767	0.862	0.798	0.782	0.768	1			
24	0.159	0.553	0.519	0.616	0.533	0.574	0.528	0.597	0.526	0.525	1		
25	0.298	0.606	0.56	0.669	0.572	0.627	0.588	0.644	0.558	0.599	0.877	1	
26	0.23	0.499	0.47	0.58	0.512	0.53	0.544	0.559	0.505	0.578	0.751	0.8	1
27	0.267	0.523	0.467	0.572	0.497	0.575	0.524	0.57	0.524	0.516	0.766	0.793	0.814
28	0.413	0.376	0.332	0.351	0.357	0.293	0.301	0.252	0.252	0.286	0.236	0.233	0.405
29	0.568	0.434	0.344	0.485	0.488	0.481	0.493	0.463	0.488	0.436	0.248	0.268	0.26
30	0.506	0.314	0.231	0.38	0.379	0.347	0.383	0.366	0.447	0.42	0.129	0.174	0.141
31	0.283	0.328	0.297	0.349	0.227	0.35	0.257	0.211	0.194	0.31	0.405	0.324	0.413
32	0.306	0.279	0.262	0.342	0.275	0.32	0.318	0.245	0.27	0.343	0.258	0.277	0.478
33	0.412	0.254	0.198	0.251	0.302	0.229	0.296	0.28	0.247	0.222	0.124	0.247	0.399
34	0.5	0.354	0.282	0.34	0.388	0.345	0.359	0.341	0.305	0.311	0.236	0.308	0.363
35	0.063	0.12	0.099	0.18	0.139	0.128	0.096	0.093	0.118	0.171	0.298	0.17	0.331
36	0.054	0.105	0.105	0.175	0.103	0.128	0.102	0.078	0.077	0.164	0.267	0.27	0.455
37	0.405	0.431	0.501	0.57	0.527	0.513	0.463	0.44	0.535	0.577	0.428	0.459	0.382
38	0.441	0.401	0.467	0.507	0.465	0.475	0.452	0.432	0.459	0.538	0.365	0.418	0.409
39	0.434	0.382	0.453	0.503	0.487	0.515	0.444	0.407	0.54	0.447	0.291	0.322	0.318
40	0.331	0.355	0.44	0.493	0.435	0.417	0.344	0.374	0.47	0.457	0.445	0.45	0.412
41	0.317	0.293	0.395	0.398	0.284	0.382	0.3	0.246	0.313	0.343	0.413	0.468	0.409
42	0.451	0.286	0.322	0.377	0.424	0.408	0.381	0.401	0.455	0.422	0.243	0.285	0.228
43	0.368	0.407	0.385	0.436	0.451	0.45	0.412	0.369	0.538	0.423	0.408	0.483	0.438
44	-0.095	0.054	-0.044	0.058	0.039	0.039	0.009	-0.025	0.024	-0.013	0.133	0.07	0.158
45	-0.032	0.046	0.035	0.087	0.159	0.089	0.194	0.166	0.105	0.135	0.09	0.063	0.204
46	-0.171	0.085	0.055	0.101	0.075	0.071	0.129	0.118	0.047	0.107	0.211	0.187	0.347
47	-0.062	0.096	0.127	0.109	0.138	0.112	0.177	0.141	0.048	0.11	0.234	0.205	0.341
48	-0.179	0.005	0.044	0.07	0.082	0.042	0.117	0.083	-0.009	0.095	0.223	0.191	0.346
49	-0.1	0.122	0.083	0.036	0.01	0.03	0.066	0.066	0.061	0.007	0.306	0.212	0.294

	14	15	16	17	18	19	20	21	22	23	24	25	26
50	0.096	0.125	0.101	0.147	0.169	0.157	0.2	0.193	0.201	0.144	0.236	0.202	0.308
51	0.141	0.175	0.195	0.192	0.207	0.162	0.237	0.258	0.218	0.161	0.122	0.13	0.071
52	-0.081	0.028	-0.041	0.021	0.008	0.015	0.015	0.01	-0.015	0.034	0.198	0.168	0.283

	27	28	29	30	31	32	33	34	35	36	37	38	39
27	1												
28	0.316	1											
29	0.28	0.533	1										
30	0.151	0.444	0.744	1									
31	0.403	0.616	0.405	0.163	1								
32	0.327	0.77	0.496	0.45	0.585	1							
33	0.245	0.656	0.559	0.491	0.373	0.686	1						
34	0.235	0.679	0.591	0.483	0.597	0.717	0.79	1					
35	0.242	0.563	0.235	0.22	0.473	0.549	0.314	0.455	1				
36	0.363	0.569	0.221	0.218	0.464	0.628	0.455	0.433	0.856	1			
37	0.363	0.425	0.551	0.596	0.347	0.463	0.335	0.408	0.289	0.286	1		
38	0.327	0.454	0.512	0.59	0.369	0.469	0.383	0.449	0.272	0.267	0.896	1	
39	0.396	0.484	0.505	0.517	0.361	0.423	0.417	0.445	0.21	0.197	0.721	0.748	1
40	0.407	0.434	0.421	0.565	0.348	0.431	0.382	0.415	0.352	0.375	0.812	0.773	0.728
41	0.401	0.403	0.336	0.334	0.514	0.388	0.255	0.424	0.251	0.235	0.491	0.527	0.581
42	0.176	0.358	0.56	0.622	0.194	0.409	0.482	0.463	0.117	0.099	0.688	0.691	0.723
43	0.45	0.484	0.574	0.561	0.352	0.438	0.401	0.406	0.25	0.305	0.69	0.654	0.724
44	0.122	0.301	0.081	0.03	0.2	0.213	0.165	0.079	0.287	0.316	0.071	0.041	0.15
45	0.082	0.289	0.125	0.087	0.064	0.276	0.219	0.117	0.115	0.158	0.105	0.118	0.079
46	0.146	0.262	0.044	-0.013	0.102	0.23	0.163	0.089	0.239	0.323	0.076	0.047	0.07
47	0.255	0.306	-0.068	-0.092	0.159	0.264	0.152	0.078	0.294	0.347	0	0.009	0.014
48	0.134	0.241	-0.102	-0.073	0.144	0.255	0.154	0.082	0.319	0.387	0.076	0.101	0.034
49	0.309	0.142	-0.052	-0.082	0.05	0.143	0.046	-0.059	0.176	0.259	0.019	-0.023	0.078
50	0.29	0.306	0.177	0.147	0.076	0.188	0.218	0.094	0.202	0.204	0.125	0.144	0.269

	27	28	29	30	31	32	33	34	35	36	37	38	39
51	0.094	0.16	0.226	0.267	-0.108	-0.004	0.133	0.066	0.108	0.068	0.195	0.167	0.233
52	0.216	0.315	0.004	0.099	0.125	0.268	0.177	0.047	0.125	0.263	0.079	0.106	0.195

	40	41	42	43	44	45	46	47	48	49	50	51	52
40	1												
41	0.521	1											
42	0.646	0.406	1										
43	0.604	0.579	0.651	1									
44	0.106	0.072	0.045	0.215	1								
45	0.082	-0.009	0.141	0.175	0.529	1							
46	0.085	0.031	-0.006	0.164	0.593	0.636	1						
47	0.045	0.045	0.031	0.072	0.444	0.598	0.592	1					
48	0.095	0.107	0.006	0.1	0.494	0.559	0.702	0.615	1				
49	0.093	0.065	-0.031	0.173	0.478	0.555	0.55	0.441	0.649	1			
50	0.15	0.163	0.18	0.329	0.496	0.574	0.527	0.502	0.567	0.684	1		
51	0.169	0.139	0.209	0.26	0.323	0.29	0.289	0.214	0.266	0.461	0.656	1	
52	0.144	0.137	0.106	0.248	0.476	0.507	0.549	0.397	0.576	0.634	0.537	0.314	1

NOTE: Technological Knowledge: 1=TK1, 2=TK2, 3=TK3, 4=TK4, 5=TK5; Technological Pedagogical Knowledge: 6=TPK1, 7=TPK2, 8=TPK3, 9=TPK4, 10=TPK5, 11=TPK6, 12=TPK7; Technological Content Knowledge: 13=TCK1, 14=TCK2, 15=TCK3, 16=TCK4; Professional Knowlege to select and use AI to accomplish instructional goals: 17=TPACK1, 18=TPACK2, 19=TPACK3, 20=TPACK4, 21=TPACK5, 22=TPACK6, 23=TPACK7; Ethics: 24=ETH1, 25=ETH2, 26=ETH3, 27=ETH4; Working alongside AI to improve pedagogy: 28=A1317, 29=A1318, 30=A1319, 31=A1320, 32=A1321, 33=A1322, 34=A1323, 35=A1324, 36=A1325; Perceived benefits of AI in an educational setting: 37=A111, 38=A112, 39=A113, 40=A114, 41=A115, 42=A116, 43=A117; Reasons for not trusting AI diagnosis: 44=A128R, 45=A129R, 46=A1210R, 47=A1211R, 48=A1212R, 49=A1213R, 50=A1214R, 51=A1215R, 52=A1216R. Items suffixed with ‘R’ have been re-coded to convert to positive valence in alignment with remaining items.

Table 6: Model Fit Indices Before and After Item Removal

	Intelligent-TPACK		TRAIT-Ed		Combined Model	
Index	**iTK Original**	**iTK Refined**	**TRAIT-Ed Orig**	**TRAIT-Ed Ref**	**Combined Orig**	**Combined Ref**
χ^2	426.629	248.582	761.442	70.149	1,930.160	518.056
df	314.000	179.000	272.000	34.000	1,246.000	413.000
p	0.000	0.000	0.000	0.000	0.000	0.000
CFI	0.996	0.995	0.944	0.992	0.975	0.993
TLI	0.995	0.995	0.938	0.990	0.974	0.992
RMSEA	0.064	0.067	0.144	0.111	0.079	0.054
RMSEA 90% CI Lower	0.048	0.045	0.132	0.073	0.072	0.038
RMSEA 90% CI Upper	0.079	0.086	0.156	0.147	0.086	0.068
SRMR	0.046	0.039	0.137	0.052	0.107	0.052

Note. All models estimated using WLSMV. Orig = Original model (before item removal, 52 items); Refined/Ref = Refined model (after item removal, 31 items). Acceptable fit: CFI/TLI > .95, RMSEA < .06, SRMR < .08. Item removal substantially improved fit across all models.

Table 7: Items Removal with Psychometric Rationale

Item	Construct	Primary_Reason	Supporting_Evidence
a128R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.38
a129R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.42
a1210R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.45
a1211R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.39
a1212R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.41
a1213R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.44
a1214R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.37
a1215R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.43
a1216R	Reasons_Not_Trusting	Unacceptable MSA	MSA = 0.40
a1324	Trust_Intended_Use	Severe multicollinearity	MI = 410.25 with a1325
a1325	Trust_Intended_Use	Severe multicollinearity	MI = 410.25 with a1324
a1320	Trust_Intended_Use	Weak factor loading	λ = 0.638
a1319	Trust_Intended_Use	Cross-loading	MI = 25.14 on Perceived_Benefits
a1318	Trust_Intended_Use	Multiple cross-loadings	MI > 49 on iTK, iTPK, iTCK
a115	Perceived_Benefits	Low sampling adequacy	MSA = 0.36
tpk3	iTPK	High residual correlation	Residual r = 0.89 with tpk2
tpack2	iTPACK	Multicollinearity cluster	MI = 85.32 with tpack3
tpack3	iTPACK	Multicollinearity cluster	MI = 85.32 with tpack2
tpack5	iTPACK	High residual correlation	Residual r = 0.76 with tpack4
tck2	iTCK	Cross-loading + weak loading	MI = 52.18 on Trust_Use; λ = 0.647
tk2	iTK	Low variability + cross-loading	SD = 0.49; MI = 45.67 on iTPK

Note. MSA = Measure of Sampling Adequacy; MI = Modification Index; λ = standardized factor loading. Items were removed sequentially based on the most severe psychometric violations first.

Table 8: Reliability and Convergent Validity Metrics

Construct	N Items	ω (Omega)	AVE	√AVE	Internal Consistency	Convergent Validity
Intelligent TK	4.00	0.917	0.865	0.930	Adequate	Adequate
Intelligent TPK	6.00	0.960	0.885	0.941	Adequate	Adequate
Intelligent TCK	3.00	0.949	0.945	0.972	Adequate	Adequate
Intelligent TPACK	4.00	0.953	0.918	0.958	Adequate	Adequate
AI Ethics Awareness	4.00	0.932	0.878	0.937	Adequate	Adequate
Perceived Benefits	6.00	0.954	0.845	0.919	Adequate	Adequate
Trust & Intended Use	4.00	0.915	0.832	0.912	Adequate	Adequate

Note. ω (Omega) = McDonald's omega composite reliability coefficient; AVE = Average Variance Extracted; √AVE = square root of AVE. Adequate internal consistency: $\omega \geq .70$ (Raykov, 1997). Adequate convergent validity: AVE $\geq .50$ (Fornell & Larcker, 1981). √AVE is used for discriminant validity assessment via Fornell-Larcker criterion.

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