

Adaptation of the Teachers' Trust in Artificial Intelligence–based Educational Technologies Scale into Turkish: A validity and reliability study

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Highlights

- The Teachers' Trust in AI-Based EdTech Scale was adapted into Turkish and validated with 231 K–12 teachers.
- The Turkish scale offers researchers and policymakers a valid tool for assessing teachers' trust in AI-based EdTech.
- The adapted scale offers a practical tool for planning in-service training and evaluating AI integration policies in education.

Abstract

This study aims to adapt a scale measuring teachers' trust in AI-based educational technology into Turkish and to examine its validity and reliability. Data were collected from 231 teachers across various subject areas, including biology, chemistry, geography, language, mathematics, physics, and science. Following the assessment of univariate and multivariate normality, Confirmatory Factor Analysis (CFA) and reliability analyses were conducted. Mardia's multivariate kurtosis test indicated a violation of multivariate normality. Maximum Likelihood (ML) estimation was retained for the CFA, while bias-corrected bootstrap confidence intervals and the Bollen–Stine bootstrap procedure were used to evaluate the robustness of parameter estimates and model fit under non-normality. The initial 24-item, eight-factor model was revised based on the CFA findings, resulting in a 21-item, six-factor structure. The revised model was supported by most fit indices ($\chi^2 = 340.179$, $df = 174$, $\chi^2/df = 1.955$, CFI = 0.903, RMSEA = 0.064), although the TLI value (0.883) was below the conventional .90 threshold. The six subdimensions were Perceived Benefits of AI-based EdTech; Lack of Human Characteristics of AI-based EdTech; Anxieties Related to Using AI-based EdTech; Self-efficacy in Using AI-based EdTech; Preferred Means to Increase Trust in AI-based EdTech; and AI-based EdTech vs Human Advice/Recommendation. Reliability evidence was stronger for four of the six subdimensions, whereas F2 and particularly F3 showed comparatively weaker internal consistency and convergent validity evidence. Overall, the findings provide initial support for the six-factor Turkish adaptation while indicating that the weaker subdimensions and the revised factor structure require further examination in independent samples.

Article Info: Research Article

Keywords: *Trust in AI-based EdTech, Artificial Intelligence, Scale Adaptation, Confirmatory Factor Analysis*

1. Introduction

The integration of Artificial Intelligence (AI) into education has profoundly transformed teaching and learning by enabling personalized learning experiences that help teachers and students better understand learners' needs and abilities. In this context, AI offers significant opportunities, including data-driven decision-making and strengthened pedagogical support (Hwang et al., 2020; Seyrek et al., 2024; Viberg et al., 2025; Wang et al., 2024). Through AI-based educational technologies, teachers can analyze students'

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learning behaviors, anticipate areas in which they may encounter difficulties, and provide timely, real-time feedback and support (Holmes et al., 2019).

The use of AI in school management systems, such as attendance tracking, lesson planning, and resource management, enables teachers and administrators to make more strategic decisions and optimize time management (Igbokwe, 2023; Luckin et al., 2016). International policy and guidance documents emphasize that intelligent learning and management systems integrated with AI have the potential to enhance learning outcomes by adapting instructional content based on learner data and creating learning environments responsive to individual differences (Holmes & Miao, 2023). As AI increasingly occupies a central role in educational ecosystems worldwide, policy development, research initiatives, and practical applications at the national level have likewise accelerated. This rapid expansion makes it pedagogically and ethically critical to assess teachers' trust in AI tools systematically and validly.

In Türkiye, the Ministry of National Education has implemented various projects and developed policy and guidance documents to support teachers in the effective use of AI tools. The Artificial Intelligence in Education Enhancing Opportunities (FEYZA) Project, launched in 2023, was designed to support teachers' professional development and to enable students to develop algorithmic thinking and AI-related skills. The FEYZA Project encourages teachers to take an active role in AI-based instructional processes and promotes students' early and informed engagement with these technologies. As part of the project, the *Teacher's Handbook on Artificial Intelligence Applications for Middle and High Schools* was published (Ministry of National Education [MoNE], 2023).

The *Artificial Intelligence Tools Used in Education: Teacher Handbook (2024)*, prepared by the General Directorate of Innovation and Educational Technologies of the Ministry of National Education (YEĞİTEK, 2024), serves as a practice-oriented guide to integrating artificial intelligence technologies into educational settings from pedagogical and technological perspectives. Using sample applications designed for different subject areas, the handbook provides concrete examples of how teachers can incorporate AI tools into their instructional practices to enrich learning content, personalize instruction, and monitor student learning using data-informed approaches.

National and international studies emphasize that developing teachers' cognitive and technical competencies is critical for the effective pedagogical use of artificial intelligence tools. However, the integration of AI technologies into educational settings is not limited to cognitive and technical competencies. Affective factors, such as teachers' perceived self-efficacy regarding these technologies (Ding et al., 2025), their anxieties and ethical concerns related to AI use (Farooq, 2025; Sayılı & Akman, 2025), as well as their attitudes and perceptions of trust (Taheri et al., 2025; Woodruff et al., 2023), also constitute key variables shaping AI integration. Among these affective determinants, trust emerges as an integrative factor that influences teachers' adoption of AI for pedagogical purposes, the extent to which they rely on AI-generated outputs in classroom decision-making, and whether they use the technology sustainably (Ayanwale et al., 2024; Nazaretsky et al., 2022a).

Trust in AI has mostly been measured with general-purpose instruments such as the Trust in Automation Scale (Jian et al., 2000) and its short form (McGrath et al., 2025). These were designed for generic automated systems and do not capture teachers' judgments shaped by pedagogical autonomy, classroom decision-making, and professional responsibility. In Türkiye, validated instruments exist for related but distinct constructs, namely teachers' attitudes toward AI (Alan et al., 2025) and AI anxiety (Akkaya et al., 2021), but not for trust. To our knowledge, no validated Turkish instrument currently measures teachers' trust in AI-based educational technologies. This limits the evaluation of national AI-in-education initiatives and the planning of in-service training. Consequently, the need for instruments that reliably and validly measure teachers' trust in artificial intelligence has become more pronounced. Accordingly, this study aims to adapt the trust scale for AI-based educational technologies developed by Nazaretsky, Cukurova, and Alexandron (2022b) into Turkish and to examine its psychometric properties. Nazaretsky et al. (2022b)'s scale was selected because it is the instrument designed specifically for K–12 teachers' trust in AI-based educational technologies, and it captures trust as a multidimensional construct (e.g., perceived benefits,

anxieties, self-efficacy, and preference for AI versus human advice) that general trust-in-automation scales do not address

2. Literature

2.1. Trust in Artificial Intelligence

The rapid advancement of AI technologies has made trust in these systems a more important research focus than ever before. As in human-human relationships, trust in human-AI interactions is regarded as a fundamental psychosocial mechanism that guides behavior in situations characterized by uncertainty (Lee & See, 2004). In particular, the fact that the internal functioning of AI systems is often not fully visible to users makes the role of trust in technology use more salient (Omrani et al., 2022; Qin et al., 2020). For this reason, trust in AI is not viewed merely as an indicator of acceptance; rather, it is considered a central concept for understanding the level of collaboration with AI-based decision support systems and how, to what extent, and for what purposes users engage with these technologies (Choung et al., 2023).

In educational contexts, trust plays an even more critical role because the effective functioning of learning processes depends on teachers' and students' beliefs that pedagogical decisions are fair, that the tools used are reliable, and that the data generated in these processes are managed ethically and responsibly. How teachers introduce technologies into their classrooms is largely shaped by the level of trust they develop toward those technologies (Nazaretsky et al., 2022a; Nazaretsky et al., 2022b; Shen et al., 2025). Research shows that when evaluating AI systems, teachers consider both how well these systems align with their pedagogical goals and how explainable and consistent they perceive the system outputs to be (Choi, Jang, & Kim, 2023; Shen et al., 2025). Choung et al. (2023) suggest that trust in AI has a two-dimensional structure, consisting of functional trust and anthropomorphic trust. Accordingly, teachers attend not only to technical characteristics such as accuracy, consistency, and functionality but also to the understandability and well-justification of the recommendations provided by AI systems (Feldman-Maggor et al., 2025). These two dimensions also indicate that teachers' evaluations of AI are grounded in both cognitive and affective considerations. Even when an AI system is pedagogically useful, insufficient transparency in its operation may lead teachers to approach it cautiously. This highlights that trust in AI depends not only on how the system works, but also on how it is interpreted and made sense of by teachers (Choung et al., 2023).

This two-dimensional conceptualization maps onto the multidimensional structure of the scale adapted in the present study: functional trust corresponds most closely to factors reflecting instrumental evaluation of AI systems, such as Perceived Benefits of AI-based EdTech (F1) and Self-efficacy in Using AI-based EdTech (F4), whereas anthropomorphic trust aligns with factors addressing AI's perceived lack of human qualities and its standing relative to human judgment, such as Lack of Human Characteristics of AI-based EdTech (F2) and AI-based EdTech vs. Human Advice/Recommendation (F6). This correspondence suggests that the scale's factor structure captures both dimensions identified in the broader trust-in-AI literature, rather than treating trust as a unidimensional construct.

Empirical studies clearly emphasize the influence of trust on technology acceptance. In AI-supported online learning environments, teachers' evaluations extend beyond technical accuracy to include ethical data management, institutional transparency, and the protection of students' rights (Qin et al., 2020). Studies focusing on classroom practices further indicate that teacher trust is inherently fragile. In particular, when feedback generated by AI systems conflicts with teachers' own professional judgments, trust in the technology can deteriorate rapidly (Lucas et al., 2024; Nazaretsky et al., 2021, 2022b). These findings suggest that teacher trust is not limited to technological accuracy but is closely intertwined with professional identity, pedagogical intuition, and established knowledge about students.

Recent research has demonstrated that trust has not only technical and cognitive foundations but also cultural and psychological foundations. Teachers' levels of trust in AI are shaped by their AI literacy, perceptions of professional autonomy, and positioning in relation to cultural values (Viberg et al., 2025). For example, teachers who perceive themselves as more competent in AI tend to respond more positively to new technologies, whereas those with higher perceptions of uncertainty are more likely to experience

anxiety and distrust (Celik et al., 2025; Viberg et al., 2025). Moreover, the growing emphasis on explainable AI has strengthened the central role of transparency in trust formation. When AI-generated recommendations are clear, well-justified, and adaptable to pedagogical contexts, teachers are more likely to perceive the system as both trustworthy and useful (Feldman-Maggor et al., 2025; Wang et al., 2024).

Taken together, these studies highlight that teachers' trust in AI is indispensable to sustaining educational innovation. Trust shapes the quality of teachers' engagement with technology, influences how AI is used in classroom practice, and determines whether such tools can be meaningfully integrated with pedagogical goals. For this reason, understanding teacher trust is a critical guide for the design of professional development programs and policy processes aimed at the ethical and human-centered integration of AI in education (Nazaretsky et al., 2022b).

2.2. *Measuring Trust in Artificial Intelligence*

The increasing adoption of artificial-intelligence-based systems in education, healthcare, business, and the public sector has made it necessary to evaluate these systems not only for their technical capabilities but also for their perceived trustworthiness among users. Research in the literature emphasizes that teachers' trust in artificial intelligence is a critical factor influencing the acceptance and effective use of these tools in educational settings (Bach et al., 2024; McGrath et al., 2025).

Perceived trust in artificial intelligence refers to educators' beliefs about the reliability, safety, and effectiveness of AI-driven applications in educational environments. This trust encompasses multiple dimensions, including transparency, perceived functionality, the reliability of outputs, and the ethical considerations underlying AI systems (Viberg et al., 2025; Wijaya et al., 2024). Trust in AI is particularly important for teachers, as it influences their willingness to engage with and integrate AI technologies into their instructional practices.

Because trust is multidimensional, measurement scales are needed to capture teacher-specific dimensions, particularly in educational contexts. One of the most widely used instruments for measuring trust in AI is the Trust in Automation Scale (TIAS). Originally developed by Jian et al. (2000), this scale assesses individuals' trust in automated systems through both positively and negatively worded items. However, for an extended period, the psychometric properties of this scale were not sufficiently examined in the context of artificial intelligence. More recent studies have demonstrated that TIAS is a valid and reliable instrument for measuring trust in AI. However, they have also indicated that its 12-item structure poses practical challenges, especially in experimental and longitudinal studies. As a result, a shortened three-item version, referred to as the Short Trust in Automation Scale (S TIAS), was developed and shown to be valid for assessing trust in AI (McGrath et al., 2025).

Nevertheless, general trust-in-automation scales have limited capacity to capture teachers' trust judgments that are shaped by pedagogical autonomy, classroom-based contextual decision-making, and ethical responsibilities. In this respect, measurement tools specifically designed for teachers and educational-technology contexts offer a more functional alternative. In parallel, some studies suggest that the single-factor structure of TIAS does not sufficiently explain trust in the context of artificial intelligence. Instead, a two-factor structure that distinguishes between trust and distrust has been found to yield more robust and meaningful measurement outcomes (Perrig et al., 2023; Scharowski et al., 2025). This finding indicates that artificial intelligence systems should be examined not only for their potential to foster trust but also for the risks they pose in generating distrust. Accordingly, scales used to measure trust in artificial intelligence must be context-sensitive, theoretically grounded, and supported by rigorous psychometric procedures.

Research in education indicates that trust in artificial intelligence strongly predicts technology acceptance among teachers and students. Teacher-focused studies demonstrate that perceived trust, together with perceived usefulness and perceived ease of use, plays a significant role in explaining the adoption of AI-based educational technologies (Choi et al., 2023; Lucas et al., 2024; Nazaretsky et al., 2022a). In particular, the trust scale for teachers developed by Nazaretsky, Cukurova, and Alexandron (2022b) reveals that multiple dimensions, including perceptions of transparency, pedagogical alignment, teacher autonomy, and

the comparative evaluation of AI systems in relation to human decision-making, influence trust in AI-supported educational technologies.

Similarly, student-focused studies emphasize that trust is not a unidimensional construct. Factors such as transparency, ethical concerns, data security, and pedagogical alignment are reported to shape students' perceptions of trust in artificial intelligence. Recently developed measurement instruments therefore conceptualize trust in AI-supported educational technologies as a multidimensional construct that is closely associated with students' readiness levels and perceived usefulness (Nazaretsky et al., 2025).

The valid and reliable measurement of trust not only facilitates a deeper understanding of user attitudes but also contributes to the design of AI systems that are human-centered, explainable, and accountable. In this context, the use of brief and psychometrically validated measurement tools has the potential to enhance the methodological rigor and comparability of empirical studies in the field (Nazaretsky et al., 2025; Perrig et al., 2023). In the Turkish context, there is a growing need for a validated, reliable instrument to assess teachers' trust in AI-based educational technologies across dimensions such as pedagogical alignment, autonomy, transparency, and ethics.

It is worth noting that this gap is specific to the construct of trust. Turkish-language instruments already exist for related but conceptually distinct constructs, including teachers' general attitudes toward artificial intelligence (Alan, Keçeci, & Kırbağ Zengin, 2025) and artificial-intelligence-related anxiety (Akkaya, Özkan, & Özkan, 2021). Because attitude, anxiety, and trust are theoretically and empirically distinguishable constructs, neither of these existing instruments serves as a substitute for a dedicated measure of teachers' trust in AI-based EdTech. The present adaptation therefore addresses a specific measurement need in the Turkish educational context.

3. Methodology

This study aims to adapt the scale for measuring teachers' trust in AI-based Educational Technology (EdTech), developed by Nazaretsky, Cukurova, and Alexandron (2022b), into Turkish and to test its validity and reliability in the designated sample. Accordingly, the study was conducted within the framework of systematic methods recommended for scale adaptation processes (Brislin, 1970; DeVellis, 2003). During the adaptation process, the source scale was first translated into Turkish and then submitted for expert evaluation of language, cultural adaptation, and conceptual integrity. To test the validity evidence, Confirmatory Factor Analysis (CFA) was performed using LISREL 8.80, while AMOS 24 was used for the multivariate normality test and bootstrap procedures, and SPSS 26 was used for the reliability analyses. Reliability was evaluated through Cronbach's alpha internal consistency coefficients, Composite Reliability (CR), and Average Variance Extracted (AVE) values (Fornell & Larcker, 1981; Gürbüz, 2021; Hair et al., 2010).

Prior to the CFA, the univariate normality assumption was assessed using skewness and kurtosis coefficients and their corresponding critical ratios (c.r.), whereas multivariate normality was evaluated using Mardia's multivariate kurtosis coefficient and its critical ratio (Bentler, 2006; Byrne, 2016; Mardia, 1970). Maximum Likelihood (ML) estimation was retained for the CFA. Because the multivariate normality assumption was violated, additional bootstrap procedures were employed to assess the robustness of the parameter estimates and model fit. Specifically, bias-corrected 95% confidence intervals were computed based on 500 bootstrap samples, and the Bollen–Stine bootstrap procedure was used to evaluate model fit under non-normality (Bollen & Stine, 1993; Byrne, 2016). In this section, the study participants, information on the original scale, the translation procedure, and the CFA results are described in detail.

3.1. Participants

A total of 239 K–12 teachers from various disciplines (biology, chemistry, geography, language, mathematics, physics, and science) voluntarily completed this scale. Participants across different regions of Türkiye were recruited using a non-probability convenience sampling approach. The survey link was distributed through professional teacher networks and subject-area teacher groups on social media, and teachers participated voluntarily without compensation. Eight participants did not respond to all items on

the scale and were therefore excluded from the analysis, yielding a final analytic sample of 231 teachers. For CFA, the final sample of $N = 231$ was considered adequate for the complexity of the model, meeting the commonly recommended minimum sample size of approximately 200 participants (Kline, 2016) and providing a subject-to-parameter ratio consistent with recommendations for structural equation modeling of comparable complexity (Hair et al., 2010). All procedures were conducted in accordance with ethical principles. Table 1 provides the demographic information on the participants in this study.

Table 1

Demographic Characteristics of the Participants

Variable	Subcategory	Frequency (N)	Percentage (%)
Gender	Female	159	68.83
	Male	72	31.17
Type of school	Public School	210	90.91
	Private School	21	9.09
Teaching experience (Years)	0-5	26	11.25
	6-10	58	25.11
	11-15	66	28.57
	16-20	40	17.32
	20+	41	17.75

As shown in Table 1, 68.83% ($N = 159$) of the 231 teachers were female, and 31.17% ($N = 72$) were male. Many of these teachers worked in public schools; most had 6–10 years (25.11%, $N = 58$) or 11–15 years (28.57%, $N = 66$) of experience.

3.2. Original Scale

In the original scale development study, Nazaretsky, Cukurova, and Alexandron (2022b) aimed to develop a scale to measure K–12 teachers' trust in AI-based educational technologies. The researchers examined the structure of a 25-item scale rated on a five-point Likert scale (1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree) by using data collected from 132 teachers and by conducting exploratory factor analysis (EFA).

Horn's parallel analysis suggested five-, six-, or seven-factor solutions; however, based on the model fit indices (RMSEA = 0.037, TLI = 0.928, SRMR = 0.04, $\chi^2/df = 1.19$), the seven-factor model met all recommended fit criteria. A factor-loading cutoff of 0.30 was adopted, and items were assigned to factors based on their highest loadings.

As part of the reliability analysis, Cronbach's alpha coefficients were calculated for each factor. Due to very low internal consistency ($\alpha < 0.30$), the seventh factor was excluded from further analysis. In addition, Item 8, which aimed to measure trust based on inconsistencies between AI-generated responses and teachers' own judgments, showed weak loadings on its associated factor. Removing this item substantially improved the factor's reliability; therefore, it was removed from the scale.

Although Items 13 and 20 did not exhibit clear factor loadings in the EFA, they were retained in the scale based on preliminary studies with teachers and on theoretical considerations. These items were treated as single-item subdimensions, titled "AI-based EdTech's Perceived Lack of Transparency" and "Required Shift in Pedagogy to Adopt AI-based EdTech," respectively. In the present study, confirmatory testing (reported in the Findings section) indicated identification problems with the scale's two single-item subdimensions and weak factor loadings for one additional item; as a result, three items (I8, I12, I19) and the two single-item subdimensions containing I12 and I19 were removed, yielding a 21-item, six-factor structure that is used throughout the remainder of this study. As a result, the final version of the original scale comprised 24 Likert-type items across eight dimensions.

3.3. Translation Procedure

The authors obtained ethical approval from the authors of the original scale study prior to commencing translation of the measurement instrument used in the study, which was adapted into Turkish. Subsequently, the 24-item scale was translated by three translators using the translation back-translation method developed by Brislin (1970). All three had expertise in science education. They were highly proficient in English and experienced in academic English, allowing them to accurately interpret the original items and identify potential differences in meaning during translation and back-translation. Accordingly, three experts first translated the scale from its original language into Turkish, and other experts whose expertise in educational technology and science education, subsequently reviewed these translations. During the evaluation stage, the translations were assessed for linguistic accuracy, cultural appropriateness, and conceptual consistency. The scale was then back-translated into its original language (English) independently by two experts who were not involved in the initial translation process to assess whether any loss of meaning had occurred. Finally, the translated version was reviewed by an expert, and the final form of the scale was established. The stages of the translation procedure are presented in Figure 1.

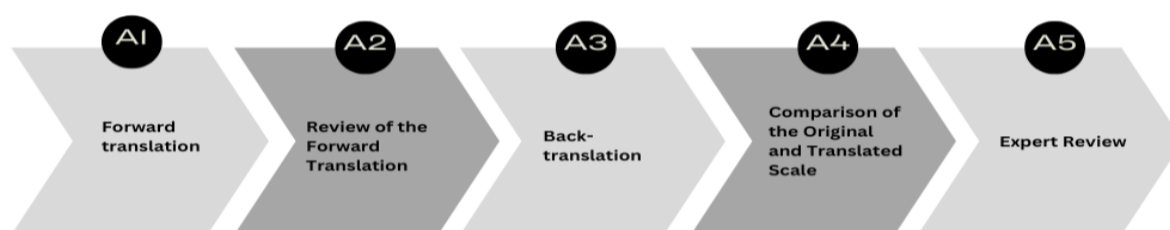


Fig. 1. Stages followed in the translation process of the scale

3.4. Findings

3.4.1. Normality Analysis of the Data

Before proceeding to the confirmatory factor analysis, the dataset's normality assumptions were evaluated in accordance with the steps recommended in the relevant literature (Byrne, 2016; Kline, 2016). For univariate normality, the skewness and kurtosis coefficients of each observed variable, together with their corresponding critical ratios (c.r.), were computed; for multivariate normality, Mardia's multivariate kurtosis coefficient was computed. The normality indicators of the items are presented in Table 2.

Table 2

Univariate and Multivariate Normality Indicators of the Items (N = 231)

Item	Min.	Max.	Skew	c.r.	Kurtosis	c.r.
I1	1.000	5.000	-0.906	-5.717	0.850	2.683
I2	1.000	5.000	-0.992	-6.260	0.965	3.045
I3	1.000	5.000	-1.169	-7.379	2.066	6.519
I4	2.000	5.000	-1.011	-6.381	0.308	0.971
I5	1.000	5.000	-0.937	-5.911	0.301	0.949
I6	2.000	5.000	-0.964	-6.086	0.400	1.263
I7	2.000	5.000	-0.985	-6.219	0.603	1.902
I9	1.000	5.000	-0.373	-2.354	-0.533	-1.683
I10	1.000	5.000	-1.295	-8.172	1.106	3.491
I11	1.000	5.000	-1.244	-7.854	1.589	5.014
I13	1.000	5.000	0.372	2.347	-0.728	-2.296
I14	1.000	5.000	0.233	1.473	-1.230	-3.881
I15	1.000	5.000	-1.035	-6.533	0.576	1.819
I16	1.000	5.000	-0.084	-0.529	-0.279	-0.880

Item	Min.	Max.	Skew	c.r.	Kurtosis	c.r.
I17	1.000	5.000	-0.473	-2.983	0.162	0.510
I18	1.000	5.000	-0.789	-4.978	1.343	4.238
I20	1.000	5.000	-0.291	-1.834	-0.413	-1.305
I21	1.000	5.000	-1.103	-6.961	1.963	6.194
I22	1.000	5.000	-0.789	-4.979	0.914	2.883
I23	1.000	5.000	0.168	1.063	-0.426	-1.344
I24	1.000	5.000	0.031	0.197	-0.539	-1.701
Multivariate Normality						
Mardia's multivariate kurtosis coefficient (b _{2,p})	528.840					
Excess multivariate kurtosis	45.840					
Critical ratio (c.r.)	11.211					

As shown in Table 2, the univariate skewness values range from -1.295 to 0.372, while the kurtosis values range from -1.230 to 2.066. These values fall within the limits of $|\text{skewness}| < 2$ and $|\text{kurtosis}| < 7$ recommended by Kline (2016), indicating that univariate normality was adequately satisfied. However, Mardia's multivariate kurtosis coefficient (b_{2,p}) was 528.840, with an excess multivariate kurtosis value of 45.840 and a corresponding critical ratio of 11.211. Because a critical ratio greater than 5 indicates substantial departure from multivariate normality (Bentler, 2006), the multivariate normality assumption was considered violated.

Maximum Likelihood (ML) estimation was retained for the CFA; however, given the violation of multivariate normality, additional bootstrap procedures were employed to evaluate the robustness of the parameter estimates and model fit. Specifically, bias-corrected 95% confidence intervals were computed using 500 bootstrap samples, and the Bollen–Stine bootstrap procedure was used to assess model fit under non-normality. Thus, the bootstrap analyses were used as a robustness check to reduce reliance on conventional ML-based inference under violated multivariate normality assumptions (Bollen & Stine, 1993; Byrne, 2016).

3.4.2. Confirmatory Factor Analysis

To test the validity of the scale within the designated sample, data obtained from participants were analyzed using LISREL 8.80 for the confirmatory factor analysis (parameter estimates, standard errors, and fit indices), AMOS 24 for the multivariate normality (Mardia) test and the bootstrap procedures (bias-corrected confidence intervals and the Bollen–Stine p value), and SPSS 26 for the reliability analyses. In the first stage, the original scale structure, consisting of 24 items and eight factors, was tested. However, in this analysis, the error variances for items I12 and I19 were negative, indicating Heywood cases (for I12, error variance = -0.031, $R^2 = 1.02$; for I19, error variance = -0.017, $R^2 = 1.02$). A Heywood case refers to a situation in which the error variance of an item is estimated as zero or negative; this condition may arise when the factor to which the item belongs is represented by that item alone, that is, when the factor has a single-indicator structure (Kline, 2016). Indeed, I12 and I19 were the single-item indicators of the two problematic single-item factors in this initial eight-factor specification, which correspond to the “AI-based EdTech's Perceived Lack of Transparency” and “Required Shift in Pedagogy to Adopt AI-based EdTech” subdimensions listed in Table 7. To avoid confusion with the F3 and F6 labels used below for the retained six-factor solution, these two original single-item factors are not referred to by factor numbers in this

section. In the structural equation modeling literature, it is widely emphasized that single-indicator factors lead to identification problems and constrain the model's degrees of freedom; therefore, in scale development and adaptation studies, it is recommended that each factor be represented by at least three indicator items (Browne & Cudeck, 1993). However, methodological studies have demonstrated that two-item factors can be retained when the indicators exhibit adequate factor loadings, represent a theoretically coherent construct, and the overall measurement model demonstrates satisfactory fit (Kline, 1998; Little et al., 2002; Marsh et al., 1998). In this study the identifiability of each latent factor was evaluated against the criterion specified by Bollen (1989), according to which a factor is identified if it has at least three indicators with uncorrelated errors, or at least two indicators with uncorrelated errors provided that either (a) the errors of both indicators are uncorrelated with the error term of a third indicator belonging to a different factor, or (b) an equality constraint is imposed on the two loadings. In the final model, F1–F5 each satisfy the three-indicator condition. At the same time, the only two-indicator factor, F6 (I23 and I24), meets condition (a): the error terms of its indicators are uncorrelated with those of items in other factors, and the two loadings (I23 = 0.936; I24 = 0.822) were estimated freely without imposing an equality constraint. F6 is therefore identified under Bollen's (1989) criterion, and the absence of any Heywood case in the final solution empirically confirms that all factors met the identifiability conditions. In cross-cultural adaptation studies, preserving the original theoretical structure is often prioritized over increasing the number of items solely to improve internal consistency, provided that the psychometric evidence supports the adequacy of the measurement model (Beaton et al., 2000; Sousa & Rojjanasirrat, 2011). In addition, the factor loading of original scale item 8 on its corresponding factor in the initial eight-factor specification remained relatively low ($\lambda = 0.27$, $R^2 = 0.076$). Items with a factor loading below 0.30 cannot be considered adequate indicators of the relevant factor; retaining such items in the model results in both measurement inefficiency and a weakened model fit (Hair et al., 2010; Worthington & Whittaker, 2006). In line with the stated psychometric rationale, original scale items 8 (AI developers lack educational experience), 12 (Lack of transparency in how AI makes decisions), and 19 (I am sure that using AI-based tools for personalization in my classroom will require me to make a significant change in my pedagogy) were removed from the model. The analysis was rerun on a 21-item, 6-factor structure. To preserve traceability to the source instrument, the 21 items retained in the final solution keep their original scale item numbers (I1–I7, I9–I11, I13–I18, and I20–I24; the removed items 8, 12, and 19 are omitted) in Tables 3 to 6 and in the following discussion; these numbers correspond to the “Item no. in the original scale” column in Appendix 1.

In the analysis of the scale's 21-item, 6-factor structure, the standards recommended by Hu and Bentler (1999) and Bentler and Bonett (1980) were used. According to these standards, the χ^2/df ratio should be less than 3, and the CFI and TLI values should be greater than 0.90. As a result of the analysis, the scale structure was found to reach a generally acceptable level of fit, with values of $\chi^2 = 340.179$, $df = 174$, $\chi^2/df = 1.955$ (< 3), CFI = 0.903 (≥ 0.90), TLI = 0.883, and RMSEA = 0.064 (< 0.08). The TLI value (.883) fell below the conventional .90 threshold; however, the model was retained because the remaining fit indices fell within acceptable ranges and rigid cutoff values should not be treated as universal "golden rules" but rather interpreted alongside multiple fit indices and substantive model considerations (Marsh, Hau, & Wen, 2004). The standard errors of the ML estimates and the corresponding z (c.r.) values are presented in Table 3. As shown in Table 3, the factor loadings of all observed variables other than the reference indicators are statistically significant ($z = 4.35 - 9.83$, $p < .001$).

Table 3.

Maximum Likelihood Parameter Estimates (Regression Weights, $N = 231$)

Item	Factor	Estimate	S.E.	c.r.	P
I1	F1	1.000	—	—	—
I2	F1	0.885	0.092	9.63	***
I3	F1	0.782	0.083	9.38	***
I4	F1	1.007	0.103	9.81	***
I5	F1	0.976	0.119	8.19	***

Item	Factor	Estimate	S.E.	c.r.	P
I6	F1	0.781	0.084	9.34	***
I7	F1	0.768	0.086	8.90	***
I9	F2	1.000	—	—	—
I10	F2	1.048	0.208	5.05	***
I11	F2	0.846	0.169	5.01	***
I13	F3	1.000	—	—	—
I14	F3	0.706	0.162	4.35	***
I15	F3	0.665	0.139	4.79	***
I16	F4	1.000	—	—	—
I17	F4	1.167	0.161	7.26	***
I18	F4	1.204	0.160	7.53	***
I20	F5	1.000	—	—	—
I21	F5	1.152	0.117	9.83	***
I22	F5	1.070	0.112	9.58	***
I23	F6	1.000	—	—	—
I24	F6	0.929	0.095	9.80	***

Note *** $p < .001$

The standardized factor loadings are presented in Table 4. When standardized estimates are examined, factor loadings range from 0.510 to 0.936. According to these observations, the loadings are above the 0.50 threshold recommended by Hair et al. (2010). The path diagram of the model is presented in Figure 2.

Table 4.

Standardized Factor Loadings (N = 231)

Item	Factor	β	R ²
I1	F1	0.684	0.468
I2	F1	0.720	0.519
I3	F1	0.699	0.488
I4	F1	0.736	0.542
I5	F1	0.601	0.361
I6	F1	0.696	0.484
I7	F1	0.659	0.434
I9	F2	0.546	0.299
I10	F2	0.634	0.402
I11	F2	0.576	0.331
I13	F3	0.677	0.459
I14	F3	0.526	0.277
I15	F3	0.510	0.260
I16	F4	0.531	0.282
I17	F4	0.729	0.532
I18	F4	0.811	0.658
I20	F5	0.635	0.403
I21	F5	0.864	0.746
I22	F5	0.807	0.651
I23	F6	0.936	0.875
I24	F6	0.822	0.675

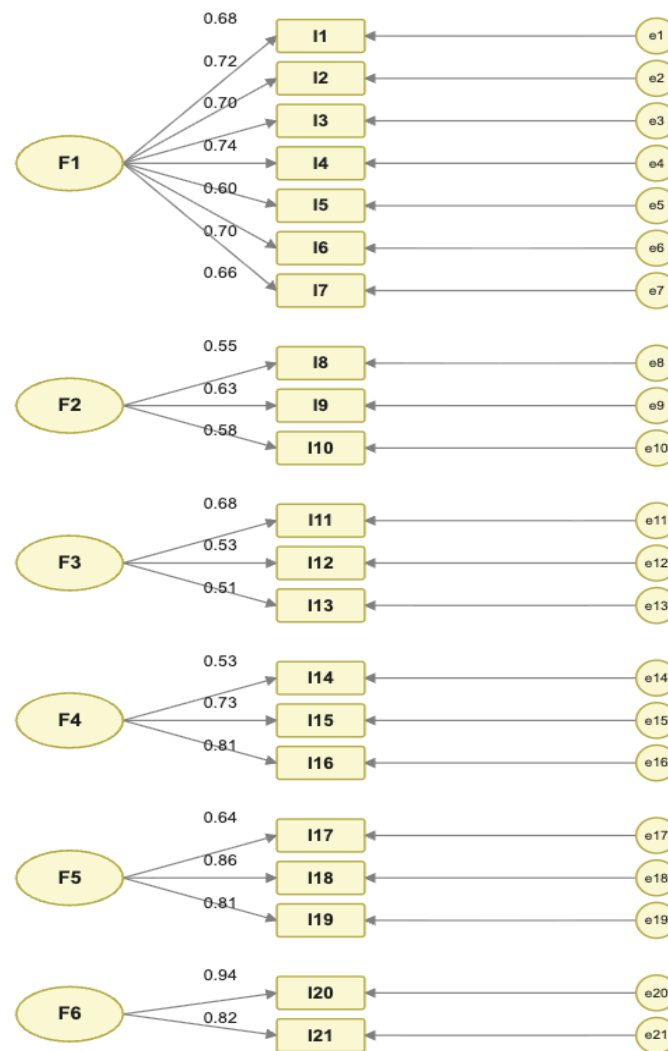


Fig. 2. Path Diagram of the Confirmatory Factor Analysis

To assess the robustness of the estimates, bias-corrected standard errors and 95% confidence intervals were computed over 500 bootstrap samples. The bootstrap standard errors, the differences between these and the standard errors obtained via ML (Bias), and the standard errors of these differences are presented in Table 5.

Table 5.

Bootstrap Standard Errors (Standardized Regression Weights)

Item	←	Factor	SE	SE-SE	Mean	Bias	SE-Bias
I1	←	F1	0.053	0.002	0.684	0.000	0.002
I2	←	F1	0.054	0.002	0.717	-0.003	0.002
I3	←	F1	0.047	0.001	0.699	0.000	0.002
I4	←	F1	0.044	0.001	0.736	0.000	0.002
I5	←	F1	0.063	0.002	0.602	0.001	0.003
I6	←	F1	0.044	0.001	0.699	0.003	0.002
I7	←	F1	0.057	0.002	0.660	0.001	0.003
I9	←	F2	0.082	0.003	0.542	-0.004	0.004
I10	←	F2	0.094	0.003	0.629	-0.005	0.004
I11	←	F2	0.104	0.003	0.571	-0.005	0.005

Item	←	Factor	SE	SE-SE	Mean	Bias	SE-Bias
I13	←	F3	0.168	0.005	0.670	-0.007	0.007
I14	←	F3	0.131	0.004	0.509	-0.017	0.006
I15	←	F3	0.162	0.005	0.514	0.004	0.007
I16	←	F4	0.061	0.002	0.530	-0.001	0.003
I17	←	F4	0.050	0.002	0.728	-0.001	0.002
I18	←	F4	0.051	0.002	0.809	-0.002	0.002
I20	←	F5	0.068	0.002	0.633	-0.001	0.003
I21	←	F5	0.043	0.001	0.859	-0.005	0.002
I22	←	F5	0.043	0.001	0.802	-0.004	0.002
I23	←	F6	0.045	0.001	0.930	-0.006	0.002
I24	←	F6	0.044	0.001	0.826	0.004	0.002

Table 5 shows that the bootstrap standard errors closely approximate those obtained via ML. The bias values are close to zero; the highest absolute bias (-0.017) was observed for item I14, indicating that it has a more variable loading structure than the other items. The bias-corrected 95% confidence intervals are presented in Table 6.

Table 6.

Bias-Corrected 95% Confidence Intervals (Standardized Regression Weights)

Item	Factor	Estimate	Lower	Upper
I1	F1	0.684	0.572	0.784
I2	F1	0.720	0.607	0.807
I3	F1	0.699	0.611	0.788
I4	F1	0.736	0.644	0.814
I5	F1	0.601	0.473	0.721
I6	F1	0.696	0.605	0.774
I7	F1	0.659	0.545	0.754
I9	F2	0.546	0.374	0.708
I10	F2	0.634	0.449	0.810
I11	F2	0.576	0.361	0.755
I13	F3	0.677	0.303	0.966
I14	F3	0.526	0.126	0.621
I15	F3	0.510	0.218	0.842
I16	F4	0.531	0.410	0.642
I17	F4	0.729	0.619	0.817
I18	F4	0.811	0.710	0.896
I20	F5	0.635	0.496	0.752
I21	F5	0.864	0.762	0.926
I22	F5	0.807	0.699	0.874
I23	F6	0.936	0.833	1.000
I24	F6	0.822	0.739	0.906

As shown in Table 6, none of the 95% confidence intervals for the standardized factor loadings include zero. This result confirms that the factor loadings are statistically significant by rejecting the null hypothesis that all factor loadings are zero (Byrne, 2016). Additionally, the model's fit to the data was tested using the

Bollen–Stine bootstrap p-value. The Bollen–Stine approach evaluates the position of the chi-square statistic from the observed data relative to the chi-square distribution generated via bootstrapping, and a p-value > .05 indicates that the proposed model is compatible with the data (Bollen & Stine, 1993; Byrne, 2016). In the present study, the Bollen–Stine p-value, computed using 500 bootstrap samples, was greater than 0.05, indicating that the model is compatible with the data. This result, when evaluated alongside the previously presented ML fit indices and bias-corrected confidence intervals, indicates that the data support the scale's six-factor structure.

Following the CFA findings, the factor- and item-level distributions of the original and adapted scales are presented in Table 7. Examination of the table shows that the adapted scale largely overlaps with the scale used in the original study, both conceptually and structurally. In the adaptation study, the core multidimensional structure was largely preserved, with modifications to three items and two single-item subdimensions warranted by the psychometric evidence. Therefore, the factor names and the items they comprise remained consistent in terms of content validity. This indicates that the translation procedure and expert evaluations carried out during the adaptation process successfully preserved the conceptual integrity of the scale.

Table 7.

Comparison of the Factor Structures of the Original Scale and the Turkish-Adapted Scale

Original Study		Adaptation Study	
Factor	Number of Items	Factor	Number of Items
Perceived Benefits of AI-based EdTech	7	Perceived Benefits of AI-based EdTech	7
AI-based EdTech's Lack of Human Characteristics	4	AI-based EdTech's Lack of Human Characteristics	3
Anxieties Related to Using AI-based EdTech	3	Anxieties Related to Using AI-based EdTech	3
Self-efficacy in Using AI-based EdTech	3	Self-efficacy in Using AI-based EdTech	3
Preferred Means to Increase Trust in AI-based EdTech	3	Preferred Means to Increase Trust in AI-based EdTech	3
AI-based EdTech vs Human Advice/Recommendation	2	AI-based EdTech vs Human Advice/Recommendation	2
AI-based EdTech's Perceived Lack of Transparency	1		
Required Shift in Pedagogy to Adopt AI-based EdTech	1		
Total Number of Items	24		21

3.4.3. Reliability

As indicated in Table 8, the Cronbach's alpha coefficients of the scale adapted to Turkish range from 0.551 to 0.868, while the composite reliability (CR) coefficients range from 0.594 to 0.873. The Average Variance Extracted (AVE) values ranged from 0.332 to 0.776.

Table 8.Reliability Coefficients of the Scale Adapted into Turkish (Cronbach's α , CR, and AVE)

Factor	Number of Items	Cronbach α	CR	AVE
F1	7	0.854	0.861	0.471
F2	3	0.602	0.610	0.344
F3	3	0.551	0.594	0.332
F4	3	0.710	0.737	0.490
F5	3	0.791	0.816	0.600
F6	2	0.868	0.873	0.776
Total	21	0.694	—	—

When Table 8 is examined, it can be seen that in terms of both Cronbach's alpha and Composite Reliability (CR) coefficients, factors F1 ($\alpha = 0.854$; CR = 0.861), F4 ($\alpha = 0.710$; CR = 0.737), F5 ($\alpha = 0.791$; CR = 0.816), and F6 ($\alpha = 0.868$; CR = 0.873) meet the 0.70 criterion recommended by Hair et al. (2010) and Gürbüz (2021). Although the reliability coefficients of factors F2 ($\alpha = 0.602$; CR = 0.610) and F3 ($\alpha = 0.551$; CR = 0.594) are relatively low, their composite reliabilities follow a pattern parallel to their Cronbach's alpha values. In the original-scale study, the subdimensions corresponding to these two factors (AI-based EdTech's Lack of Human Characteristics [original scale: $\alpha = 0.66$] and Anxieties Related to Using AI-based EdTech [original scale: $\alpha = 0.69$]) exhibited lower reliability than the other factors. When the Average Variance Extracted (AVE) values are examined, factors F5 (AVE = 0.600) and F6 (AVE = 0.776) exceed the 0.50 threshold recommended by Fornell and Larcker (1981). Fornell and Larcker (1981) and Gürbüz (2021) state that in cases where AVE < 0.50 but CR $\geq$ 0.60, convergent validity may still be considered acceptable; accordingly, it can be said that factors F1 and F4 are at an acceptable level in terms of convergent validity. For factor F3, both the AVE (.332) and CR (.594) were below the commonly recommended thresholds, indicating comparatively weak convergent validity evidence for this subdimension.

Overall, the reliability evidence varied across the six subdimensions. Four factors (F1, F4, F5, and F6) met commonly recommended thresholds for internal consistency and composite reliability. F2 showed comparatively lower internal consistency ($\alpha = .602$), although its composite reliability (CR = .610) was slightly above .60, suggesting that this subdimension should be interpreted with caution. F3 yielded the weakest psychometric evidence, with both Cronbach's alpha ($\alpha = .551$) and composite reliability (CR = .594) falling below commonly recommended thresholds, together with a relatively low AVE value (.332).

It is noteworthy that the corresponding subdimensions also showed comparatively modest internal consistency in the original study, with $\alpha = .66$ for AI-based EdTech's Lack of Human Characteristics and $\alpha = .69$ for Anxieties Related to Using AI-based EdTech (Nazaretsky et al., 2022b). However, the coefficients obtained in the present study, particularly for F3, were lower than those reported in the original instrument. Therefore, the reliability and convergent validity evidence for F2, and especially F3, should be interpreted cautiously and examined further in independent samples.

The findings indicate that interactions among pedagogical, affective, and ethical dimensions shape teachers' trust in AI-based educational technologies. The factor structure that emerged in the Turkish adaptation of the scale provides important clues regarding how this perception of trust is constituted in the Turkish context. The following section discusses these findings in light of the relevant literature.

In this study, the Scale of Trust in AI-Based Educational Technologies developed by Nazaretsky, Cukurova, and Alexandron (2022b) was adapted into Turkish, and validity and reliability studies were conducted. The findings revealed that the 21-item, 6-factor Turkish form of the scale demonstrated acceptable construct validity and reliability in a sample of N = 231 teachers. The univariate and multivariate normality analyses conducted on the dataset showed that univariate normality was approximately achieved, but multivariate normality was violated. Therefore, in addition to maximum likelihood estimation, the CFA was conducted

using distribution-free bootstrap procedures rather than a scaled chi-square correction, including bias-corrected confidence intervals computed from 500 bootstrap samples. The model's fit to the data was further assessed using the Bollen–Stine bootstrap p-value, which supported the model fit.

Item I8's factor loadings on Factor F2 throughout the adaptation period were low, indicating that the item has little influence on the underlying factor structures being sought and that removing it is likely to add clarity to the solution (Watson & Thompson, 2006). The lack of educational experience of developers was noted in I8; however, in Türkiye, teachers may not consider a developer's educational background as a primary consideration in determining how valid or trustworthy it is. It is more likely that teachers assess AI tools based on how they perform when used in their classrooms, how easy they are to use, how well they align with their curricula, and how accurate the information produced by the programs is. Therefore, the lack of formal education among developers may not be a distinctive aspect of educators' views of AI developers; this may explain the weak correlation between this item (I8) and the underlying construct.

Additionally, two factors in the original scale, each consisting of a single-item (Factor 3 [AI-based EdTech's Perceived Lack of Transparency] and Factor 6 [Required Shift in Pedagogy to Adopt AI-based EdTech]), were reconsidered due to their limited measurability. Internally consistent coefficients are influenced by the length of the scale used, as shorter subscales generally yield lower reliability even when inter-item correlations are acceptable (Nunnally & Bernstein, 1994; Tavakol & Dennick, 2011). To address this limitation and ensure that the scale functioned more effectively within a pedagogical context, these factors were restructured. In scale adaptation studies, content validity requires that items adequately and representatively cover the domain of the construct being measured (DeVellis, 2003; Morgado et al., 2017), and it is widely acknowledged that single-item subdimensions may be insufficient to provide such representation.

The reliability evidence varied across the six subdimensions, with four factors showing stronger internal consistency, while F2 and particularly F3 demonstrated comparatively weaker psychometric performance. The six-factor structure of the scale is consistent with research suggesting that trust in artificial intelligence is not a unidimensional construct but a multidimensional phenomenon shaped by interactions among cognitive, affective, and contextual components (Omrani et al., 2022; Viberg et al., 2025). An examination of the scale's subdimensions indicates that teachers' trust cannot be reduced to a simple evaluation of technological functionality. Instead, it emerges from the interplay of cognitive and affective elements, including perceived benefits of AI-based EdTech (*F1*), *perceived* lack of human characteristics in AI-based EdTech (*F2*), anxieties *related* to using AI-based EdTech (*F3*), *self-efficacy* in using AI-based EdTech (*F4*), *preferred means to increase* trust in AI-based EdTech (*F5*), and *preference for AI-based EdTech versus human advice or recommendation* (*F6*). This finding highlights that teachers' processes for developing trust in artificial intelligence systems are complex, multilayered, and context sensitive.

Within educational settings, it is well established that teachers' decisions to integrate AI-based technologies into classroom practices are largely shaped by their level of trust in these technologies (Nazaretsky et al., 2022a; Shen et al., 2025). In particular, teachers' perceptions of the outputs generated by artificial intelligence systems, such as personalized learning opportunities, automated feedback, transparency in decision-making, and the reliability of recommendations, play a critical role in the formation of trust. These results suggest that teacher trust is closely related to how artificial intelligence systems are pedagogically designed, explained, and integrated into classroom decision-making processes (Omrani et al., 2022; Viberg et al., 2025).

In the Turkish context, policy documents and teacher guidelines published in recent years encourage the conscious, ethical, and human-centered use of artificial intelligence technologies in educational environments (MoNE, 2023; YEĞİTEK, 2025a; YEĞİTEK, 2025b). However, the successful translation of these policies into classroom practice is directly linked to teachers' ability to develop trust in such technologies. In this respect, the Turkish adapted scale is considered a potentially valuable tool for measuring teachers' trust in artificial intelligence, with demonstrated validity and reliability, thereby supporting the design of professional development programs and the evaluation of the effectiveness of policy implementation. The results from the scale can help identify the specific dimensions in which

teachers require support, such as managing anxiety, developing self-efficacy, or implementing trust-building strategies, and inform targeted in-service training initiatives. In addition, the scale may serve as a basis for monitoring the pre- and post-implementation effects of policy initiatives, including guidelines and professional development programs.

4. Conclusion and Suggestions

In conclusion, this study contributes to the literature by providing initial evidence for the structural validity and reliability of the Turkish adaptation of the scale assessing teachers' trust in artificial intelligence-based educational technologies. The six-factor structure was generally supported by the CFA results; however, the reliability and convergent validity evidence was weaker for F2 and particularly F3, and the revised structure requires further examination in an independent sample. Developing a conscious, balanced, and critical understanding of trust requires teachers to consider ethical, pedagogical, and technological dimensions simultaneously. In this regard, the adapted scale may provide a useful basis for assessing teachers' trust profiles in research and professional development contexts, while findings related to the weaker subdimensions should be interpreted with caution. Identifying teachers' trust profiles can inform the restructuring of these programs to focus not only on technical skills but also on trust-supporting dimensions such as ethical awareness, explainability, and pedagogical alignment.

Future research should examine the relationships between teachers' trust in artificial intelligence-based educational technologies, as measured by this scale, and variables such as technology acceptance, intention to use, pedagogical beliefs, self-efficacy, and artificial intelligence anxiety. Additionally, testing the scale with different teacher groups based on subject area, years of experience, and school type, as well as with diverse samples, would enhance its generalizability.

Furthermore, longitudinal studies investigating how teachers' trust in artificial intelligence-based educational technologies evolves and how professional development programs influence this change in trust could make significant contributions to the field. Similarly, multilevel studies that employ this scale alongside trust scales designed for students and school administrators may enable a more comprehensive examination of the dynamics of artificial intelligence integration in education.

Nevertheless, the study has certain limitations. First, the scale's validity and reliability were examined using cross-sectional data. This limits the ability to directly capture changes in teachers' perceptions of trust over time or to examine how factors such as professional experience, in-service training, and policy implementation influence trust. As a result, the findings reflect teachers' perceptions at a specific point in time rather than capturing the developmental and dynamic nature of trust.

Another limitation is that the sample was limited to specific groups of teachers. Although pedagogical and theoretical foundations strengthened the scale adaptation process, this study did not examine whether the scale exhibits similar psychometric properties across subject areas, school types, and levels of teaching experience. Retesting the scale across diverse contexts and samples would therefore enhance the generalizability of the findings.

Finally, the reliance on self-report data represents an important limitation. Teachers' trust in artificial intelligence was measured through self-reported perceptions and evaluations, making it difficult to directly observe potential discrepancies between perceived trust and actual classroom use and to assess the influence of social desirability. Consequently, the findings primarily reflect teachers' attitudes toward and trust in artificial intelligence, while offering limited insight into how these perceptions are translated into classroom practices.

A further limitation concerns the scope of the evidence of validity presented. Beyond the structural (factorial) evidence provided by the CFA, this study did not assess discriminant validity via the Fornell-Larcker criterion or the heterotrait-monotrait ratio of correlations (Fornell & Larcker, 1981; Henseler et al., 2015) through inter-factor correlations, concurrent or criterion-related validity against conceptually related constructs (e.g., technology acceptance, AI anxiety, or technological self-efficacy), test-retest reliability, or measurement invariance across subject areas, school types, or levels of experience. In

addition, because the retained six-factor, 21-item structure was derived and then re-evaluated on the same sample, the confirmatory analysis reported here functions in part as a post hoc refinement rather than as an independent confirmatory test; the model should be cross-validated on an independent sample before its fit indices are interpreted as fully confirmatory evidence. Similarly, the reliability and convergent validity evidence for F2, and particularly F3, remains weaker than for the other subdimensions; strengthening these subscales by adding items and providing new evidence of content validity is recommended for future revisions of the scale. Addressing these points will require additional data collection and will be left for future research.

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

During the preparation of this manuscript, generative AI tools were used in a limited and supportive manner, primarily to improve language clarity, grammar, and readability. AI-assisted tools were not used to generate research findings, conduct data analysis, or make scientific interpretations. The authors reviewed and revised all AI-assisted suggestions and take full responsibility for the content, accuracy, and integrity of the manuscript.

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Appendix 1: Turkish Adaptation of the Teachers' Trust in Artificial Intelligence-based Educational Technologies Scale

Yapay Zekâ Temelli Eğitim Teknolojilerine Güven Ölçeği

Aşağıda yapay zekâ temelli eğitim teknolojilerine yönelik görüşleri tanımlayan ifadeler yer almaktadır. Her bir ifadeyi dikkatle okuyarak size ne ölçüde uygun olduğunu 1 ile 5 arasında değişen dereceler üzerinde işaretleyiniz (1 = Kesinlikle Katılmıyorum; 5 = Kesinlikle Katılıyorum).

The statements below describe views on AI-based educational technologies. Please read each statement carefully and rate the extent to which it reflects you on a scale ranging from 1 to 5 (1 = Strongly disagree; 5 = Strongly agree).

Orijinal ölçekteki madde no. Item no. in the original scale	Maddeler (Türkçe Form)	Items (English)*	Kesinlikle Katılmıyorum (1) Strongly disagree	Katılmıyorum (2) Disagree	Kısmen Katılıyorum (3) Partly agree	Katılıyorum (4) Agree	Kesinlikle Katılıyorum (5) Strongly agree
F1. Yapay Zekâ Temelli Eğitim Teknolojilerinin Algılanan Faydaları Perceived Benefits of AI-based EdTech							
1	Yapay zeka karmaşık uygulamaların biçimlendirici değerlendirmesine yardımcı olarak (Örneğin; açık uçlu sorular sorma, bilimsel muhakemenin kalitesini ortaya koyma) kişiye özel gerçek zamanlı geri bildirim önerebilir.	Artificial Intelligence can assist in formative assessment of complex tasks (e.g., open questions, quality of scientific reasoning), and suggest personalized feedback in real-time.					
2	Yapay zeka öğrencilerin kendi kendilerine öğrenmeleri için bireyselleştirilmiş öğrenme yollarının belirlenmesine yönelik otomatik sistemlerin geliştirilmesine yardımcı olabilir.	Artificial Intelligence can assist in the development of automated systems for assigning individualized learning paths for students' self-learning.					
3	Yapay zeka, öğrenme arkadaşları veya öğretim asistanları olarak hizmet verebilecek akıllı araçların (Robot veya yazılımlar) oluşturulmasına yardımcı olabilir.	Artificial Intelligence can assist in creating intelligent agents (robots or software) that may serve as learning pals or teaching assistants.					
4	Yapay zeka, öğretmenlerin öğrencilerinin ihtiyaçlarına uygun kişiye özel görevler verilmesine yardımcı olmak için öğrencilerin zorlandıkları konuların belirlenmesini destekleyebilir (Örneğin; yapay zeka teşhisi yapması ve öğretmenin uygulamaya karar vermesi)	Artificial Intelligence can assist in diagnosing students' difficulties to help teachers assign personalized tasks that match individual needs (AI makes the diagnosis, the teacher decides intervention).					

Orijinal ölçekteki madde no. Item no. in the original scale	Maddeler (Türkçe Form)	Items (English)*	Kesinlikle Katılmıyorum (1) Strongly disagree	Katılmıyorum (2) Disagree	Kısmen Katılıyorum (3) Partly agree	Katılıyorum (4) Agree	Kesinlikle Katılıyorum (5) Strongly agree
5	Yapay zeka, derse katılmayan öğrencilerin belirlenmesi gibi sınıf yönetimi süreçlerinde öğretmenlere yardımcı olabilir.	Artificial Intelligence can assist teachers with in-class management activities, such as identifying students who are off-task.					
6	Yapay zeka, ders saatinden önce dersin içeriğini ve etkinliklerini hazırlama gibi süreçleri planlamada öğretmenlere yardımcı olabilir.	Artificial Intelligence can assist teachers in planning tasks such as preparing lessons and activities before class time.					
7	Yapay zeka öğretmenlerin mesleki gelişimlerine katkı sağlayabilir (Örneğin, yapay zeka temelli avatar oluşturarak öğretim uygulamalarını canlandırma imkanı sunma)	Artificial Intelligence can improve teacher professional training, for example using AI-based avatars to simulate and practice teaching scenarios.					
F2. Yapay Zekâ Temelli Eğitim Teknolojilerinin İnsan Özellikleri Açısından Sınırlılığı AI-based EdTech's Lack of Human Characteristics							
8	Yapay zeka algoritmaları, öğretimde oldukça önemli olan sosyal, duygusal ve motivasyonel faktörleri dikkate almıyor.	AI algorithms do not understand social, emotional, and motivational factors that are very important in teaching.					
9	Öğretmenlerin gerçek yaşam deneyimleri ve sezgileri bilgisayarlardan üstündür.	The superiority of the teachers' real-life experience and intuition over a computer's.					
10	Yapay zeka algoritmaları, öğrencilerin yapay zeka sistemi dışındaki geçmişini bilmiyor.	AI algorithms do not know the history of the student outside the system.					
F3. Yapay Zekâ Temelli Eğitim Teknolojilerinin Kullanımına Yönelik Kaygılar Anxieties Related to Using AI-based EdTech							
11	Yapay zeka özerkliği ve kontrolü öğretmenden alıp kendisine verir.	Removes autonomy and control from teachers to AI.					
12	Yapay zeka yaygın hale geldikçe, daha az öğretmene ihtiyaç duyulacaktır.	When AI becomes more prevalent, fewer teachers will be required.					
13	Yapay zekada verilerin kullanımı, öğretmen ve öğrenci gizliliğine (mahremiyetine) yönelik riskleri artırmaktadır.	Use of data raises risks to teacher and learner privacy.					

F4. Yapay Zekâ Temelli Eğitim Teknolojilerinin Kullanımına Yönelik Öz Yeterlik Self-efficacy in Using AI-based EdTech

14	Sınıfımda yapay zeka temelli kişiye özel öğrenme araçlarının kullanımına tamamen güvenirim.	I fully trust using AI-based personalized learning tools in my classroom.
15	Sınıfımda kişiselleştirme için yapay zeka temelli araçları kullanmam gerektiğinde başarılı olacağıma inanıyorum.	I believe I will be successful in using AI-based tools for personalization in my classroom when and if they will be available to me.
16	Sınıfımda yapay zeka temelli araçlara erişim imkanım olduğunda kişiselleştirme için kullanırım.	I will use AI-based tools for personalization in my class when and if they will be available to me.

F5. Yapay Zekâ Temelli Eğitim Teknolojilerine Yönelik Güveni Artırmaya Yönelik Tercih Edilen Yollar Preferred Means to Increase Trust in AI-based EdTech

17	Kişiselleştirilmiş öğrenmeye yönelik yapay zeka temelli araçlar yaygınlaştıkça bu araçlara daha fazla güven duyarım.	As they become more prevalent, AI-based tools for personalized learning will gain my full trust.
18	Yapay zeka temelli bir aracın nasıl karar verdiği hakkında ne kadar çok şey bilirim, bu araçlara o kadar çok güvenirim.	The more I know how an AI-based tool makes decisions, the more I will be able to trust it.
19	Yapay zeka temelli araçlar için daha fazla veri ortaya konulduğunda, bu araçların açıklamalarına daha çok güvenirim.	The more data is available for AI-based tool, the more I will be able to trust its insights.

F6. Yapay Zekâ Temelli Eğitim Teknolojileri ile İnsan Tavsiyelerinin/Önerilerinin Karşılaştırılması AI-based EdTech vs Human Advice/Recommendation

20	Yapay zeka tabanlı bir aracın tavsiyesine en az bir öğretmen arkadaşımın tavsiyesine güvendiğim kadar güvenirim.	I rely on the recommendation of an AI-based tool at least as much as I trust a recommendation from a fellow teacher.
21	Yapay zeka tabanlı bir aracın tavsiyesine en az bir uzmanın (Örneğin, fen eğitimi anabilim dalından bir araştırmacı) tavsiyesine güvendiğim kadar güvenirim.	I rely on the recommendation of an AI-based tool at least as much as I trust a recommendation from an expert (e.g., a researcher from the department of science teaching).