RESEARCH ARTICLE

Journal of Pedagogical Sociology and Psychology
Volume 8, Issue 2, 2026, e47460
https://doi.org/10.33902/JPSP.202647460

Mapping the dimension-level links between self-reported teaching practices and attitudes toward artificial intelligence: A psychometric network approach

Serdan Kervan[1], Shemsi Morina[2] and Esen Spahi Kovac[3]

[1]Prizren University "Ukshin Hoti", Faculty of Education, Kosovo (ORCID: 0000-0003-4575-8029)
[2]Prizren University "Ukshin Hoti", Faculty of Education, Kosovo (ORCID: 0000-0003-2826-2654)
[3]Prizren University "Ukshin Hoti", Faculty of Education, Kosovo (ORCID: 0000-0002-3122-2592)

Corresponding Author: Shemsi Morina, shemsi.morina@uni-prizren.com

Submitted: 8 June 2026 Revised: 18 July 2026 Accepted: 22 July 2026

Abstract

This study examined the pattern of relationships between the dimensions of teachers' self-reported teaching practices and their attitudes toward artificial intelligence within the framework of psychometric network analysis. A cross-sectional correlational design was used, and data were collected from 376 teachers (300 women, 76 men) working in Kosovo. Self-reported teaching practices were assessed with a five-dimensional scale and attitudes toward artificial intelligence with a three-dimensional scale, both administered in Albanian. A regularized partial correlation network was estimated across the eight dimension scores, and bridge centrality was used to identify the dimensions linking the two constructs. In the primary composite network the cross-construct association appeared to be concentrated in learner-centered instruction; this pattern, however, was not robust. Under reliability-adjusted, alternative-structure, and split-sample analyses, the association was weak and distributed across several teaching-practice dimensions rather than concentrated in one, and the stability of the bridge estimates was low. The perception of artificial intelligence's transformative potential was not linked to any teaching-practice dimension. Perceived competence regarding artificial intelligence decreased consistently with age and seniority, whereas the network structure did not differ by gender under the present specification. The findings map the dimension-level relationship between self-reported teaching practices and attitudes toward artificial intelligence in an under-studied, non-Western context, and indicate that the connection between the two constructs is weak and diffuse rather than mediated by a single bridging dimension.

Keywords: Attitudes toward artificial intelligence; Bridge centrality; Psychometric network analysis; Self-reported teaching practices; Teachers

1. Introduction

The rapid integration of artificial intelligence [AI] into education has brought teachers' attitudes, competence, and readiness to the forefront of research. Because teachers play a central role in determining whether and how AI is incorporated into classroom practice, their attitudes toward AI are important for understanding the educational uptake of this technology. Higher levels of teacher digital competence have been associated with more positive attitudes toward AI, while recent evidence indicates that technological pedagogical content knowledge [TPACK] and technology-related self-efficacy are linked to teachers' AI acceptance and adoption intentions (Çakır & Güner, 2026; Galindo-Domínguez et al., 2024; Ismaniati et al., 2025). Teachers' responses to new technologies, however, are shaped not only by their perceptions of the technologies themselves but also by their existing pedagogical beliefs, efficacy judgments, and instructional orientations. Technology-enabled pedagogical change therefore depends on more than access or technical proficiency; it also requires alignment with teachers' beliefs and established practices (Ertmer & Ottenbreit-Leftwich, 2013). Consistent with this view, teachers' prior digital learning experiences and digital teaching efficacy have been found to predict their digital instructional practices (Park & Kim, 2026). Consequently, examining the relationship between teachers' self-reported teaching practices and their attitudes toward AI is important for clarifying how established pedagogical orientations may facilitate or constrain the classroom integration of AI.

Teaching practices and attitudes toward AI are addressed in the literature as multidimensional constructs. Teaching performance encompasses various dimensions ranging from learner-centered and teacher-centered instruction to classroom climate and planning (Mu et al., 2022). Similarly, attitudes toward AI include relatively independent components such as perceived professional competence, instructional functionality, and transformative potential (Zhang et al., 2023). Such multidimensionality implies that the relationship between the two constructs may function as an inter-dimensional pattern rather than as a generic link, so that the association between a given teaching-practice dimension and a given AI-attitude dimension need not be uniform. A concentration of the relationship on particular dimensions would point to one or more bridging dimensions between the two constructs, whereas a diffuse pattern would indicate that the connection is distributed.

The current literature, however, falls short of directly revealing this dimension-level pattern. The relationship between the two constructs has mostly been examined through correlation or regression methods using composite scores. While these approaches have shown whether the two scales are related, they have not revealed through which dimensions the relationship operates. Directional models, while testing specific pathways, cannot comprehensively map the pattern of mutual relationships among all dimensions. This situation leaves two questions unanswered. The first is through which dimension or dimensions the link between self-reported teaching practices and attitudes toward AI is established. The second is whether this connection is concentrated in a single bridging dimension or distributed across several. This gap can be addressed by psychometric network analysis, which models variables as nodes that interact directly with one another (Borsboom et al., 2021). The network approach makes the pattern of relationships between dimensions, and the nodes that serve as bridges, visible on the basis of partial correlations (Epskamp & Fried, 2018; Jones et al., 2021).

The context in which this study was conducted further highlights this gap. The relationship between dimensions of teaching quality and student outcomes is known to vary according to cultural context, and it therefore needs to be re-examined in different educational systems (Bellens et al., 2019; Liu et al., 2024). The dimension-level relationship between teaching practices and attitudes toward AI has nonetheless been examined primarily in Western and typically monolingual contexts. Kosovo offers an under-studied, non-Western setting in which different languages of instruction, such as Turkish and Albanian, coexist. At the policy level, the Kosovo Education Strategy 2022–2026 set digitalization as a strategic priority and explicitly targeted the development of teachers' digital competences (Ministry of Education, Science, Technology and Innovation [MESTI], 2022). Empirical work in Kosovo indicates that technology integration remains constrained by infrastructural limitations, uneven access, and limited teacher preparation, with effective use depending heavily on individual teachers' competence and initiative (Ismajli, 2026; Orhani et al., 2023). In a recent study of Kosovar primary-school teachers, inadequate training and infrastructure, together with ethical and data-protection concerns, were identified as the main barriers to AI use, even as teachers acknowledged its potential (Kryeziu et al., 2026). The integration of AI into schooling can therefore be regarded as being at an early and unevenly supported stage, and the existing Kosovar evidence is largely descriptive or qualitative. These characteristics make Kosovo a suitable context for examining the relationship between teaching practices and attitudes toward AI beyond the findings obtained in Western-centered samples. It should be noted, however, that although the setting is multilingual, the present study administered its instruments in a single language; the multilingual character of the context is therefore treated here as a contextual feature rather than as a measured one.

The theoretical framework of this study rests on two axes. The first is the view that teachers' pedagogical orientation is a determinant of technology adoption. According to this view, once external barriers are removed, teachers' beliefs about teaching and learning become the true determinants of technology integration, and a learner-centered orientation in particular is associated with higher-level and transformative use of technology (Ertmer & Ottenbreit-Leftwich, 2013; Tondeur et al., 2017). The second axis is the network psychometrics approach, which treats structures not as indicators of an underlying common cause but as directly interacting components (Borsboom et al., 2021). Considered together, these two axes suggest that the relationship between teaching practices and attitudes toward AI need not be distributed equally across all dimensions, and that, if a bridging dimension exists, a learner-centered orientation is a plausible candidate.

Because constructivist, learner-centered teachers tend to engage technology as a concrete tool for supporting student-centered learning rather than as an abstract prospect (Ertmer & Ottenbreit-Leftwich, 2013; Hsu, 2016; Tondeur et al., 2017), such an orientation might relate primarily to the practice-near components of AI attitudes, that is, to perceptions of instructional functionality and professional competence, whereas the more visionary component concerning AI's transformative potential reflects an expectation about the future of education that need not be tied to any particular teaching-practice dimension. Bridge centrality provides a suitable framework for examining these possibilities empirically (Jones et al., 2021), without presupposing that a single bridge exists.

This study aims to describe the pattern of relationships between teachers' self-reported teaching-practice dimensions and their attitudes toward AI within the framework of psychometric network analysis. It specifically aims to identify the dimension or dimensions that link the two constructs and to examine whether this pattern varies according to teachers' demographic characteristics. In this way, the study aims to contribute to the literature by addressing the relationship between the two constructs not as an integrated link but as a pattern at the dimensional level, and by examining it in an under-studied, non-Western context. Because of the cross-sectional design, the relationships identified are non-directional; this study is a correlational analysis rather than an analysis of effects. The study is exploratory and does not test directional hypotheses. The framework outlined above leads to no more than a tentative expectation that, should the two constructs prove to be connected, a learner-centered orientation would be among the dimensions involved, linked on the AI side to instructional functionality and professional competence; this expectation is used to guide interpretation rather than as a hypothesis to be confirmed. Accordingly, the following research questions were formulated.

RQ 1) What structure does the standardized partial correlation network between teachers' self-reported teaching practices and their attitudes toward AI exhibit, and which dimensions are interconnected?

RQ 2) Through which dimension or dimensions is the connection between the two constructs established, and is this connection concentrated in a single bridging dimension or distributed across several?

RQ 3) Do dimension scores and the inter-dimensional network structure vary according to teachers' demographic characteristics such as gender, age, educational background, subject area, seniority, and language of instruction?

2. Literature Review

2.1. Teaching Practices and Their Dimensions

Teaching performance is not a trait that can be explained by a single quality. In research on teaching quality, there is a clear consensus that classroom instruction should not be evaluated as a unidimensional structure but should be addressed through at least three fundamental dimensions (Mu et al., 2022). These dimensions are typically referred to as cognitive engagement, supportive classroom climate, and classroom management, and they point to the interactions between teachers and students (Fauth et al., 2019; Gonzalez-Berruga, 2025). This three-dimensional framework serves as a common starting point for measuring teaching quality.

This three-dimensional model has been shown to mediate the relationship between teacher competence and student achievement. Fauth et al. (2019) found that the effect of teacher competence on students' motivation and achievement in primary science education is largely attributable to the quality of classroom instruction. The number of dimensions and the degree to which they are conceptually distinct nonetheless remain debated. In some studies the dimensions are not sufficiently distinct from one another, and recent findings indicate that four-factor solutions can fit the data better than a three-factor model (Šeďová & Sedláček, 2026). Dierendonck (2023) similarly noted that dimensions of teaching quality are commonly characterized by cross-loadings, which calls for a flexible factor solution rather than a rigid basic structure. It is difficult to generalize, but it can be said that the dimensional structure of teaching quality is context- and measurement-dependent.

The scale used in this study addresses these core dimensions in a more detailed structure and defines teaching across five dimensions, as developed by Morina et al. (in press) for the Kosovan context. Because the instrument relies on teachers' self-reports, its scores are treated throughout as self-reported teaching practices rather than as observed classroom performance. The five dimensions are named learner-centered instruction and assessment, teacher-centered pedagogical practices, interpersonal relations, planning and preparation, and classroom climate. The distinction between learner-centered and teacher-centered instruction rests on a well-established theoretical foundation, in which teacher-centered models are rooted in the behaviorist and direct-instruction tradition while learner-centered approaches are grounded in constructivist learning theory (Treve, 2024). Meta-analytic findings support a moderate positive effect of learner-centered education on academic achievement (Li et al., 2024). The evidence is not always consistent, however; Bremner et al. (2022) systematically reviewed the outcomes of learner-centered pedagogy in low- and middle-income countries and noted that objective evidence regarding its effectiveness remains relatively limited. It therefore seems more appropriate to view learner-centered and teacher-centered orientations not as mutually exclusive poles but as pedagogical tendencies that can coexist.

The association between student outcomes and teaching-quality dimensions is moreover contingent on the cultural context. Teacher support and disciplinary climate have been found to predict achievement fairly consistently, whereas the student-centered instruction and classroom management dimensions have been negatively related to achievement in many countries, and the effect of cognitive activation is inconsistent across time periods and countries (Liu et al., 2024). Bellens et al. (2019) similarly noted the difficulty of conceptualizing and measuring aspects of quality instruction comparably across nations, observing that the cognitive activation dimension might not even be quantified consistently as a single construct. These results indicate that the dimensional structure of teaching quality needs to be re-considered in different educational systems, which is especially relevant given that the present study was conducted in Kosovo.

2.2. Teachers' Attitudes toward Artificial Intelligence

Teachers' attitudes toward AI have rapidly become a subject of research with the introduction of AI into education. Attitude is viewed not as a single positive or negative orientation but as a multidimensional construct comprising cognitive, affective, and behavioral components (Asio & Gadia, 2024). In the literature, teachers' attitudes toward AI have mostly been examined within the framework of technology acceptance models, and perceived usefulness and perceived ease of use have been reported as the primary factors predicting usage intention (Bilgin & Güngören, 2025; Zhang et al., 2023). It can be argued, however, that attitude is not limited to acceptance intent but also encompasses perceptions regarding the instructional functionality of AI, the teacher's professional competence, and the potential to transform education. The scale developed by Demirdağ et al. (2025) addresses perceptions toward AI in a multidimensional manner. Although the original form of the scale was reported as two-dimensional, it exhibited a three-factor structure in the present Kosovo sample. This discrepancy can be attributed to the application of the scale in a different linguistic and cultural context, and the literature emphasizes that the factor pattern of attitude structures may vary with the cultural and educational context of the sample (Dorsah et al., 2025). The three-factor structure is theoretically interpretable, as instructional functionality, professional competence, and transformative potential correspond to conceptually distinct domains of perception; the details and limitations of this structure are reported in the Method and in the Supplementary Material.

Teachers' perceived professional and digital competence [AI-PC] concerns the professional and digital competencies required to use AI effectively and ethically. AI-supported instructional functionality [AI-IF] concerns the potential of AI to support instructional processes and teaching decisions tailored to student needs. AI's transformative potential [AI-TP] concerns the perceived transformative effects of AI on the teacher's role, creativity, equity, and classroom management.

Teachers' attitudes toward AI are closely related to their perceptions of AI literacy and professional competence. Ng et al. (2023) emphasized that digital-competency frameworks must be expanded to include AI technologies. Al-Abdullatif (2024) found that AI literacy is one of the strongest predictors of the adoption of generative AI, with perceived trust and AI-supported technological pedagogical content knowledge mediating this relationship, and the development of tools to measure teachers' AI competence reflects these efforts (Chiu et al., 2025). These findings support treating perceived professional and digital competence regarding AI as a distinct dimension of attitude, represented here by the AI-PC factor. The direction of this relationship is not always consistent, however. Lucas et al. (2024) reported that teachers' trust in AI is primarily predicted by AI knowledge, while digital competence alone is not a significant predictor, and found no significant difference in attitudes across levels of digital competence. It can be said that the perception of competence shapes attitude not on its own but in conjunction with other perceptions such as knowledge and trust.

A third dimension of attitude concerns perceptions regarding the potential of AI to transform the teacher's role and instructional processes. Zhai (2025) argued that generative AI transforms the teacher's role and proposed a framework classifying teachers into four roles, namely observer, adopter, collaborator, and innovator, according to their level of engagement with AI. Kong and Yang (2024) similarly emphasized that teachers are increasingly becoming facilitators in AI-supported instruction. The reflection of this transformative expectation in actual teaching practice is not always direct; Wijaya et al. (2024) highlighted that the risk of over-reliance may increase among teachers with high AI literacy and confidence, which points to the need for a balanced assessment of expectations regarding transformative potential. This dimension is represented here by the AI-TP factor.

Whether teachers' attitudes toward AI vary with demographic characteristics has also been widely investigated. Cabero-Almenara et al. (2024) reported that teachers' adoption of AI is influenced by age and teaching modality, while gender does not create a significant difference in acceptance dimensions but affects pedagogical beliefs, and that constructivist pedagogical attitudes were positively correlated with AI adoption. Dringó-Horváth et al. (2025) pointed to gender, subject area, age, and seniority as determinants of the relationship between AI literacy and digital competence, which implies that a one-size-fits-all approach to developing AI literacy would be insufficient. Galindo-Domínguez et al. (2024) demonstrated that the association between teachers' digital competence and their attitude toward AI depends on the subject taught, being stronger among STEM teachers, whereas Lucas et al. (2024) found the attitude to be independent of age, gender, and seniority. These contradictory results show that the effect of demographic variables may be context- and sample-dependent. Taken together, these studies indicate that teachers' attitudes toward AI constitute a multidimensional structure whose components can operate relatively independently and must be considered in conjunction with the educational context and teacher characteristics.

2.3. The Relationship between Pedagogical Orientation and Technology Adoption

How and to what extent teachers incorporate technology into the classroom is closely related not only to technological resources but also to their pedagogical beliefs. It has long been accepted that teachers' pedagogical orientations play a decisive role in technology adoption (Berhe et al., 2025; Ertmer & Ottenbreit-Leftwich, 2013). This relationship is most often examined through the distinction between constructivist and traditional pedagogical beliefs. Teachers with a constructivist orientation tend to use technology as a tool that supports student-centered learning, develops higher-order thinking skills, and facilitates the student's active participation in the knowledge-building process, whereas teachers with a traditional orientation generally position technology as a tool that supports content delivery, teacher-centered presentations, and direct instruction (Mailizar et al., 2026; Tondeur et al., 2017).

This association is further supported by quantitative studies. Gurer and Akkaya (2022) found that constructivist pedagogical beliefs have a significant impact on all components of the technology acceptance model, whereas traditional beliefs had no significant effect on perceived usefulness and attitude and, counter to expectations, a favorable effect on perceived ease of use. Almerich et al. (2024) similarly found that a constructivist perspective, rather than a traditional pedagogical orientation, was the main predictor of classroom technology use. Antonietti et al. (2025) analyzed teachers' technology-integration profiles through latent profile analysis and distinguished digital constructivists, who use technology to help students develop new knowledge, from digital presenters, who use it only to transmit content. These results suggest that pedagogical orientation shapes not only the level of technology use but also its quality.

Evidence that a similar relationship holds in the context of AI is growing. Choi et al. (2023) found that teachers with constructivist beliefs were more inclined to use instructional AI tools than teachers with a transmissionist orientation, and Cabero-Almenara et al. (2024) and Acosta-Enriquez et al. (2025) reported a positive association between constructivist pedagogical beliefs and the adoption of AI. Awofala et al. (2025) reported a comparable pattern in the Nigerian setting. Considered together, these studies suggest that a student-centered pedagogical orientation is associated with views about AI and with AI adoption behavior. The strength of the association differs across studies, however. Cheng et al. (2021) found that constructivist pedagogical beliefs were not a significant predictor once other beliefs were controlled, and Lai et al. (2022) found that school culture, professional development, and technological pedagogical content knowledge were stronger predictors of technology use than teaching-learning views. The impact of pedagogical orientation therefore cannot be examined in isolation but must be assessed in relation to school climate, institutional support, opportunities for professional learning, and teachers' competence regarding technology.

The inconsistency between beliefs and practice is a further consideration. Liu et al. (2019) demonstrated a significant relationship between teachers' intention to use technology and teacher-centered technology use, but not between intention and student-centered use, a situation researchers have linked to facilitating conditions, prior experience, and technological pedagogical content knowledge. Abedi (2024) reported that teachers use technology mostly for lesson preparation and direct instruction, with limited use in constructivist and student-centered applications, and Aleksieva et al. (2025) identified three degrees of technology use, namely supporting, expanding, and transforming, observing that transformative use occurs to a very limited extent. These findings suggest that holding student-centered ideals does not necessarily translate into student-centered technology use in every setting.

Taken together, these studies converge on a consistent association between learner-centered, constructivist orientations and the adoption of technology and AI, yet they also reveal important boundary conditions. The influence of pedagogical beliefs weakens once school culture, institutional support, and technological pedagogical competence are taken into account (Cheng et al., 2021; Lai et al., 2022), and a recurring belief-practice gap suggests that student-centered orientations do not automatically translate into student-centered or transformative technology use (Abedi, 2024; Aleksieva et al., 2025; Liu et al., 2019). Read at the dimensional level, this pattern carries a specific implication. If the two constructs are connected, a learner-centered orientation is a plausible candidate for a bridging role, and any such association is more likely to run through the practice-near components of AI attitudes, namely perceived instructional functionality and professional competence, than through the visionary component of transformative potential, which the belief-practice literature suggests often remains decoupled from actual practice. The present study examines this expectation directly, using bridge centrality to identify the dimension or dimensions, if any, through which the two constructs are connected, and to assess whether the connection is concentrated or distributed.

2.4. Network Psychometrics in Educational Research

Latent variable approaches have long dominated the study of psychological and educational structures, treating observed variables as reflections of an unobserved common latent factor. Network psychometrics, in contrast, models variables not as indicators of a common cause but as components of a system that interact directly with one another (Borsboom & Cramer, 2013). In this framework, observed variables are represented as nodes and the conditional relationships between them as edges (Borsboom et al., 2021), which makes the pattern of relationships between variables visible rather than reducing a structure to a single dimension. In cross-sectional data, network edges are typically estimated using a Gaussian graphical model based on partial correlations (Epskamp & Fried, 2018), and regularization based on the graphical lasso and the extended Bayesian information criterion is widely used to reduce sampling-based false-positive edges (Epskamp et al., 2018). The importance of nodes is assessed using centrality measures, while nodes connecting two clusters are evaluated using bridge centrality (Jones et al., 2021).

The metrics provided by network analysis must nonetheless be interpreted with caution. Bringmann et al. (2019) highlighted that centrality metrics are derived from social network theory and cannot always be interpreted directly in psychological networks, and the reliability of the estimated network structure and centrality rankings depends on sample size and on stability analyses based on resampling (Epskamp et al., 2018). Network findings in cross-sectional data should therefore be evaluated as descriptive and exploratory rather than causal. It can be said that network psychometrics is a suitable method for revealing the relationship patterns between the dimensions of two scales and the dimensions that serve as bridges, provided that the accuracy and stability of the estimates are examined explicitly.

3. Method

3.1. Research Design

This study employed a cross-sectional correlational design to describe the pattern of relationships between teachers' self-reported teaching practices and their attitudes toward artificial intelligence at the level of the established dimensions of the two scales. The relationships were examined within the framework of psychometric network analysis, which models observed variables not as reflections of a latent variable but as nodes that interact directly with one another (Borsboom & Cramer, 2013). Because the design is cross-sectional, the relationships obtained are undirected, and they describe the strength of mutual dependence between dimensions rather than the direction of an effect.

3.2. Participants

The study was conducted with 376 teachers working in the Prizren district of Kosovo. Of the participants, 300 (79.8%) were women and 76 (20.2%) were men. In terms of age, 105 teachers were 40 years or younger, 64 were between 41 and 50, and 207 were 50 years or older. Regarding professional seniority, 192 teachers (51.1%) had 20 or more years of service. Most participants held a bachelor's degree (295; 78.5%), and the remainder held a graduate degree (81; 21.5%). With respect to the language of instruction, 104 teachers (27.7%) taught in Turkish and 272 (72.3%) in Albanian. The sample was demographically unbalanced, particularly with respect to gender, age, and seniority, and this was treated as a limitation in the interpretation of the findings. The school level at which the participants taught was not among the recorded demographic variables, which is acknowledged as a limitation. Data were collected through convenience sampling during the fall semester of the 2025–2026 academic year, with the permission of the District Education Directorate and on the basis of voluntary participation.

3.3. Instruments

3.3.1. Artificial Intelligence in Education Perception Scale

Teachers' perceptions of the use of artificial intelligence in education were measured with the scale developed by Demirdağ et al. (2025). The original 22-item instrument was reported as a two-factor structure. For use in the present context, the scale was translated into Albanian and back-translated, and its content and cultural appropriateness were evaluated by three experts in educational sciences. A single Albanian version was administered to all participants; a separate Turkish version was not used. In the present Kosovo sample, the original two-factor structure did not fit adequately, and, following exploratory structural equation modeling and item reduction, a

13-item three-factor structure was adopted, distinguishing perceived professional and digital competence, instructional functionality, and transformative potential. This structure was supported by a parallel analysis but showed only limited model fit, RMSEA = .102, together with several cross-loadings, and it is therefore treated as tentative throughout. The internal consistency of the three subscales was high, with alpha values between .85 and .88. Because the measurement structure was derived in the same sample used for the network analysis, the structure was treated as provisional and its robustness was examined directly (see the Findings and the Supplementary Material). The full item content, the model-comparison and factor-loading tables, the parallel analysis, and the rationale for the removed items are reported in the Supplementary Material (Section A).

3.3.2. Teacher In-Class Performance Scale

Teachers' self-reported in-class performance was measured with the scale developed by Morina et al. (in press) for the Kosovan context. The instrument comprises 27 items distributed across five subscales, namely learner-centered instruction, teacher-centered practices, interpersonal relations, planning and preparation, and classroom climate. Sample items and the full item content are provided in the Supplementary Material (Section B). Because coefficient alpha is a function of the number of items and penalizes short subscales, the mean inter-item correlation is reported alongside alpha (Table 1). The internal-consistency values of the teaching-practice subscales in the present sample were modest, ranging from .41 to .74, and the teacher-centered subscale in particular showed limited coherence; the findings that involve the teaching-performance dimensions are therefore interpreted with caution.

Because both instruments rely on teachers' self-reports, the teaching-performance scores are referred to throughout as self-reported teaching practices or perceived instructional performance rather than as observed classroom performance. Moreover, although the study was conducted in a multilingual educational setting, the measurement itself was monolingual, as all instruments were administered in Albanian; the multilingual character of the context is therefore treated as contextual rather than as a measured feature, and it is not used to support any claim of cross-language measurement equivalence.

3.4. Data Analysis

Analyses were conducted in R using the qgraph, bootnet, and networktools packages (Epskamp et al., 2018; Jones et al., 2021). The eight dimension scores were defined as the nodes of a regularized partial correlation network, that is a Gaussian graphical model, estimated with the graphical lasso (Friedman et al., 2008) under the extended Bayesian information criterion (Foygel & Drton, 2010) (γ = 0.5). Spearman correlations were used given the ordinal nature of the items. The network was estimated with the additional edge-thresholding step (threshold = TRUE) used in the original analysis. Of the 28 possible edges, 9 were retained as non-zero in the primary network. Re-estimating the network with Pearson correlations produced a closely corresponding structure, with edge weights correlating at r = .97, which indicates that the solution was robust to the choice of correlation coefficient. The complete edge-weight table for the primary and the two sensitivity networks is provided in the Supplementary Material (Section C).

Bridge centrality was computed to identify the dimensions linking the two scales, with the teaching-performance and artificial intelligence dimensions defined as the two communities (Jones et al., 2021). The accuracy and stability of the network were examined with non-parametric and case-dropping bootstrap procedures based on 2,000 resamples, and stability was summarized with the correlation-stability coefficient (Epskamp et al., 2018). Prior to the analyses, the response patterns of all participants were screened for careless and inconsistent responding using long-string, Mahalanobis-distance, and person-total-consistency indices (Yentes & Wilhelm, 2021); the procedure and its results are reported in the Findings and in the Supplementary Material (Section D).

Differences in dimension scores across demographic groups were tested with non-parametric procedures, because the Shapiro-Wilk test indicated a significant departure from normality for all eight dimensions (all $p < .001$) and several dimensions were markedly skewed. The Mann-Whitney U test was used for two-group comparisons and the Kruskal-Wallis test for comparisons of three or more groups, with Benjamini-Hochberg false-discovery-rate correction applied within each demographic variable (Benjamini & Hochberg, 1995). Effect sizes were reported as Cliff's delta for two-group comparisons and epsilon-squared for multi-group comparisons. The Network Comparison Test was used to compare the network structure across groups (van Borkulo et al., 2023).

Because the measurement structure and the network were estimated in the same sample, and because most of the teaching-performance subscales were measured with limited reliability, three robustness analyses were conducted. First, the network was re-estimated from latent factor scores, which are less affected by measurement error. Second, it was re-estimated under alternative artificial intelligence factor structures, namely the original two-factor solution and a single general factor. Third, a split-sample cross-fit was performed, in which the measurement model was calibrated on one random half of the sample and the network was estimated on the other, repeated across many random splits. These analyses are summarized in the Findings and reported in full in the Supplementary Material (Section E).

4. Findings

4.1. Preliminary Data Screening

Prior to the main analyses, the response patterns of all 376 participants were screened for careless and inconsistent responding. Three indicators were computed: the longest string of identical consecutive responses, the Mahalanobis distance across the dimension scores, and the correlation between each respondent's answers and the sample item means (Yentes & Wilhelm, 2021). Fourteen participants, that is 3.7% of the sample, were flagged by at least two of these indicators. The internal consistency of the subscales did not improve when these cases were removed, and the network results were substantively unchanged. Hence, it can be said that careless responding does not account for the measurement properties reported below, and all participants were retained in the analyses.

4.2. Descriptive Statistics and Reliability

Table 1 presents the descriptive statistics and internal-consistency estimates for the eight dimensions.

Table 1
Descriptive statistics and internal consistency of the eight dimensions

Dimension	*Scale*	*k*	*M*	*SD*	α	*Mean r*
LCT — Learner-centered instruction	TP	9	3.99	0.45	.74	.29
TCT — Teacher-centered practices	TP	6	3.32	0.49	.41	.10
IR — Interpersonal relations	TP	4	3.98	0.57	.53	.28
PP — Planning and preparation	TP	4	3.22	0.76	.62	.29
CC — Classroom climate	TP	4	3.67	0.59	.51	.22
AI-IF — Instructional functionality	AI	6	3.29	0.78	.88	.56
AI-PC — Professional competence	AI	3	3.66	0.80	.85	.65
AI-TP — Transformative potential	AI	4	3.30	0.79	.85	.59

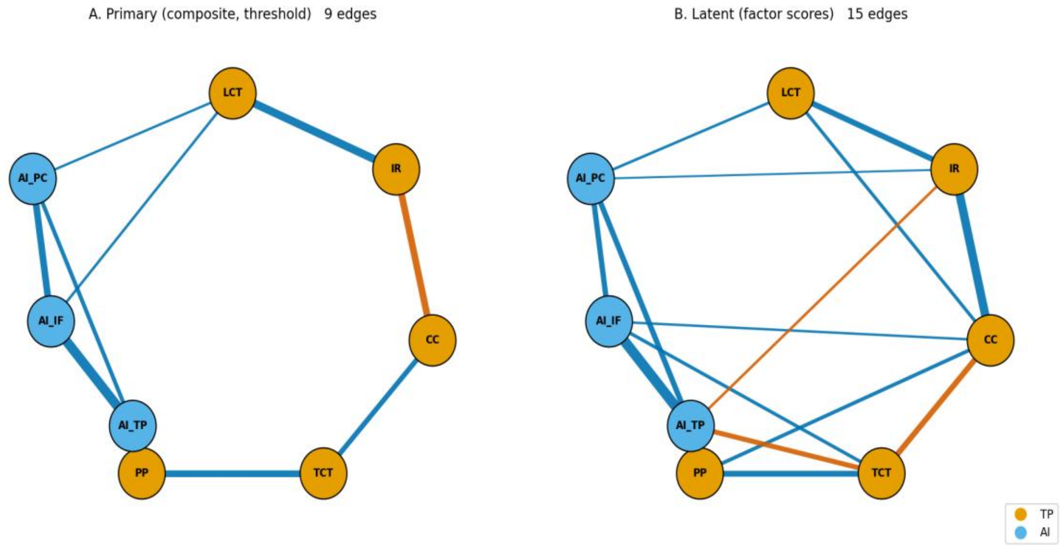
Note. N = 376. Scores are item means on a 5-point scale. Mean r = mean inter-item correlation after coherent keying.

The three artificial intelligence dimensions were measured reliably, with Cronbach's alpha values ranging from .85 to .88. The teaching-performance dimensions were more variable. Learner-centered instruction reached a satisfactory level, and planning and preparation was acceptable, whereas interpersonal relations, classroom climate, and, in particular, teacher-centered practices fell below the conventional threshold. Because coefficient alpha is a function of the number of items and penalizes short subscales, the mean inter-item correlation is also reported (Clark & Watson, 1995; Cortina, 1993). The mean inter-item correlations of the four-item teaching-performance subscales remained within the range recommended for short scales, with the exception of teacher-centered practices, whose items showed little coherence. It can be said that the teaching-performance subscales, and teacher-centered practices above all, are measured with limited precision in this sample, and the findings that involve them should be interpreted with corresponding caution.

4.3. The Dimension-Level Network

Figure 1 presents the regularized partial correlation network estimated across the eight dimensions.

Figure 1
Regularized partial correlation networks



Note. A: composite dimension scores. B: latent factor scores. Blue edges are positive, red edges negative.

In the primary composite specification, 9 of the 28 possible edges were non-zero, which points to a relatively selective set of relationships. The two scales largely clustered within themselves. The artificial intelligence dimensions were strongly interconnected, the strongest edge being between instructional functionality and transformative potential. The teaching-performance dimensions formed a looser structure. In this specification, learner-centered instruction was linked to instructional functionality and to perceived professional competence, and these two cross-block edges were weak in absolute terms, considerably smaller than the within-block edges. Hence, it can be said that the association between teaching performance and attitudes toward artificial intelligence, in this sample, is both limited in magnitude and selectively located.

4.4. Bridge Centrality and Its Robustness

Bridge centrality was examined to identify the dimensions through which the two scales are connected. As can be seen in Figure 2 and Table 2, the specification mattered.

In the published specification, which is based on the as-scored composite dimensions, learner-centered instruction was the only teaching-performance dimension with non-zero bridge strength, and this had been read as a single learner-centered bridge. However, the low reliability of most teaching-performance subscales raises the possibility that the absence of bridging edges for the remaining dimensions reflects measurement attenuation rather than a true absence of association. The analysis was therefore repeated under two respecifications that are less sensitive to this problem, namely coherently keyed composites and latent factor scores. Under both respecifications, several teaching-performance dimensions retained non-zero bridge strength, and learner-centered instruction no longer stood apart as the dominant bridge. It ranked in the lower-to-middle range, while teacher-centered practices and interpersonal relations carried the strongest

Figure 2

Bridge strength of each dimension under the published composite, coherently keyed composite, and latent factor-score specifications

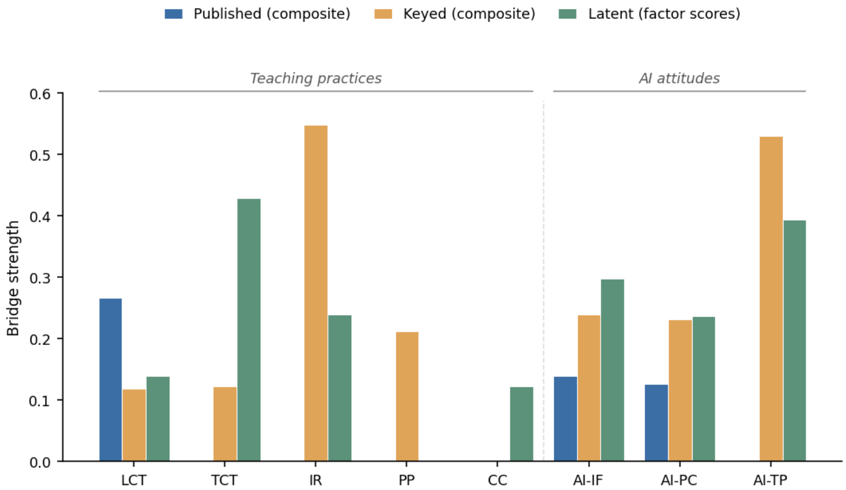


Table 2

Bridge strength by specification

Dimension	*Community*	*Published (composite)*	*Keyed (composite)*	*Latent (factor scores)*
LCT	TP	.27	.12	.14
TCT	TP	.00	.12	.43
IR	TP	.00	.55	.24
PP	TP	.00	.21	.00
CC	TP	.00	.00	.12
AI-IF	AI	.14	.24	.30
AI-PC	AI	.13	.23	.24
AI-TP	AI	.00	.53	.39

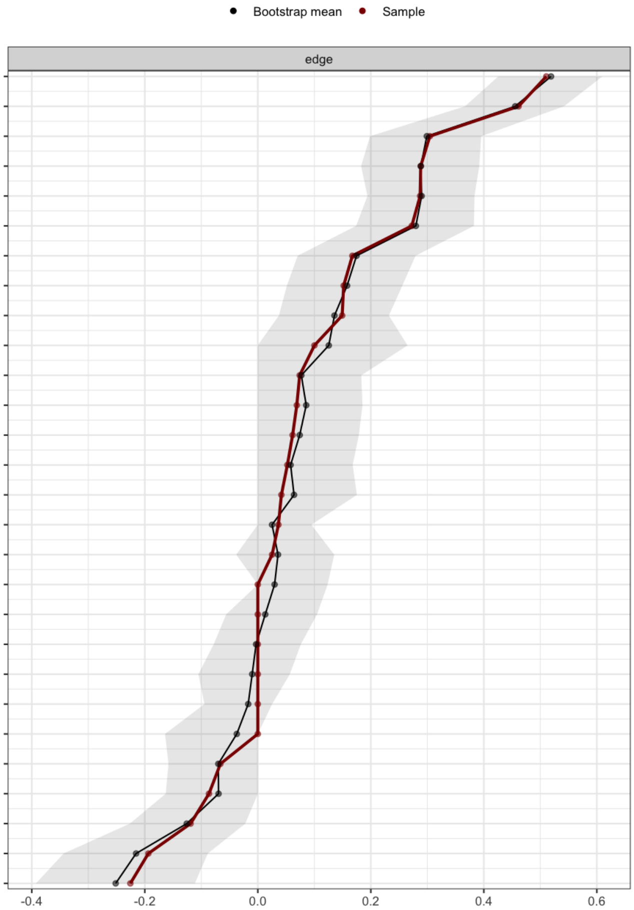
Note. Bridge strength (sum of the absolute cross-community edge weights) from EBICglasso networks estimated with the same tuning (γ = .5) and edge-selection threshold as the primary network. Published = as-scored composites; Keyed = coherently reverse-keyed composites; Latent = single-factor scores.

cross-construct bridges. The dimension with the highest bridge strength differed across specifications, being interpersonal relations in the keyed composite network and teacher-centered practices in the latent network, which is itself consistent with the low stability of the bridge ranking reported below. These respecifications, together with an analysis under alternative artificial intelligence factor structures and a split-sample cross-fit, are reported in the Supplementary Material (Section E) and converge on the same conclusion. Hence, it can be said that the concentration of the bridging function in a single dimension is not robust, and that it partly reflects the differential reliability of the teaching-performance subscales. The more defensible reading is that the two constructs are connected weakly, and through several teaching-performance dimensions rather than through learner-centered instruction alone.

4.5. Network Accuracy and Stability

The accuracy and stability of the network were examined with non-parametric and case-dropping bootstrap procedures. The case-dropping bootstrap of the primary latent network yielded a stability coefficient of .21 for bridge strength and .67 for expected influence. The bridge-strength coefficient, although a marked improvement over the value obtained from the composite network, which was .05, remains below the .25 threshold ordinarily taken as the lower bound for interpretation (Epskamp et al., 2018). As can be seen in Figure 4, the bootstrapped confidence intervals of the cross-community edges were wide and included zero, whereas the within-block edges among the artificial intelligence dimensions were estimated precisely. Hence, it can be said that the ranking of dimensions by bridge strength cannot be interpreted with confidence, and that the connection between the two constructs, although present, is estimated with limited precision.

Figure 4
Bootstrapped 95% confidence intervals of the edge weights (latent network), ordered by sample value



4.6. Differences across Demographic Groups and Subgroup Networks

The most consistent demographic pattern concerned perceived professional and digital competence regarding artificial intelligence, which decreased with both age, H(2) = 33.83, $p < .001$, $\varepsilon^2 = .09$, and professional seniority, H(2) = 57.67, $p < .001$, $\varepsilon^2 = .15$. Younger and less experienced teachers reported higher perceived competence. The teaching-performance dimensions showed smaller and less consistent differences.

Differences across subject area and educational background were examined at the level of dimension scores with Kruskal-Wallis tests, with the two teachers in the physical-education group excluded from the subject-area analysis. Subject area was reliably related to the perception of artificial intelligence's transformative potential, H(4) = 22.81, $p < .001$, $\varepsilon^2 = .06$. This perception was highest among classroom teachers (M = 3.48) and lowest among mathematics (M = 3.07) and science teachers (M = 3.01), with foreign-language (M = 3.23) and history-geography teachers (M = 3.13) intermediate. Smaller differences by subject area were also present for the teacher-centered, H(4) = 18.64, p = .001, interpersonal-relations, H(4) = 15.29, p = .004, planning, H(4) = 18.34, p = .001, and classroom-climate dimensions, H(4) = 11.02, p = .026, whereas the remaining two artificial-intelligence dimensions did not differ. Educational background showed no reliable association with the artificial-intelligence dimensions, including transformative potential, H(2) = 2.37, p = .31; the scattered differences that reached significance on some teaching-performance dimensions rested on a very small postgraduate subgroup (n = 5) and are not interpreted. Because the subject-area and educational-background groups were small and, in several cases, numerous, the network structure itself was compared only across the larger gender, language, and seniority splits reported below.

The Network Comparison Test was used to examine whether the network structure differed across gender, language of instruction, and professional seniority (see Table 3). Global connection strength did not differ significantly in any comparison. The network structure did not differ significantly by gender or by language of instruction. Although the edge between learner-centered instruction and artificial intelligence's transformative potential, which carried the gender finding in the earlier analysis, differed in sign between women (edge weight = .16) and men (edge weight = −.39), this apparent difference was not statistically significant (structural invariance p = .11), a result that is unsurprising given the small and unstable male subgroup (n = 76).

Table 3

Network Comparison Test results across demographic groups

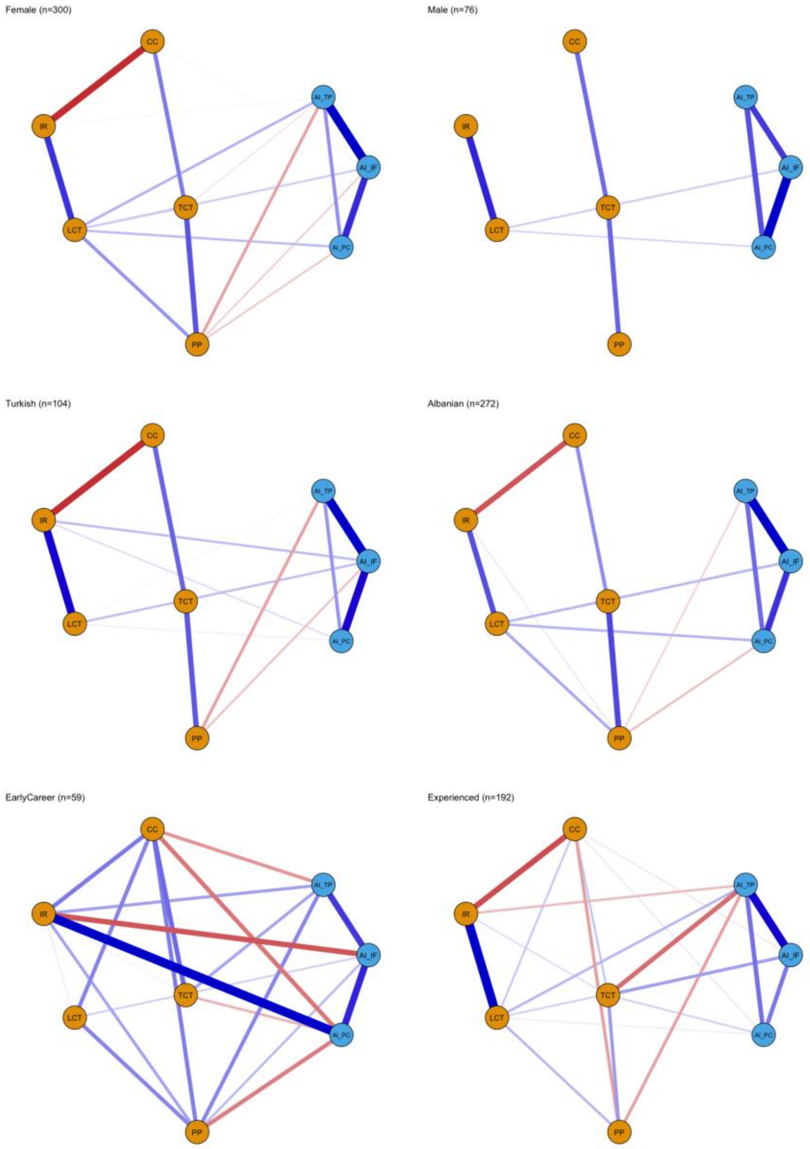
Comparison	*Global strength (p)*	*Structure (p)*	*Significant difference*
Gender (300 vs 76)	.31	.11	No
Language (104 vs 272)	.88	.28	No
Seniority (59 vs 192)	.05	.001	Structure only

Note. Based on 2,000 permutations. Global strength = invariance of overall connectivity; Structure = invariance of the edge-weight pattern.

A significant structural difference was found by seniority. As can be seen in Figure 3, however,

Figure 3

Subgroup networks by gender, language of instruction, and professional seniority



the early-career network is estimated from a small subgroup, and it is correspondingly dense and unstable, so this difference should be read as exploratory. The seniority-related difference is nonetheless consistent with the experience-dependent functioning of the teacher-centered subscale reported below. It can be said that the gender difference reported in the earlier analysis was not reproduced as a statistically reliable effect under the present specification, and that the subgroup comparisons, taken together, are best regarded as preliminary and in need of replication with larger and more balanced samples.

4.7. A Note on the Teacher-Centered Subscale

A closer inspection of the teacher-centered subscale offers a possible account of its low reliability. The teacher-centered items were reverse-keyed on the assumption that endorsing teacher-centered practice is opposed to a learner-centered orientation. This assumption appears to hold for early-career teachers but not for their more experienced colleagues. Among teachers with ten years of service or less, teacher-centered and learner-centered endorsements were unrelated, $r = -.06$, whereas among teachers with twenty years of service or more the two were positively associated, $r = .37$, and the difference between these correlations was significant, Fisher $z = -2.97$, $p = .003$. The internal consistency of the teacher-centered subscale was correspondingly higher in the early-career group than in the experienced group. It can be said that experienced teachers appear to regard teacher-centered and learner-centered practices as compatible rather than opposed, so that the reverse-keyed items do not function coherently in the pooled sample. This pattern is exploratory, and it is offered as an explanation for the measurement limitation rather than as a substantive finding.

5. Discussion

This study aimed to describe the pattern of relationships between teachers' self-reported teaching-practice dimensions and their attitudes toward AI within the framework of network analysis. The study's contribution lies in analyzing this relationship not as an integrated link but as a pattern at the dimensional level through bridge centrality. The findings can be summarized under three points. First, the connection between the two constructs is weak and, once measurement error and the choice of measurement structure are taken into account, distributed across several teaching-practice dimensions rather than concentrated in a single bridge. Second, perceptions of competence regarding AI decline consistently with age and seniority. Third, the network structure does not differ across groups once the analysis is placed on a defensible footing, apart from an exploratory difference by seniority. These findings are discussed below in relation to the literature.

In the primary composite network, learner-centered instruction was the teaching-practice dimension most clearly linked to the AI dimensions, which is consistent with the established literature showing that teachers with constructivist and learner-centered beliefs adopt technology to a greater extent (Ertmer & Ottenbreit-Leftwich, 2013; Tondeur et al., 2017). Hsu (2016) reports that teachers with learner-centered pedagogical beliefs tend to use technology in ways that support higher-order thinking, and Galindo-Domínguez et al. (2024) found a significant relationship between teachers' digital competence and their attitudes toward AI. This apparent concentration in a single dimension, however, did not survive closer scrutiny. When the network was re-estimated from latent factor scores, under alternative AI factor structures, and in a split-sample cross-fit, several teaching-practice dimensions carried cross-construct associations and learner-centered instruction was no longer distinctive, ranking among the lowest rather than the highest. Hence, it can be said that the initial single-bridge impression was partly an artifact of the differential reliability of the teaching-practice subscales, and that the association between the two constructs is more accurately described as weak and diffuse.

That a learner-centered orientation is nonetheless among the dimensions associated with AI attitudes is in line with findings across contexts that constructivist orientations relate to AI adoption (Acosta-Enriquez et al., 2025; Awofala et al., 2025; Choi et al., 2023). On the AI side, the cross-construct associations, where present, ran through the practice-near components of instructional functionality and professional competence rather than through transformative potential, which is consistent with studies emphasizing that AI literacy and digital competence predict attitude (Al-Abdullatif, 2024; Ng et al., 2023). Because these cross-construct edges were weak in absolute terms and unstable, this pattern is offered as a tentative description rather than as evidence of a specific mediating pathway.

The perception of AI's transformative potential was not retained as a unique edge with any teaching-practice dimension. It should be emphasized that an edge shrunk to zero under graphical lasso indicates the absence of a unique conditional association under the present specification rather than the absence of any association. With this caution in mind, the pattern is consistent with a repeatedly reported gap between intention and behavior: Liu et al. (2019) found a significant relationship between teachers' intention to use technology and teacher-centered use but not student-centered use; Abedi (2024) reported that teachers use technology mostly for lesson preparation and direct instruction, with limited transformative use; and Aleksieva et al. (2025) observed that transformative use occurs to a very limited extent. Because the present study measured self-reported teaching practices rather than observed classroom behavior, any interpretation in terms of a vision-practice gap is necessarily tentative. Filiz et al. (2025) reported that teachers in the Turkish context found AI valuable for efficiency and interaction yet faced obstacles such as curriculum mismatch and difficulties in adapting AI to the local context, which suggests that additional conditions may be needed for transformative expectations to translate into concrete classroom applications.

Within the teaching-practice block, the strongest edges were the positive association between learner-centered instruction and interpersonal relations and a comparatively large negative association between interpersonal relations and classroom climate. This negative edge is theoretically unexpected and should be interpreted with caution, since it may reflect the reverse-keyed and disciplinary content of several classroom-climate items and the limited reliability of that subscale rather than a substantive opposition between the two dimensions.

The perception of professional and digital competence regarding AI declined consistently with both age and years of experience, with younger and less experienced teachers reporting higher perceived competence. This coincides with studies indicating that younger teachers are more favorable toward AI (Cabero-Almenara et al., 2024; Yim & Wegerif, 2024) and with the observation of Dringó-Horváth et al. (2025) that the relationship between AI literacy and digital competence differs by age, seniority, and subject. Lucas et al. (2024), by contrast, found attitude to be independent of age, gender, and seniority, which suggests that the role of demographic factors is context- and sample-dependent. The effect sizes were small, so the direction and consistency of these differences, rather than their magnitude, should be the focus of interpretation.

With respect to the network structure, global connection strength did not differ across gender, language of instruction, or seniority. Under the present specification the network structure did not differ significantly by gender, so the gender-based structural difference reported in the earlier analysis was not reproduced and should not be treated as an established finding. A structural difference by seniority was observed, but it rested on a small early-career subgroup and is best regarded as exploratory. This seniority-related pattern is nonetheless consistent with a further observation from the present data, namely that teacher-centered and learner-centered endorsements were unrelated among early-career teachers but positively associated among experienced teachers, so that the two orientations appear to be treated as opposed by early-career teachers and as compatible by their more experienced colleagues.

Taken together, these findings offer a methodological contribution. The relationship between teaching practices and attitudes toward AI has been examined primarily through correlation or regression using composite scores, which can show whether the two constructs are related but not the dimensions through which any relationship operates. Psychometric network analysis maps this pattern by treating dimensions as directly interacting nodes (Borsboom et al., 2021), and bridge centrality decomposes the connection into individual dimensions (Jones et al., 2021). Applied here, and examined for robustness, this approach indicated that the connection between the two constructs is weak and distributed rather than concentrated in a single dimension. The value of the approach in this case lies less in identifying a specific bridge than in showing, with explicit attention to stability and measurement, that no single bridge can be sustained.

The practical implications should be read in light of the weak magnitude of the cross-construct associations, so that the recommendations below are offered as plausible directions rather than as established effects. Because the association between teaching practices and attitudes toward AI is diffuse, professional development aimed at supporting AI integration is unlikely to be advanced by targeting a single pedagogical dimension; a broader approach that links the concrete pedagogical functionality of AI to teachers' everyday practices is more consistent with the evidence. The demographic patterns sharpen this picture. Perceived AI competence declined consistently with age and seniority, and this was the strongest demographic effect observed, which suggests that professional development for more experienced teachers should target digital and AI competence directly. Because perceptions of AI's transformative potential were highest among classroom teachers and lowest among mathematics and science teachers, the framing of AI's pedagogical value may also need to be contextualized by subject.

6. Limitations and Future Research

Several limitations should be considered. First, and most importantly, the measurement structure of the AI scale was derived in the same sample used to estimate the network, and most of the teaching-practice subscales were measured with limited internal consistency. Deriving the measurement model and estimating the substantive network in a single sample can inflate apparent structure and understate uncertainty. For this reason the central finding was examined directly through reliability-adjusted, alternative-structure, and split-sample analyses, all of which indicated that the weak and distributed character of the association does not depend on these measurement decisions; the measurement structure should nonetheless be regarded as provisional and validated in independent samples. Second, four of the five teaching-practice subscales fell below the conventional reliability threshold, and the teacher-centered subscale in particular showed limited coherence, so findings involving these dimensions should be interpreted with caution.

Third, the sample was demographically unbalanced, with most participants being women (n = 300) and relatively few men (n = 76), and with older and more experienced teachers predominating; this limits statistical power and generalizability and is especially consequential for the subgroup network comparisons, which should be treated as preliminary. Fourth, the school level at which participants taught was not among the recorded demographic variables, which constrains the characterization of the sample. Fifth, all instruments were administered on a single occasion and in a single language, so the study speaks to a multilingual context but not to cross-language measurement equivalence, and the possibility of common-method variance cannot be excluded; a Harman single-factor test indicated that the first unrotated factor accounted for 17.9% of the variance, which does not point to a dominant method factor but does not by itself rule out common-method bias (Podsakoff et al., 2003). Finally, the cross-sectional design means that the relationships are non-directional and do not support causal inference, and the low stability of the bridge estimates means that the ranking of dimensions by bridge strength should not be interpreted.

Future research would benefit from replication in independent and more balanced samples, from longitudinal designs that could clarify the direction of the relationship between teaching practices and attitudes toward AI, and from the incorporation of measures beyond teacher self-report. Validating the AI attitude structure in an independent sample and testing measurement invariance across cultural and language groups would also strengthen the basis for dimension-level network comparisons.

7. Conclusion

This study examined the pattern of relationships between teachers' self-reported teaching-practice dimensions and their attitudes toward AI within the framework of psychometric network analysis. In the primary composite network the connection between the two constructs appeared to be concentrated in learner-centered instruction, but this impression was not robust: under reliability-adjusted, alternative-structure, and split-sample analyses the association was weak and distributed across several teaching-practice dimensions, and the stability of the bridge estimates was low. The perception of AI's transformative potential was not retained as a unique edge with any teaching-practice dimension. Perceptions of competence regarding AI declined consistently with age and seniority, whereas the network structure did not differ by gender under the present specification. Because the design was cross-sectional, these dimension-level patterns describe associations rather than directional or causal effects.

Theoretically, the study analyzes the relationship between the two constructs not as an integrated link but as a pattern at the dimensional level, and, by examining that pattern for robustness, it shows that the connection between pedagogical orientation and attitudes toward AI is weaker and more diffuse than a single-bridge account would imply. In practical terms, professional development aimed at supporting AI integration would benefit from linking the concrete pedagogical functionality of AI to teachers' everyday practices and from targeting digital and AI competence among more experienced teachers, rather than from concentrating on a single pedagogical dimension. Several directions follow for future research: replication in other cultural and linguistic settings to determine whether the weak and distributed pattern generalizes; longitudinal designs to test the direction of the relationship; larger and more balanced samples to improve the stability of the estimates; and the validation of the measurement structures in independent samples together with measures beyond teacher self-report.

Author contributions: Shemsi Morina: Investigation, Data curation, Validation, Writing – review & editing. Serdan Kervan: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. Esen Spahi-Kovaç: Conceptualization, Methodology, Supervision, Validation, Writing – review & editing.

Data availability: Data supporting the findings of this study are available upon reasonable request from the corresponding author. The data are not publicly shared to protect participant confidentiality.

Declaration of generative AI and AI-assisted technologies: During the preparation of this article, Claude Opus 4.8 AI tool was used solely for language-level editing and to improve the readability of the text. All decisions regarding the study design, data analysis, interpretation of findings, and scientific content are the sole responsibility of the authors. All outputs generated by generative AI tool has been reviewed and verified by the authors. The authors assume full responsibility for the content of the article.

Declaration of interest: The authors declare that they have no conflicts of interest.

Ethics declaration: The study was conducted in accordance with ethical principles regarding research involving human participants and the Declaration of Helsinki. The necessary permission for the fieldwork was obtained from the District Education Directorate in Prizren, Kosovo. During the data collection process, the purpose of the study was explained to the participants, and voluntary participation was the basis. The collected data were recorded anonymously without containing any identifying information and were stored securely solely for research purposes. Informed consent was obtained from all teachers participating in the study. Participants were informed that participation in the study was voluntary and that they could withdraw at any time.

Funding: This research has not received any special support from any public, commercial, or non-profit institution.

References

Abedi, E. A. (2024). Tensions between technology integration practices of teachers and ICT in education policy expectations: Implications for change in teacher knowledge, beliefs, and teaching practices. *Journal of Computers in Education, 11*(4), 1215–1234. https://doi.org/10.1007/s40692-023-00296-6

Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Guzmán Valle, M. de los Á., Morales Angaspilco, J. E., Blanco-García, L. E., Campoverde Ventura, G., Castañeda Requejo, J. D., & Carranza Torre, M. (2025). Determinants of AI use in university teachers: The role of leadership, teaching concerns, and constructivist pedagogical beliefs. *Human Behavior and Emerging Technologies, 2025*, 4834893. https://doi.org/10.1155/hbe2/4834893

Al-Abdullatif, A. M. (2024). Modeling teachers' acceptance of generative artificial intelligence use in higher education: The role of AI literacy, intelligent TPACK, and perceived trust. *Education Sciences, 14*(11), 1209. https://doi.org/10.3390/educsci14111209

Aleksieva, L., Racheva, V., & Peytcheva-Forsyth, R. (2025). Talking tech, teaching with tech: How primary teachers implement digital technologies in practice. *Informatics, 12*(3), 99. https://doi.org/10.3390/informatics12030099

Almerich, G., Gargallo-Jaquotot, P., & Suárez-Rodríguez, J. (2024). ICT integration by teachers: A basic model of ICT use, pedagogical beliefs, and personal and contextual factors. *Teaching and Teacher Education, 145*, 104617. https://doi.org/10.1016/j.tate.2024.104617

Antonietti, C., Consoli, T., Schmitz, M.-L., Cattaneo, A., Gonon, P., & Petko, D. (2025). Digital constructivists, activators, or presenters? Different profiles of technology integration among Swiss upper secondary school teachers. *Computers & Education, 227*, 105225. https://doi.org/10.1016/j.compedu.2024.105225

Asio, J. M. R., & Gadia, E. D. (2024). Predictors of student attitudes towards artificial intelligence: Implications and relevance to the higher education institutions. *International Journal of Didactical Studies, 5*(2), 27763. https://doi.org/10.33902/ijods.202427763

Awofala, A. O. A., Bazza, M. B., Ojo, O. T., Oladipo, A. J., Olabiyi, O. S., & Arigbabu, A. A. (2025). Structural equation modeling of Nigerian science, technology, and mathematics teachers' adoption of educational artificial intelligence tools. *Digital Education Review, 46*, 51–64. https://doi.org/10.1344/der.2025.46.51-64

Bellens, K., Van Damme, J., Van Den Noortgate, W., Wendt, H., & Nilsen, T. (2019). Instructional quality: Catalyst or pitfall in educational systems' aim for high achievement and equity? An answer based on multilevel SEM analyses of TIMSS 2015 data in Flanders (Belgium), Germany, and Norway. *Large-scale Assessments in Education, 7*, 1. https://doi.org/10.1186/s40536-019-0069-2

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological), 57*(1), 289–300. https://doi.org/10.1111/j.2517-6161.1995.tb02031.x

Berhe, G. T., Weldeyesus, K. M., Weldeana, H. N., Weldeslassie, A. T., & Tareke, A. A. (2025). Challenges in integrating GeoGebra for mathematics instruction in Ethiopian universities. *International Journal of Didactical Studies, 6*(3), 34086. https://doi.org/10.33902/ijods.202534086

Bilgin, S., & Güngören, Ö. C. (2025). A detailed examination of faculty acceptance of artificial intelligence: Insights from key variables. *Journal of Pedagogical Sociology and Psychology, 7*(3), 64–77. https://doi.org/10.33902/jpsp.202534245

Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology, 9*, 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki, A. C., van Borkulo, C. D., van Bork, R., & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers, 1*(1), 58. https://doi.org/10.1038/s43586-021-00055-w

Bremner, N., Sakata, N., & Cameron, L. (2022). The outcomes of learner-centered pedagogy: A systematic review. *International Journal of Educational Development, 94*, 102649. https://doi.org/10.1016/j.ijedudev.2022.102649

Bringmann, L. F., Elmer, T., Epskamp, S., Krause, R. W., Schoch, D., Wichers, M., Wigman, J. T. W., & Snippe, E. (2019). *What do centrality measures measure in psychological networks? Journal of Abnormal Psychology, 128*(8), 892–903. https://doi.org/10.1037/abn0000446

Cabero-Almenara, J., Palacios-Rodríguez, A., Loaiza-Aguirre, M. I., & de Rivas-Manzano, M. del R. (2024). Teachers' acceptance of educational artificial intelligence and its relationship with certain variables and pedagogical beliefs. *Education Sciences, 14*(7), 740. https://doi.org/10.3390/educsci14070740

Cheng, S.-L., Chen, S.-B., & Chang, J.-C. (2021). Examining the multiplicative relationships between teachers' competence, values, and pedagogical beliefs regarding technology integration. *British Journal of Educational Technology, 52*(2), 734–750. https://doi.org/10.1111/bjet.13052

Chiu, T. K. F., Ahmad, Z., & Çoban, M. (2025). Development and validation of the Teacher Artificial Intelligence (AI) Competence Self-Efficacy (TAICS) Scale. *Education and Information Technologies, 30*(5), 6667–6685. https://doi.org/10.1007/s10639-024-13094-z

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human–Computer Interaction, 39*(4), 910–922. https://doi.org/10.1080/10447318.2022.2049145

Clark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, *7*(3), 309–319. https://doi.org/10.1037/1040-3590.7.3.309

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology*, *78*(1), 98–104. https://doi.org/10.1037/0021-9010.78.1.98

Çakır, D., & Güner, P. (2026). The current landscape of teachers' artificial intelligence acceptance: Relationships with TPACK and technostress. *International Journal of Didactical Studies, 7*(3), e43911. https://doi.org/10.33902/ijods.202643911

Demirdağ, S., Ünver, A. K., & Gürez, İ. (2025). Development of teachers' attitude scale towards artificial intelligence: A validity and reliability study. *Asya Studies, 9*(33), 1–22. https://doi.org/10.31455/asya.1712885

Dierendonck, C. (2023). Measuring the classroom level of the Dynamic Model of Educational Effectiveness through teacher self-report: Development and validation of a new instrument. *Frontiers in Education, 8*, 1281431. https://doi.org/10.3389/feduc.2023.1281431

Dorsah, P., Amedeker, M. K., & Ngman-Wara, E. I. (2025). Exploring the factor structure of the Epistemic Beliefs Inventory. *International Journal of Didactical Studies, 6*(2), 33004. https://doi.org/10.33902/ijods.202533004

Dringó-Horváth, I., Rajki, Z., & T. Nagy, J. (2025). University teachers' digital competence and AI literacy: Moderating role of gender, age, experience, and discipline. *Education Sciences, 15*(7), 868. https://doi.org/10.3390/educsci15070868

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods, 23*(4), 617–634. https://doi.org/10.1037/met0000167

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods, 50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2013). Removing obstacles to the pedagogical changes required by Jonassen's vision of authentic technology-enabled learning. *Computers & Education, 64*, 175–182. https://doi.org/10.1016/j.compedu.2012.10.008

Fauth, B., Decristan, J., Decker, A.-T., Büttner, G., Hardy, I., Klieme, E., & Kunter, M. (2019). The effects of teacher competence on student outcomes in elementary science education: The mediating role of teaching quality. *Teaching and Teacher Education, 86*, 102882. https://doi.org/10.1016/j.tate.2019.102882

Filiz, O., Kaya, M. H., & Adiguzel, T. (2025). Teachers and AI: Understanding the factors influencing AI integration in K-12 education. *Education and Information Technologies, 30*(13), 17931–17967. https://doi.org/10.1007/s10639-025-13463-2

Foygel, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. In J. D. Lafferty, C. K. I. Williams, J. Shawe-Taylor, R. S. Zemel, & A. Culotta (Eds.), *Advances in neural information processing systems* (Vol. 23, pp. 604–612). Curran Associates. https://proceedings.neurips.cc/paper_files/paper/2010/hash/072b030ba126b2f4b2374f342be9ed44-Abstract.html

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics, 9*(3), 432–441. https://doi.org/10.1093/biostatistics/kxm045

Galindo-Domínguez, H., Delgado, N., Campo, L., & Losada, D. (2024). Relationship between teachers' digital competence and attitudes toward artificial intelligence in education. *International Journal of Educational Research, 126*, 102381. https://doi.org/10.1016/j.ijer.2024.102381

Gonzalez-Berruga, M. Á. (2025). Measuring educational quality in the classroom: Validation of the Effective Teaching in Secondary Education Questionnaire. *International Journal of Didactical Studies, 6*(1), 31584. https://doi.org/10.33902/ijods.202531584

Gurer, M. D., & Akkaya, R. (2022). The influence of pedagogical beliefs on technology acceptance: A structural equation modeling study of pre-service mathematics teachers. *Journal of Mathematics Teacher Education, 25*(4), 479–495. https://doi.org/10.1007/s10857-021-09504-5

Hsu, P.-S. (2016). Examining current beliefs, practices, and barriers regarding technology integration: A case study. *TechTrends, 60*(1), 30–40. https://doi.org/10.1007/s11528-015-0014-3

Ismajli, B. (2026). Comparing upper-secondary students' perceptions of ICT integration in natural and social sciences gymnasiums in Kosovo. *Frontiers in Education, 11,* 1783563. https://doi.org/10.3389/feduc.2026.1783563

Ismaniati, C., Khairaty, N. I., Yusuf, N., & Supramono, A. (2025). Harnessing self-efficacy: Mediating the connection between TPACK and AI intentions among teachers. *Journal of Pedagogical Research, 9*(2), 109–126. https://doi.org/10.33902/JPR.202531937

Jones, P. J., Ma, R., & McNally, R. J. (2021). Bridge centrality: A network approach to understanding comorbidity. *Multivariate Behavioral Research, 56*(2), 353–367. https://doi.org/10.1080/00273171.2019.1614898

Kong, S.-C., & Yang, Y. (2024). A human-centered learning and teaching framework using generative artificial intelligence for self-regulated learning development through domain knowledge learning in K–12 settings. *IEEE Transactions on Learning Technologies, 17,* 1588–1599. https://doi.org/10.1109/TLT.2024.3392830

Kryeziu, V., Maloku, F., Avdiu-Kryeziu, S., & Mehmeti, G. (2026). The role of artificial intelligence in teaching: Perspectives from primary school teachers. *Human Research in Rehabilitation, 16*(1), 196–210. https://doi.org/10.21554/hrr.042616

Lai, C., Wang, Q., & Huang, X. (2022). The differential interplay of TPACK, teacher beliefs, school culture, and professional development with the nature of in-service EFL teachers' technology adoption. *British Journal of Educational Technology, 53*(5), 1389–1411. https://doi.org/10.1111/bjet.13200

Li, Y.-D., Ding, G.-H., & Zhang, C.-Y. (2024). Effects of learner-centered education on academic achievement: A meta-analysis. *Educational Studies, 50*(3), 285–298. https://doi.org/10.1080/03055698.2021.1940874

Liu, H., Wang, L., & Koehler, M. J. (2019). Exploring the intention-behavior gap in the technology acceptance model: A mixed-methods study in the context of foreign-language teaching in China. *British Journal of Educational Technology, 50*(5), 2536–2556. https://doi.org/10.1111/bjet.12824

Liu, X., Yang-Hansen, K., Valcke, M., & De Neve, J. (2024). A decade of PISA: Student perceived instructional quality and mathematics achievement across European countries. *ZDM – Mathematics Education, 56*(5), 859–891. https://doi.org/10.1007/s11858-024-01630-7

Lucas, M., Zhang, Y., Bem-Haja, P., & Vicente, P. N. (2024). The interplay between teachers' trust in artificial intelligence and digital competence. *Education and Information Technologies, 29*, 22991–23010. https://doi.org/10.1007/s10639-024-12772-2

Mailizar, M., Umam, K., & Elisa, E. (2026). Examining the impact of teachers' knowledge on the integration of dynamic mathematics software into constructivist pedagogy. *Journal of Pedagogical Research, 10*(1), 209–226. https://doi.org/10.33902/JPR.202636113

Ministry of Education, Science, Technology and Innovation [MESTI]. (2022). *Education strategy 2022–2026.* Republic of Kosovo. https://kryeministri.rks-gov.net/wp-content/uploads/2024/10/ASSESSMENT-OF-THE-IMPLEMENTATION-OF-THE-EDUCATION-STRATEGY-2022-2026.pdf

Morina, Sh., Kervan, S., Kovac, E. S. (in press). A scale development study on teachers' classroom teaching-learning process performance: Validity and reliability analysis. *Journal of Educational and Social Research.*

Mu, J., Bayrak, A., & Ufer, S. (2022). Conceptualizing and measuring instructional quality in mathematics education: A systematic literature review. *Frontiers in Education, 7*, 994739. https://doi.org/10.3389/feduc.2022.994739

Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational Technology Research and Development, 71*, 137–161. https://doi.org/10.1007/s11423-023-10203-6

Orhani, S., Kolukaj, M., Saramati, F., & Saramati, E. (2023). ICT as a didactic tool to facilitate the learning process in the subject of mathematics in combined classes. *International Journal of Innovative Research in Multidisciplinary Education, 2*(5), 184–193. https://doi.org/10.58806/ijirme.2023.v2i5n01

Park, K., & Kim, G. (2026). The influence of learning experience and social-cognitive factors on teachers' digital instructional practice. *Journal of Pedagogical Research, 10*(2), 1–16. https://doi.org/10.33902/JPR.202641859

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Šeďová, K., & Sedláček, M. (2026). Who benefits from teaching quality: The role of prior achievement in Czech lower secondary schools. *Frontiers in Education, 10*, 1712000. https://doi.org/10.3389/feduc.2025.1712000

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. *Educational Technology Research and Development, 65*(3), 555–575. https://doi.org/10.1007/s11423-016-9481-2

Treve, M. (2024). Comparative analysis of teacher-centered and student-centered learning in the context of higher education: A co-word analysis. *Iberoamerican Journal of Science Measurement and Communication, 4*(2), 1–12. https://doi.org/10.47909/ijsmc.119

van Borkulo, C. D., van Bork, R., Boschloo, L., Kossakowski, J. J., Tio, P., Schoevers, R. A., Borsboom, D., & Waldorp, L. J. (2023). Comparing network structures on three aspects: A permutation test. *Psychological Methods, 28*(6), 1273–1285. https://doi.org/10.1037/met0000476

Wijaya, T. T., Yu, Q., Cao, Y., He, Y., & Leung, F. K. S. (2024). Latent profile analysis of AI literacy and trust in mathematics teachers and their relations with AI dependency and 21st-century skills. *Behavioral Sciences, 14*(11), 1008. https://doi.org/10.3390/bs14111008

Yentes, R. D., & Wilhelm, F. (2021). *Careless: Procedures for computing indices of careless responding* [R package]. CRAN. https://CRAN.R-project.org/package=careless

Yim, I. H. Y., & Wegerif, R. (2024). Teachers' perceptions, attitudes, and acceptance of artificial intelligence (AI) educational learning tools: An exploratory study on AI literacy for young students. *Future in Educational Research, 2*(4), 318–345. https://doi.org/10.1002/fer3.65

Zhai, X. (2025). Transforming teachers' roles and agencies in the era of generative AI: Perceptions, acceptance, knowledge, and practices. *Journal of Science Education and Technology, 34*(6), 1323–1333. https://doi.org/10.1007/s10956-024-10174-0

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. *International Journal of Educational Technology in Higher Education, 20*(1), 49. https://doi.org/10.1186/s41239-023-00420-7