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Original article

Artificial Intelligence Mentorship Perception Scale for Preservice Teachers: Development and Preliminary Psychometric Evidence

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Abstract

The integration of artificial intelligence (AI) into education has expanded mentoring practices toward technology-supported guidance systems. Although prior studies have examined AI acceptance, attitudes toward AI, and AI literacy, limited research has focused on AI-based mentorship as a perceived source of pedagogical and developmental support. This study aimed to develop the Artificial Intelligence Mentorship Perception Scale and provide initial psychometric evidence regarding its use with preservice teachers. A scale development design was employed. The process included construct definition, item pool generation, expert review, pilot testing, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), item discrimination analysis, and reliability testing. The initial pool included 33 items based on mentoring, e-mentoring, AI-supported learning, and teacher education literature. Following expert evaluation and pilot testing, the form was reduced to 18 items. The EFA sample included 233 preservice teachers, and the CFA sample included 240 preservice teachers. EFA suggested a four-factor structure explaining 65.12% of the variance: Pedagogical Planning, Performance Evaluation, Academic Guidance, and Professional Development. During CFA, one item was removed, and the revised 17-item model showed acceptable but not optimal fit. Reliability coefficients ranged from .79 to .91 across subdimensions and .955 for the overall scale. The findings provide preliminary psychometric evidence for the scale within a Turkish preservice teacher sample.

Keywords: Artificial Intelligence, AI-Based Mentorship, Preservice Teachers, Scale Development, Psychometric Validation

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INTRODUCTION

Mentorship is one of the supportive relationships employed in learning and development processes. With roots tracing back to Ancient Greece, mentorship is defined as a structured process of learning and guidance through which individuals support one another's development by sharing knowledge, skills, and experience. In its classical sense, mentorship refers to a relationship in which a more experienced individual supports the career and personal development of a less experienced person (Kram, 1983). According to Kram (1983), career-related functions of mentorship include coaching, sponsorship, and increasing visibility, whereas psychosocial functions involve role modeling and counseling. Mentorship therefore extends beyond knowledge transmission; it also encompasses social learning and identity development. Social learning theory emphasizes learning through observation and interaction, providing one of the theoretical foundations of mentorship (Bandura, 1977). This perspective highlights that learning within mentorship relationships emerges not only from content delivery but also from interactive processes. Meta-analytic studies conducted in organizational settings have further demonstrated that mentorship has significant effects on career success, job satisfaction, and organizational commitment (Allen et al., 2004; Eby et al., 2013).

Traditional mentorship practices often encounter structural constraints such as time and space limitations, matching difficulties, and a restricted pool of qualified mentors. These challenges can hinder the continuity of mentorship processes, particularly in large-scale educational and organizational settings. The sustainability of the mentorship relationship, alongside its quality, plays a central role in determining implementation success. In response to these limitations, e-mentoring practices have emerged, enabling mentorship relationships to operate independently of physical location through digital communication tools (Single & Single, 2005). Ensher et al. (2003) report that online mentoring programs offer flexibility, accessibility, and scalability, and can connect individuals across different geographical regions. The digitalization of mentorship thus represents not merely a technical shift but a restructuring that enhances inclusivity. Recent studies similarly indicate that integrating digital technologies into mentorship increases flexibility, scalability, and accessibility, enabling interaction across diverse contexts (Choudhary et al., 2024).

Advances in artificial intelligence (AI) and machine learning have expanded mentorship beyond e-mentoring. Technologies such as natural language processing (NLP) and large language models (LLMs) enable the generation of personalized feedback and real-time responses to user input (Russell & Norvig, 2021). These developments transform not only the communication channel but also the nature of guidance provided within mentorship processes. In education, AI-based adaptive learning systems have been shown to optimize learning by delivering content and feedback tailored to students' performance (Holmes et al., 2019). AI-supported mentorship platforms can process user input and provide continuous, real-time guidance aligned with individual needs and goals (Bagai & Mane, 2023; Patel et al., 2024). AI-based mentorship therefore represents a further stage in this evolution, combining the accessibility advantages of digital systems with increased personalization. Meta-analytic findings also demonstrate that intelligent tutoring systems positively influence learning outcomes (Ma et al., 2014).

Despite these advantages, AI-based mentorship systems cannot fully replicate the emotional depth and empathic dimensions characteristic of human mentorship. While AI systems excel in data processing, pattern recognition, and consistent feedback generation, they may show limitations in relational trust, ethical reasoning, and contextual sensitivity (Holmes et al., 2019). Mentorship is inherently multidimensional and extends beyond cognitive support alone. Hybrid models in which humans and AI collaborate are therefore considered more sustainable (Qadir et al., 2024). AI systems enhance efficiency and access, whereas human mentors contribute developmental guidance, ethical evaluation, and relationship-based support. Generative AI tools demonstrate strong performance in technical assistance and information production; however, human interaction remains critical for developmental mentoring, identity formation, and relational support (Lawani, 2025; Lee & Esposito, 2025).

The rapid integration of AI tools into educational environments has made the nature of interaction between these systems and both teachers and pre-service teachers a significant research concern. AI use in education requires a human-centered, ethical, and pedagogically grounded approach, along with capacity building to ensure safe and purposeful implementation (Miao & Holmes, 2023). Evaluations of AI in education must therefore address pedagogical appropriateness and user experience, rather than focusing solely on technical efficiency. Pre-service teachers represent a particularly important group, as they simultaneously develop professional identity, pedagogical decision-making skills, and technology integration competencies. Research on AI competence and literacy among teachers indicates that AI-related skills, while partially overlapping with general digital competence, constitute a distinct domain (Tenberga & Daniela, 2024). This suggests that pre-service teachers' experiences with AI-based mentorship should be examined as a specific construct rather than as a general technology attitude.

The present study conceptualizes this construct across four dimensions aligned with the professional development needs of pre-service teachers: Pedagogical Planning, Performance Evaluation, Academic Guidance, and Professional Development. AI-based mentorship experience is evaluated in terms of planning and adapting instruction to learner characteristics, supporting assessment and feedback processes, providing guidance for classroom practice and management, facilitating access to pedagogical content knowledge, and enabling professional networking and development opportunities. This framework extends beyond general indicators of technology acceptance, such as perceived usefulness or ease of use, and focuses on mentorship-specific functions reflected in teaching practice. Measurement of this construct therefore requires attention to perceptions directly related to mentorship functions rather than solely to general technology acceptance or usage frequency. Clearly defining conceptual boundaries and theoretically justifying subdimensions are essential for establishing construct validity in scale development.

The present study conceptualizes AI-based mentorship perception across four dimensions aligned with both mentorship functions and the professional development needs of preservice teachers: Pedagogical Planning, Performance Evaluation, Academic Guidance, and Professional Development. These dimensions are not intended to represent general attitudes toward AI; rather, they reflect perceived mentorship functions within teacher education. Pedagogical Planning refers to the perceived role of AI-supported systems in designing instructional processes, adapting teaching strategies, and organizing learning activities. Performance Evaluation refers to perceptions of AI-supported feedback, assessment interpretation, and improvement-oriented evaluation. Academic Guidance refers to the perceived role of AI in supporting academic decision-making, access to pedagogical knowledge, and guidance related to coursework or teaching practice. Professional Development refers to perceptions of AI as a resource for career-oriented learning, professional awareness, and continuous development.

This dimensional structure is grounded in the view that mentorship involves both career-related and psychosocial/developmental support functions. In classical mentoring theory, mentorship includes guidance, coaching, feedback, role modeling, and support for professional growth (Kram, 1983). In teacher education, these functions may be reflected in planning instruction, evaluating teaching-related performance, receiving academic direction, and developing a professional identity. Therefore, the four dimensions proposed in this study represent context-specific expressions of broader mentoring functions within AI-supported teacher education environments. Although these dimensions are expected to be related, they address different aspects of perceived support: planning concerns the preparation of teaching processes, performance evaluation concerns feedback on current or completed performance, academic guidance concerns educational decision-making, and professional development concerns longer-term growth.

Given the conceptual proximity among these dimensions, particularly among Pedagogical Planning, Performance Evaluation, and Academic Guidance, the present study treats them as related but distinguishable components of AI-based mentorship perception. This assumption is examined through exploratory and confirmatory factor analyses. At the same time, high correlations among factors would indicate that AI-based mentorship perception may also include a strong general perception component. Therefore, the dimensional structure should be interpreted cautiously and examined further in future studies through competing models such as second-order, bifactor, or alternative factor structures.

The growing adoption of AI-supported mentorship in education and the workplace necessitates the scientific measurement of user experience, perceived benefit, and effectiveness. In psychological and social sciences, scale development grounded in robust theoretical foundations is critical for assessing latent constructs that cannot be directly observed (Boateng et al., 2018). A measurement instrument must not only be practical but also provide reliable and valid evidence regarding the construct it represents. Systematic evaluation of content validity, construct validity, and reliability is therefore required during scale development (DeVellis, 2016). Establishing the psychometric properties of a new instrument and confirming its structure across samples constitute essential scientific requirements (Chen et al., 2016).

Although various AI-related measurement tools exist, most assess constructs associated with AI rather than AI-based mentorship itself. Studies grounded in the Technology Acceptance Model (TAM) primarily measure beliefs about usefulness and ease of use, following Davis's (1989) original framework; this approach has recently been applied in higher education within the context of ChatGPT (Barakat et al., 2025). Attitude scales developed for pre-service teachers focus on cognitive, affective, and behavioral attitudes toward AI rather than mentorship functions (Calp et al., 2025). AI literacy instruments typically assess knowledge, competence, and critical evaluation skills, including self-assessment tools for teachers (Tenberga & Daniela, 2024) and the Scale for the Assessment of Non-Experts' AI Literacy (SNAIL) developed by Laupichler et al. (2023). While these tools contribute substantially to understanding AI acceptance, attitudes, and literacy, they do not directly capture the mentorship-specific dimensions of AI-based systems.

In this study, AI-based mentorship perception is conceptualized as a distinct but related construct. It does not refer merely to accepting AI technologies, holding positive attitudes toward AI, or possessing AI-related knowledge. Rather, it refers to users' perceptions of whether AI-supported systems can provide mentorship-related support, including pedagogical planning, feedback and performance evaluation, academic guidance, and professional development assistance. From this perspective, AI-based mentorship perception is positioned at the intersection of mentoring functions, AI-supported educational guidance, and teacher professional learning. This distinction is important because a preservice teacher may have a positive attitude toward AI or perceive AI as useful without necessarily perceiving it as a source of mentoring support.

The construct also differs from general AI-supported learning or intelligent tutoring concepts. AI-supported learning systems often focus on adaptive content delivery, automated feedback, or learner performance optimization, whereas mentorship implies a broader developmental process involving guidance, reflection, decision-making support, and professional growth. Therefore, the present study does not treat AI-based mentorship perception as a replacement for existing constructs such as AI literacy, AI attitude, or technology acceptance. Instead, it addresses a more specific perceptual domain concerning the extent to which AI-supported systems are evaluated as performing mentorship-like functions in teacher education.

This study introduces the Artificial Intelligence Mentorship Perception Scale, designed to measure pre-service teachers' perceived benefits and experiences of AI-based mentorship. The study aims to provide initial psychometric evidence for the scale through content validity procedures, exploratory and confirmatory factor analyses, item discrimination analysis, reliability testing, and convergent validity evidence based on CR and AVE values. By doing so, the study contributes a specialized measurement tool that may support further research on the pedagogical and developmental implications of AI-supported mentorship in teacher education. However, the scale should be interpreted as an initial instrument requiring further validation through criterion-related validity, incremental validity, measurement invariance, and cross-contextual studies.

METHODOLOGY

This study was designed as a scale development study aiming to develop the Artificial Intelligence Mentorship Perception Scale and provide initial psychometric evidence for its use with preservice teachers. The research process consisted of establishing the theoretical framework, generating an item pool, obtaining expert feedback for content validity, conducting a pilot study, performing exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), analyzing item discrimination, and assessing reliability. The reliability of the scale was evaluated using Cronbach's alpha coefficients at both the EFA and CFA stages. Following CFA, Composite Reliability (CR) and Average Variance Extracted (AVE) values were calculated to provide additional evidence regarding construct reliability and convergent validity. Since no external criterion variables were included in the study, criterion-related validity, incremental validity, and predictive validity were not examined. Therefore, the study should be interpreted as providing initial rather than comprehensive validation evidence.

Research Group

The study sample consisted of preservice teachers enrolled in teacher education programs. To examine the factorial structure of the scale and cross-validate the measurement model, two independent samples were used: one for exploratory factor analysis (EFA; $n = 233$) and one for confirmatory factor analysis (CFA; $n = 240$).

In the EFA sample, 153 participants (65.7%) were female and 80 (34.3%) were male. In the CFA sample, 158 participants (65.8%) were female and 82 (34.2%) were male. Regarding grade level, the EFA sample included 50 first-year (21.5%), 60 second-year (25.8%), 58 third-year (24.9%), and 65 fourth-year students (27.9%). The CFA sample included 60 first-year (25.0%), 58 second-year (24.2%), 63 third-year (26.3%), and 52 fourth-year students (21.7%). Detailed demographic characteristics of both samples are presented in Table 1.

Table 1. Demographic Characteristics of the EFA and CFA Samples

Variable	Category	EFA (n = 233), n	EFA (%)	CFA (n = 240), n	CFA (%)
Gender	Female	153	65.7	158	65.8
	Male	80	34.3	82	34.2
Grade level	1st year	50	21.5	60	25.0
	2nd year	60	25.8	58	24.2
	3rd year	58	24.9	63	26.3
	4th year	65	27.9	52	21.7
Total		233	100.0	240	100.0

Table 1 presents the demographic characteristics of the participants. Participants were preservice teachers enrolled in teacher education programs at a public university in Türkiye. Participants were selected using convenience sampling. Data were collected during the 2025–2026 academic year through an online questionnaire. Participation in the study was voluntary, and informed consent was obtained from all participants prior to data collection. Ethical approval for the study was obtained from the Social and Human Sciences Ethics Committee of [University name].

Although two independent samples were used for EFA and CFA, both samples were drawn from the same public university context through convenience sampling. Therefore, the samples should be considered appropriate for initial psychometric examination rather than for establishing broad generalizability across institutions, regions, or national contexts. Since AI-based mentorship perceptions may vary depending on institutional AI policies, access to AI tools, course requirements, prior AI experience, and teacher education systems, the findings should be interpreted within the context of preservice teachers in Türkiye. Further validation studies with samples from different universities, teacher education programs, in-service teachers, and cross-cultural contexts are needed to examine the stability and generalizability of the scale structure.

Scale Development Process

The development of the Artificial Intelligence Mentorship Perception Scale (AIMPS) followed a multi-stage procedure grounded in scale development principles and psychometric validation practices. The process included (a) construct definition and item pool generation, (b) expert review for content validity, (c) pilot testing, and (d) item refinement during psychometric analyses.

Construct Definition and Item Pool Generation

In the first stage, the construct of AI-based mentorship perception was conceptually defined based on the literature on mentoring, e-mentoring, AI-supported guidance, teacher education, and pedagogical support processes. In the present study, AI-based mentoring was conceptualized as a broader and multidimensional guidance process extending beyond chatbot-based information delivery, encompassing personalized support, feedback, instructional guidance, resource recommendation, and development-oriented interaction.

Based on this conceptual framework and the target population (preservice teachers), an initial item pool was generated to reflect AI-supported mentoring experiences in teacher education contexts. During item writing, attention was paid to clarity, single-idea wording, appropriateness for preservice teachers' experience levels, and alignment with the construct domain. Accordingly, an initial pool of 33 items was developed. All items were written in a Likert-type format to assess participants' perceptions of AI-based mentoring experiences.

All items were rated on a 5-point Likert-type scale ranging from 1 (Strongly disagree) to 5 (Strongly agree). Higher scores indicate a more positive perception of AI-based mentoring. Scale scores can be calculated at both the factor level and the total score level, with higher scores reflecting stronger perceived support and mentoring-related benefits from AI-based systems.

The final 17-item form of the scale is provided in Appendix A in English and Appendix B in Turkish. The appendices include the retained item structure after the removal of Item 12 during CFA.

Expert Review and Content Validity

The initial 33-item pool was submitted to an expert panel for content validation. The panel consisted of four experts: one specialist in Curriculum and Instruction, one specialist in Measurement and Evaluation, one language expert, and one artificial intelligence expert with Web of Science-indexed publications in the field. The expert review form included separate evaluation fields for content relevance, clarity of expression, comprehensibility, and appropriateness for preservice teachers. For each item, experts were asked to recommend one of three decisions: retain, revise, or remove. They were also invited to provide written comments explaining their decisions.

Expert feedback was evaluated qualitatively by comparing areas of agreement and disagreement across the four expert forms. Because the expert review form was designed as a qualitative evaluation procedure rather than a quantitative relevance-rating form, item-level and scale-level Content Validity Index (CVI) values were not calculated. This should be considered a limitation of the content validity evidence. Future studies should obtain quantitative expert ratings and report item-level CVI (I-CVI) and scale-level CVI (S-CVI) values to strengthen the evidence for content validity.

Based on expert feedback, 15 items were removed from the initial pool. The removed content mainly involved three types of items: items that measured general attitudes toward AI rather than mentorship-specific support, items that overlapped conceptually with other items, and items with double-barreled or overly broad wording. For example, items focusing only on whether AI is useful in education, items combining feedback and career guidance in a single statement, and items repeating the same planning function with minor wording differences were eliminated. The remaining items were revised to improve clarity, conceptual representativeness, and alignment with the four intended dimensions.

Pilot Testing

The revised 18-item draft form was pilot-tested to assess item comprehensibility, response process clarity, and administration feasibility. The pilot study was conducted with a group of 30 preservice teachers who were not included in the main study samples. This pilot sample size was considered adequate for identifying wording problems and administration-related issues prior to large-scale data collection.

During the pilot administration, participants were asked not only to respond to the scale items but also to indicate any statements they found difficult to understand and, where necessary, provide brief comments. At the end of the administration, participants were also asked short follow-up questions regarding overall comprehensibility, potentially redundant items, and any difficulties experienced during completion. The average completion time was approximately 8–10 minutes.

Based on the pilot findings, no major structural changes were made to the scale; however, minor linguistic revisions were implemented in several items to improve readability and wording precision. The revised form was then finalized for the main administrations used in the exploratory and confirmatory factor analyses.

Data Analysis

Exploratory Factor Analysis (EFA), item discrimination analyses, and reliability analyses were conducted in SPSS 28, whereas confirmatory factor analysis (CFA) was performed using AMOS 24. The analysis criteria were specified before the findings were interpreted so that the Results section could focus on reporting outcomes rather than repeating methodological justifications.

Prior to the main analyses, the datasets were screened for missing values, outliers, and distributional characteristics. Missing data were checked at the item level. Standardized z-scores were used to identify univariate outliers, and values exceeding ±3 were considered extreme. Normality was evaluated using skewness and kurtosis values, with values within ±2 interpreted as acceptable for social science data (George & Mallery, 2010; Hair et al., 2014).

EFA was conducted to identify the underlying factor structure of the scale. The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) coefficient and Bartlett's test of sphericity. KMO values of .60 or above and a significant Bartlett's test were considered evidence of factorability. Factor retention decisions were based on eigenvalues, explained variance, factor loadings, cross-loading patterns, and theoretical interpretability. A primary factor loading of .40 or higher was used as the minimum criterion for item retention, and factor loadings below .40 were suppressed in the rotated factor matrix to improve readability. In the social sciences, a total explained variance of 50% or higher was considered acceptable (Büyüköztürk, 2020; Hair et al., 2014).

Reliability was evaluated using Cronbach's alpha coefficients for the total scale and each subdimension. Alpha coefficients of .70 or higher were interpreted as acceptable evidence of internal consistency (George & Mallery, 2003; Nunnally & Bernstein, 1994). After CFA, Composite Reliability (CR) and Average Variance Extracted (AVE) values were also calculated. CR values of .70 or higher were considered adequate, and AVE values of .50 or higher were interpreted as evidence of convergent validity (Fornell & Larcker, 1981; Hair et al., 2014). Discriminant validity was examined using the Fornell-Larcker criterion; however, this criterion was interpreted cautiously because high inter-factor correlations may weaken discriminant validity evidence.

CFA was conducted on an independent sample to test the four-factor structure obtained from EFA. Model fit was evaluated using multiple fit indices, including χ^2/df, RMSEA, NFI, CFI, GFI, and AGFI. Values of χ^2/df below 3, RMSEA values between .05 and .08, and incremental fit indices around .90 or higher were interpreted as indicating acceptable fit, whereas values closer to .95 were interpreted as stronger evidence of fit (Hu & Bentler, 1999; Kline, 2016). GFI and AGFI were reported for completeness, but their interpretation was treated cautiously because these indices may be sensitive to sample size and model complexity.

No external criterion variables were included in the dataset. Therefore, criterion-related validity, predictive validity, and incremental validity analyses could not be conducted in the present study. HTMT analysis was also not conducted; consequently, discriminant validity evidence should be interpreted as preliminary. Measurement invariance across gender or grade level was not tested because the study was designed as an initial scale development study and subgroup sizes, especially across grade levels, were modest for multi-group CFA. These issues are addressed as limitations and as priorities for future validation studies.

Item Retention and Refinement

Item retention decisions were based on the criteria established in the Data Analysis section. In the EFA stage, items were retained when they showed a primary factor loading of .40 or higher, did not show problematic cross-loading, and were conceptually consistent with the intended factor. The EFA results supported an 18-item four-factor structure.

During CFA, Item 12 was removed because its standardized factor loading did not meet the predetermined criterion and its retention weakened the measurement quality of the Academic Guidance factor. The model was then re-estimated after the item removal while retaining the same four-factor structure. This decision improved the statistical adequacy of the model but introduced a post hoc element into the confirmatory phase.

Because Item 12 was removed during CFA and the revised model was re-estimated using the same CFA sample, the 17-item structure should be interpreted as a revised preliminary model rather than as a fully cross-validated final model. A third independent sample was not available in the present study. Therefore, future studies should retest the 17-item form in a new independent sample before the structure is considered firmly established.

RESULTS

Exploratory Factor Analysis (EFA)

Exploratory factor analysis was conducted to examine the initial factor structure of the Artificial Intelligence Mentorship Perception Scale. Prior to factor extraction, the suitability of the dataset for factor analysis was evaluated using the KMO coefficient and Bartlett's test of sphericity. The KMO value was .918, and Bartlett's test was statistically significant, $\chi^2(153) = 2183.443$, $p < .001$, indicating that the data were suitable for factor analysis.

The EFA results suggested a four-factor structure with eigenvalues greater than 1. These four factors explained 65.12% of the total variance. The first factor explained 20.33% of the variance, the second factor 15.63%, the third factor 15.25%, and the fourth factor 13.91%. The factor structure was considered interpretable in relation to the theoretical dimensions of AI-based mentorship perception.

Table 2. Descriptive Statistics of the EFA Data

n	**Mean**	**Variance**	**Standard Deviation**	**Skewness**	**Kurtosis**
233	66.92	90.330	9.50	-.709	2.189

Table 2 presents the descriptive statistics for the dataset used in the exploratory factor analysis (EFA). A total of 233 participants were included in the analysis. The mean total score obtained from the scale was 66.92, with a standard deviation of 9.50. The skewness value of -0.709 indicates a slight negative skew, whereas the kurtosis value of 2.189 suggests a relatively peaked distribution. Both values were within the predefined acceptable range for further analyses.

Table 3. Results of the KMO and Bartlett's Test of Sphericity

Kaiser–Meyer–Olkin Measure of Sampling Adequacy		**0.918**
Bartlett's Test of Sphericity	Approximate Chi-Square	2183.443
	df	153
	Significance (p)	.000

Table 3 presents the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity results used to assess sampling adequacy and the suitability of the dataset for factor analysis. The KMO value was calculated as .918, indicating a high level of sampling adequacy for factor analysis.

Bartlett's test of sphericity yielded a chi-square value of 2183.443 with 153 degrees of freedom and a significance level of $p < .001$. This result demonstrates the presence of statistically significant relationships among the variables at a level sufficient to justify factor analysis.

Based on these findings, the dataset was considered appropriate for conducting exploratory factor analysis.

Table 4. Total Variance Explained

Factor	Eigenvalue	Variance (%)	Cumulative Variance (%)
1	3.66	20.33	20.33
2	2.81	15.63	35.96
3	2.75	15.25	51.21
4	2.50	13.91	65.12

Table 4 presents the eigenvalues and explained variance ratios obtained from the exploratory factor analysis. Four factors with eigenvalues greater than 1 were identified. The first factor explains 20.33% of the total variance, the second factor 15.63%, the third factor 15.25%, and the fourth factor 13.91%. The four-factor structure accounts for 65.12% of the total variance, exceeding the predetermined 50% threshold for social science research. These findings suggest that the scale exhibits a multidimensional structure with adequate explanatory power.

Table 5. Rotated Component Matrix of the Artificial Intelligence Mentorship Scale

AIM Items	Factor Loading			
	1	2	3	4
Item 1	**.76**			
Item 2	**.67**			
Item 3	**.80**			
Item 4	**.65**			
Item 5	**.58**			
Item 6	**.61**			
Item 7			**.60**	
Item 8			**.81**	
Item 9	.40		**.61**	
Item 10			**.65**	
Item 11				**.77**
Item 12				**.71**
Item 13				**.72**
Item 14				**.44**
Item 15		**.73**		
Item 16		**.71**		
Item 17		**.79**		
Item 18		**.68**		

Table 5 presents the rotated factor loading matrix for the scale. To improve readability, factor loadings below the predetermined .40 threshold were suppressed. The items clustered under four factors. Items 1-6 loaded on the first factor, Items 7-10 on the second factor, Items 11-14 on the third factor, and Items 15-18 on the fourth factor. Most items had factor loadings above .50. Item 14 had a relatively lower loading (.441), but it remained above the minimum criterion of .40 and was retained due to its conceptual relevance to the factor.

Overall, the EFA results provided initial support for a four-factor structure. However, because the factors were conceptually related and later factor correlations were high in CFA, the dimensional structure should be interpreted as preliminary and requiring further testing with alternative models and independent samples.

Table 6. Independent Samples t-Test Results Comparing Upper 27% and Lower 27% Groups for Scale Items

Item		**x̄ ± Ss**	**t**	**p**	**Item**		**x̄ ± Ss**	**t**	**p**
i1	Lower	2.98±0.77	20.717	p < .001	i10	Lower	3.02±0.61	25.866	p < .001
	Upper	5.00±0.00				Upper	5.00±0.00		
i2	Lower	2.94±0.64	21.155	p < .001	i11	Lower	3.19±0.67	18.610	p < .001
	Upper	4.87±0.34				Upper	4.90±0.30		
i3	Lower	3.13±0.79	18.748	p < .001	i12	Lower	2.86±0.47	29.249	p < .001
	Upper	5.00±0.00				Upper	4.90±0.30		
i4	Lower	3.22±0.77	18.293	p < .001	i13	Lower	3.11±0.60	25.043	p < .001
	Upper	5.00±0.00				Upper	5.00±0.00		
i5	Lower	3.13±0.66	22.535	p < .001	i14	Lower	2.81±0.59	21.910	p < .001
	Upper	5.00±0.00				Upper	4.79±0.41		
i6	Lower	2.98±0.71	20.705	p < .001	i15	Lower	2.59±0.64	21.253	p < .001
	Upper	4.94±0.25				Upper	4.70±0.46		
i7	Lower	2.70±0.53	22.619	p < .001	i16	Lower	2.73±0.51	25.936	p < .001
	Upper	4.70±0.46				Upper	4.83±0.38		
i8	Lower	2.79±0.51	25.734	p < .001	i17	Lower	2.56±0.67	20.708	p < .001
	Upper	4.84±0.37				Upper	4.68±0.47		
i9	Lower	2.84±0.37	31.373	p < .001	i18	Lower	2.67±0.54	26.445	p < .001
	Upper	4.86±0.35				Upper	4.84±0.37		

Table 6 presents the results of the independent samples t-test conducted to examine item discrimination by comparing the item mean scores of the lower 27% and upper 27% groups. The findings indicate statistically significant differences between the lower and upper groups for all items ($t = 18.293–31.373$, $p < .001$).

The higher mean scores observed in the upper group across all items demonstrate that the items effectively reflect the measured construct and consistently distinguish between individuals with low and high levels of the trait. Based on these results, all 18 items included in the scale were found to have adequate item discrimination.

Table 7. Reliability Analysis of the Artificial Intelligence Mentorship Perception Scale Following EFA

Factor	**Factor Name**	**Cronbach Alpha**
Factor 1	Pedagogical Planning	.889
Factor 2	Performance Evaluation	.875
Factor 3	Academic Guidance	.824
Factor 4	Professional Development	.837
Total		**.937**

Table 7 indicates that the Artificial Intelligence Mentorship Perception Scale demonstrated adequate to high internal consistency following the exploratory factor analysis. The Cronbach's alpha coefficients for the subdimensions were .889, .875, .824, and .837. These values exceeded the predetermined .70 threshold. The total Cronbach's alpha coefficient was .937, indicating high reliability for the overall scale score. However, the reliability evidence should be interpreted with attention to subscale-level differences rather than as identical across all dimensions.

For conceptual clarity, the factor numbering was reorganized after the exploratory factor analysis. Accordingly, the factor including Items 7–10 was labeled as Factor 2 (Performance Evaluation), the factor including Items 11–14 as Factor 3 (Academic Guidance), and the factor including Items 15–18 as Factor 4 (Professional Development). This numbering was applied consistently in the subsequent analyses.

Confirmatory Factor Analysis (CFA)

For the confirmatory factor analysis (CFA), data obtained from the revised 18-item version of the scale following the EFA were used (n = 240). Prior to conducting the CFA, descriptive analyses were performed to evaluate the suitability of the dataset for further statistical analyses.

Table 8. Descriptive Statistics of the CFA Data

N	Mean	Variance	Standard Deviation	Skewness	Kurtosis
240	68.63	187.019	13.67	-1.012	1.813

Table 8 presents the descriptive statistics for the dataset used in the confirmatory factor analysis. The study was conducted with data obtained from 240 participants. The mean total score of the scale was 68.63, and the standard deviation was 13.67. The skewness value was -1.012 and the kurtosis value was 1.813. Both values were within the predefined acceptable range, indicating that the data were suitable for the planned CFA procedures.

Table 9. CFA Model Fit Indices

Fit Index	Good Fit	Acceptable Fit	Scale Value
p	$0.05 < p \leq 1.00$	$0.01 \leq p \leq 0.05$	.01
χ^2 /df	$0 \leq X^2/df \leq 2$	$2 < X^2/df \leq 3$	2.426
RMSEA	$0 \leq RMSEA \leq 0.05$	$0.05 < RMSEA \leq 0.08$	.077
NFI	$0.95 \leq NFI \leq 1.00$	$0.90 \leq NFI < 0.95$	.917
CFI	$0.97 \leq CFI \leq 1.00$	$0.95 \leq CFI < 0.97$	.949
GFI	$0.95 \leq GFI \leq 1.00$	$0.90 \leq GFI < 0.95$	.884
AGFI	$0.90 \leq AGFI \leq 1.00$	$0.85 \leq AGFI < 0.90$	.843

Table 9 presents the fit indices obtained from the confirmatory factor analysis. The χ^2/df value was 2.426, indicating an acceptable level of fit. The RMSEA value was .077, which also falls within the acceptable range. The NFI value (.917) suggested acceptable fit. However, the CFI value (.949) was slightly below the commonly recommended .950 threshold, indicating borderline fit. In addition, the GFI (.884) and AGFI (.843) values were below the recommended criteria. Taken together, these findings suggest that the four-factor model demonstrated an acceptable but not strong level of fit. Therefore, the CFA results should be interpreted cautiously, and the proposed model should be further tested with alternative model specifications and independent samples.

Table 10. CFA Item Analysis

Factor	Item	β_0	β_1	S.E.	C.R.	p
F1	i1	.82	1			
	i2	.82	.927	.061	15.115	*
	i3	.81	1.042	.070	14.799	*
	i4	.85	1.139	.072	15.868	*
	i5	.76	1.015	.075	13.526	*
	i6	.76	.986	.074	13.398	*
F2	i7	.75	1			
	i8	.83	1.133	.084	13.456	*
	i9	.87	1.115	.078	14.322	*
	i10	.83	1.122	.083	13.552	*
F3	i11	.76	1			
	i13	.76	.976	.081	12.101	*
	i14	.74	1.004	.085	11.766	*
F4	i15	.84	1			
	i16	.86	.963	.060	16.191	*
	i17	.83	.986	.063	15.577	*
	i18	.81	.967	.064	14.999	*

Note. β0 = standardized factor loading; β1 = unstandardized factor loading; S.E. = standard error; C.R. = critical ratio. *$p < .05$.

Table 11. Composite Reliability and Average Variance Extracted (AVE) of the Factors

Factor	CR	AVE
F1-Pedagogical Planning	.92	.65
F2-Performance Evaluation	.89	.67
F3-Academic Guidance	.80	.57
F4-Professional Development	.90	.70

Table 11 presents the Composite Reliability (CR) and Average Variance Extracted (AVE) values for the factors. The CR values ranged between .80 and .92, and the AVE values ranged between .57 and .70. These results met the predetermined criteria for construct reliability and convergent validity. Discriminant validity was examined using the Fornell-Larcker criterion, but the high correlations among some factors indicate that this evidence should be interpreted cautiously. Because HTMT values were not calculated in the present study, discriminant validity should be regarded as preliminary rather than fully established.

Table 12. Correlations Among the Factors of the Scale

Factor	F1	F2	F3	F4
F1-Pedagogical Planning	1	.860**	.831**	.616**
F2-Performance Evaluation	.860**	1	.762**	.610**
F3-Academic Guidance	.831**	.762**	1	.648**
F4-Professional Development	.616**	.610**	.648**	1

Note. N = 240. **p < .01 (two-tailed).

Table 12 presents the correlations among the factors of the scale. All factors were positively and significantly correlated with one another. The correlations between F1 and F2 (r = .860) and between F1 and F3 (r = .831) were particularly high, indicating substantial overlap among these dimensions. These findings suggest that the factors are closely related components of AI-based mentorship perception rather than fully independent dimensions.

Conceptually, these high correlations may be explained by the common mentorship function underlying the dimensions. In teacher education, pedagogical planning, performance evaluation, and academic guidance are not experienced as isolated processes; AI-supported systems may provide instructional suggestions, feedback, and academic direction within the same interaction. Therefore, preservice teachers may perceive these dimensions as closely connected facets of a broader AI-based mentorship perception. This conceptual overlap does not remove the psychometric concern; rather, it indicates that the four-factor interpretation should be compared with second-order, bifactor, single-factor, and more parsimonious competing structures in future research.

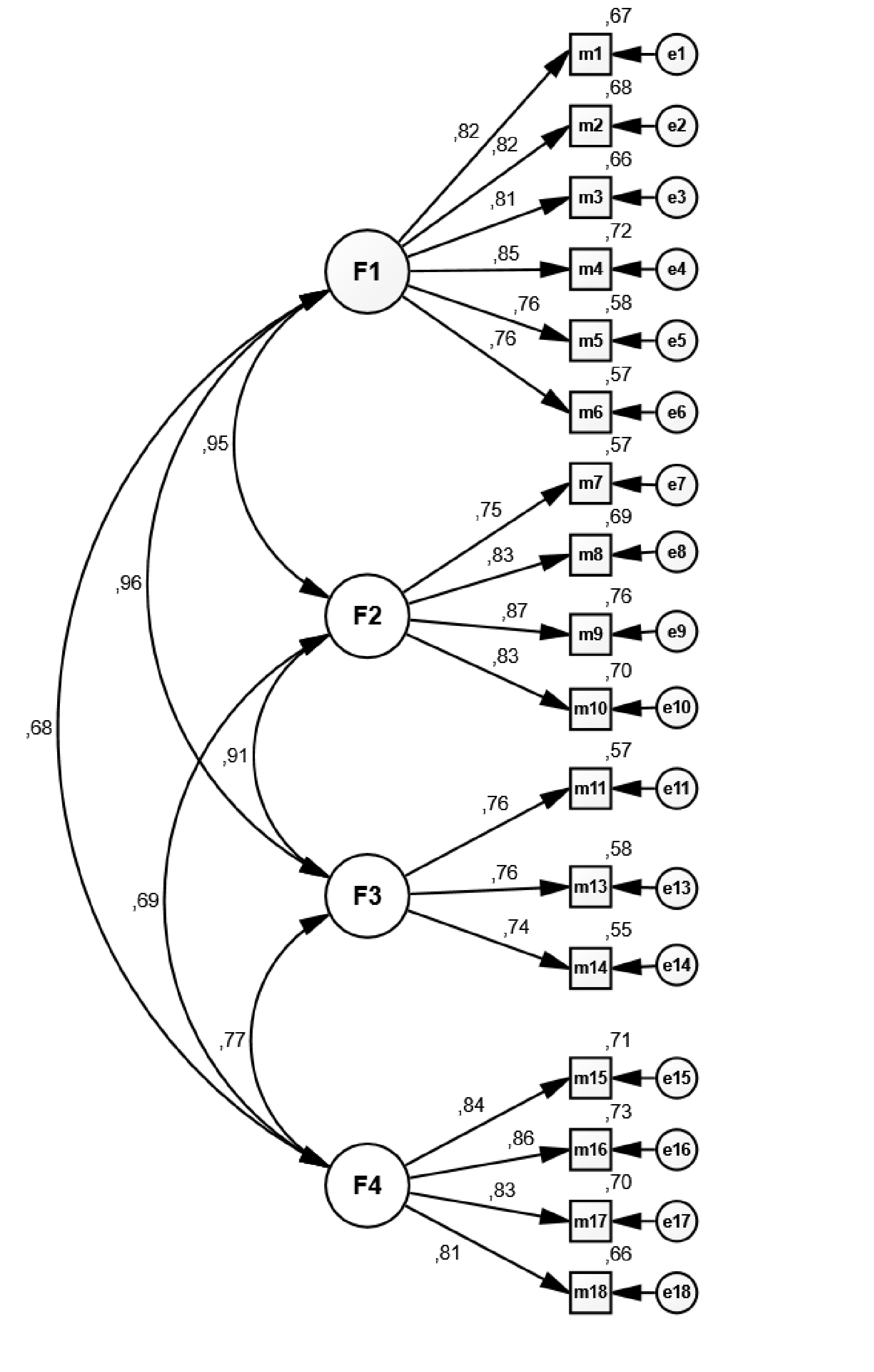

Figure 1. Standardized Confirmatory Factor Analysis Model

Standardized factor loadings were examined to evaluate the contribution of each item to its latent factor. During CFA, Item 12 was removed because its standardized factor loading did not meet the predetermined criterion and its retention weakened the measurement quality of the corresponding factor. After this item was removed, the model was re-estimated while retaining the same four-factor structure.

The remaining standardized factor loadings were within acceptable ranges. However, because one item was removed during CFA and the revised model was tested on the same CFA sample, the resulting 17-item form should be cross-validated in a new independent sample.

Table 13. Reliability Analysis of the Artificial Intelligence Mentorship Perception Scale Following CFA

Factor	Cronbach Alpha
F1-Pedagogical Planning	.913
F2-Performance Evaluation	.893
F3-Academic Guidance	.794
F4-Professional Development	.903
Total	.955

Table 13 presents the reliability analysis results of the scale following the confirmatory factor analysis. The Cronbach's alpha coefficients were .913 for Pedagogical Planning, .893 for Performance Evaluation, .794 for Academic Guidance, and .903 for Professional Development. The overall reliability coefficient of the scale was .955. These findings indicate high internal consistency for the total score and strong reliability for most subdimensions. The Academic Guidance factor met the acceptable reliability criterion but should be interpreted more cautiously than the other subdimensions because its alpha coefficient was lower than the others.

CONCLUSION

This study developed the Artificial Intelligence Mentorship Perception Scale and provided initial psychometric evidence regarding its use with preservice teachers in Türkiye. The scale development process began with a 33-item pool based on the literature on mentoring, e-mentoring, AI-supported guidance, and teacher education. Following expert review and pilot testing, the draft form was reduced to 18 items. Exploratory factor analysis suggested a four-factor structure consisting of Pedagogical Planning, Performance Evaluation, Academic Guidance, and Professional Development, explaining 65.12% of the total variance.

Confirmatory factor analysis was conducted with an independent sample to test the structure identified through EFA. During CFA, one item was removed due to insufficient factor loading, and the revised 17-item model was re-estimated. The CFA results indicated an acceptable but not strong level of model fit. While χ^2/df, RMSEA, and NFI values were within acceptable ranges, CFI was borderline and GFI and AGFI were below recommended thresholds. Therefore, the factor structure should be interpreted cautiously and should not be regarded as fully established without further cross-validation.

The reliability findings indicated satisfactory internal consistency for the total scale and its subdimensions. CR and AVE values also provided evidence of construct reliability and convergent validity. However, the high correlations among some factors, particularly between Pedagogical Planning and Performance Evaluation and between Pedagogical Planning and Academic Guidance, suggest that these dimensions may share a strong general AI-based mentorship perception component. Therefore, the discriminant validity evidence should be interpreted cautiously.

Overall, the findings suggest that the Artificial Intelligence Mentorship Perception Scale may be used as an initial instrument for examining preservice teachers' perceptions of AI-based mentorship. The scale appears promising for research on AI-supported pedagogical and developmental support in teacher education. However, the evidence should be interpreted as preliminary because the revised 17-item structure requires further validation in independent samples.

Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, although separate samples were used for EFA and CFA, both samples consisted of preservice teachers from a single public university in Türkiye and were recruited through convenience sampling. Therefore, the findings should not be generalized to all preservice teachers, in-service teachers, or international teacher education contexts. Future studies should test the scale with samples from different universities, teacher education programs, regions, and cultural contexts.

Second, the study focused on internal psychometric evidence, including expert review, EFA, CFA, item discrimination, internal consistency, CR, and AVE values. However, no external criterion variables were included. Therefore, criterion-related validity, predictive validity, and incremental validity could not be examined. Future studies should investigate the relationships between AI-based mentorship perception and related constructs such as AI literacy, AI attitudes, perceived usefulness, technology readiness, teacher self-efficacy, mentoring quality, and actual AI use in teacher education.

Third, the CFA results indicated an acceptable but not optimal level of model fit. The CFI value was borderline, whereas the GFI and AGFI values were below commonly recommended thresholds. In addition, Item 12 was removed during CFA and the revised model was re-estimated using the same CFA sample. This procedure limits the strictly confirmatory interpretation of the CFA findings. Future studies should retest the 17-item structure in a third independent sample and compare the four-factor model with alternative structures, including second-order, bifactor, single-factor, and more parsimonious competing models.

Fourth, discriminant validity evidence was limited. Although CR and AVE values supported construct reliability and convergent validity, the high correlations among Pedagogical Planning, Performance Evaluation, and Academic Guidance indicate that additional discriminant validity procedures are needed. HTMT analysis was not conducted in the present study; therefore, the distinctiveness of these dimensions should be examined in future validation studies using HTMT values and competing measurement models.

Finally, measurement invariance was not tested across gender, grade level, or different samples. Therefore, it remains unclear whether the scale functions equivalently across groups. Since some subgroup sizes were modest for multi-group CFA, especially when grade level was considered, invariance testing was left for future studies with larger and more balanced samples. Future research should examine configural, metric, scalar, and strict invariance before using the scale for group comparisons.

Declarations

Author Contributions: The study is single-authored.

Conflicts of Interest: The author declares that there is no conflict of interest regarding the publication of this study.

Ethical Approval: Ethical approval for this study was obtained from the Social and Human Sciences Ethics Committee of [University Name] (Approval No: XXXX, Date: XXXX). All procedures performed in this study involving human participants were conducted in accordance with the ethical standards of the institutional research committee.

Data Availability Statement: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

REFERENCES

Allen, T. D., Eby, L. T., Poteet, M. L., Lentz, E., & Lima, L. (2004). Career benefits associated with mentoring for protégés: A meta-analysis. *Journal of Applied Psychology, 89*(1), 127–136. https://doi.org/10.1037/0021-9010.89.1.127

Bagai, R., & Mane, V. (2023). Designing an AI-powered mentorship platform for professional development: Opportunities and challenges. *International Journal of Computer Trends and Technology, 71*(4), 108-114. https://doi.org/10.14445/22312803/IJCTT-V71I4P114

Bandura, A. (1977). *Social learning theory*. Prentice Hall.

Barakat, M., Salim, N. A., & Sallam, M. (2025). University educators perspectives on ChatGPT: A Technology Acceptance Model-based study. *Open Praxis, 17*(1), 129–144. https://doi.org/10.55982/openpraxis.17.1.718

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health, 6*, 149. https://doi.org/10.3389/fpubh.2018.00149

Büyüköztürk, Ş. (2020). *Sosyal bilimler için veri analizi el kitabı* [The data analysis handbook for social sciences] (28th ed.). Pegem Akademi.

Calp, R., Mukba, G., & Şata, M. (2025). Preservice teachers' attitudes toward artificial intelligence: A scale development study. *Journal of University Research, 8*(4), 608–621. https://doi.org/10.32329/uad.1740270

Chen, Y., Watson, R., & Hilton, A. (2016). A review of mentorship measurement tools. *Nurse Education Today, 40*, 20-28. https://doi.org/10.1016/j.nedt.2016.01.020

Choudhary, P., Ali, I., Rehman, K., Sharma, K., Sharma, K., Borasi, M., & Bhargava, P. (2024). Enhancing mentorship through technology: A comprehensive review of current practices and future directions. *International Journal of Multidisciplinary Research and Growth Evaluation, 5*(6), 634-645.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). Sage Publications.

Eby, L. T., Allen, T. D., Evans, S. C., Ng, T., & DuBois, D. L. (2013). Does mentoring matter? A multidisciplinary meta-analysis comparing mentored and non-mentored individuals. *Journal of Vocational Behavior, 72*(2), 254–267. https://doi.org/10.1016/j.jvb.2007.04.005

Ensher, E. A., Heun, C., & Blanchard, A. (2003). Online mentoring and computer-mediated communication: New directions in research. *Journal of Vocational Behavior, 63*(2), 264–288. https://doi.org/10.1016/S0001-8791(03)00044-7

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

George, D., & Mallery, P. (2010). *SPSS for Windows step by step: A simple guide and reference* (10th ed.). Pearson.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Pearson.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Kram, K. E. (1983). Phases of the mentor relationship. *Academy of Management Journal, 26*(4), 608-625.

Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023). Development of the "Scale for the assessment of non-experts' AI literacy"–An exploratory factor analysis. *Computers in Human Behavior Reports*, *12*, 100338.

Lawani, A. S. (2025). Assessing the efficacy of traditional mentoring in the era of artificial intelligence (AI) and technology. *Unizik Journal of Educational Research and Policy Studies, 19*(4), 327-341.

Lee, J., & Esposito, A. G. (2025). Evaluating generative AI as a mentor resource: Bias and implementation challenges. *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics*, 126-132.

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology, 106*(4), 901–918. https://doi.org/10.1037/a0037123

Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Patel, K. M., Diddi, S. M., & Bogam, N. B. (2024). The next generation of learning: AI mentorship for a transformative educational experience. *International Journal of Advanced Research in Science, Communication and Technology, 4*(3), 464-467. https://doi.org/10.48175/IJARSCT-19969

Qadir, J., Attique, M. A., Shoaib, S., & Ghaznavi, S. I. (2024). Can AI chatbots provide coaching in engineering? Beyond information processing toward mastery. *Proceedings of EDULEARN24*, 8418-8428.

Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Single, P. B., & Single, R. M. (2005). E-mentoring for social equity: Review of research to inform program development. *Mentoring & Tutoring: Partnership in Learning, 13*(2), 301-320.

Tenberga, I., & Daniela, L. (2024). Artificial intelligence literacy competencies for teachers through self-assessment tools. *Sustainability, 16*(23), 10386. https://doi.org/10.3390/su162310386

APPENDIX A

Final English Form of the Artificial Intelligence Mentorship Perception Scale

Response options: 1 = Strongly disagree, 2 = Disagree, 3 = Moderately agree, 4 = Agree, 5 = Strongly agree. Higher scores indicate a more positive perception of AI-based mentorship. Item 12 from the EFA form was removed during CFA; therefore, the final form includes 17 items. There are no reverse-coded items.

Final Item No.	Original Item ID	Factor	Item wording
1	Item 1	Pedagogical Planning	The AI mentor can provide suggestions aligned with my learning preferences when preparing a lesson plan.
2	Item 2	Pedagogical Planning	The AI mentor can provide timely feedback on the lesson plans I prepare.
3	Item 3	Pedagogical Planning	The AI mentor can help me choose among different teaching methods.
4	Item 4	Pedagogical Planning	The AI mentor can support me in adapting in-class activities according to students' needs.
5	Item 5	Pedagogical Planning	The AI mentor can suggest alternative solutions for classroom management problems I may encounter.
6	Item 6	Pedagogical Planning	The AI mentor can help me create a beginning-of-term plan for classroom rules and daily routines.
7	Item 7	Performance Evaluation	The AI mentor can evaluate my classroom practice performance according to objective criteria.
8	Item 8	Performance Evaluation	The AI mentor can analyze my performance in virtual classroom practices and offer suggestions.
9	Item 9	Performance Evaluation	The AI mentor can provide concrete improvement suggestions for my performance by presenting examples of successful teachers' lesson practices.
10	Item 10	Performance Evaluation	Following an evaluation, the AI mentor can suggest the next goal for areas in which I need improvement based on objective criteria.
11	Item 11	Academic Guidance	The AI mentor can suggest appropriate ways for me to access current educational research.
12	Item 13	Academic Guidance	The AI mentor can make complex educational concepts more understandable.
13	Item 14	Academic Guidance	The AI mentor can make pedagogical concepts more understandable by concretizing them with classroom examples.
14	Item 15	Professional Development	The AI mentor can encourage me to participate in online communities and groups related to the teaching profession.
15	Item 16	Professional Development	The AI mentor can guide me toward workshops and seminars aligned with my teaching goals.
16	Item 17	Professional Development	The AI mentor can guide me in contacting expert teachers and academics in my subject area.
17	Item 18	Professional Development	The AI mentor can notify me in a timely manner about opportunities appropriate for my teacher development (e.g., workshops, certificates, competitions).

APPENDIX B

Yapay Zekâ Mentorluk Algı Ölçeği Türkçe Formu

Yanıt seçenekleri: 1 = Kesinlikle katılmıyorum, 2 = Katılmıyorum, 3 = Orta derecede katılıyorum, 4 = Katılıyorum, 5 = Kesinlikle katılıyorum. Yüksek puanlar yapay zekâ temelli mentorluk algısının daha olumlu olduğunu gösterir. AFA formundaki 12. madde DFA aşamasında çıkarılmıştır; bu nedenle nihai form 17 maddeden oluşmaktadır. Ölçekte ters kodlanmış madde yoktur.

Nihai Madde No.	**Özgün Madde Kodu**	**Faktör**	**Madde metni**
1	Madde 1	Pedagojik Planlama	YZ mentor, ders planı hazırlarken öğrenme tercihlerime uygun öneriler sunabilir.
2	Madde 2	Pedagojik Planlama	YZ mentor, hazırladığım ders planları hakkında zamanında geri bildirim verebilir.
3	Madde 3	Pedagojik Planlama	YZ mentor, farklı öğretim yöntemleri arasında seçim yapmamda yardımcı olabilir.
4	Madde 4	Pedagojik Planlama	YZ mentor, ders içi etkinlikleri öğrencilerin ihtiyaçlarına göre uyarlamamda destek olabilir.
5	Madde 5	Pedagojik Planlama	YZ mentor, sınıf yönetimiyle ilgili karşılaşacağım sorunlarda alternatif çözümler önerebilir.
6	Madde 6	Pedagojik Planlama	YZ mentor, sınıf kuralları ve günlük rutinler için dönem başı planı oluşturmamda yardımcı olabilir.
7	Madde 7	Performans Değerlendirme	YZ mentor, sınıf içi uygulama performansımı nesnel ölçütlere göre değerlendirebilir.
8	Madde 8	Performans Değerlendirme	YZ mentor, sanal sınıf uygulamalarında performansımı analiz ederek öneriler sunabilir.
9	Madde 9	Performans Değerlendirme	YZ mentor, başarılı öğretmenlerin ders uygulamalarını örnek göstererek performansım için somut geliştirme önerileri sunabilir.
10	Madde 10	Performans Değerlendirme	YZ mentor, değerlendirme sonrası nesnel ölçütlere dayanarak eksik olduğum konular için bir sonraki hedefi önerebilir.
11	Madde 11	Akademik Rehberlik	YZ mentor, güncel eğitim araştırmalarına erişmem için uygun yollar önerebilir.
12	Madde 13	Akademik Rehberlik	YZ mentor, karmaşık eğitim kavramlarını daha anlaşılır hâle getirebilir.
13	Madde 14	Akademik Rehberlik	YZ mentor, pedagojik kavramları sınıf içi örneklerle somutlaştırarak daha anlaşılır hâle getirebilir.
14	Madde 15	Mesleki Gelişim	YZ mentor, öğretmenlik mesleğiyle ilgili çevrim içi topluluk ve gruplara katılmamı teşvik edebilir.
15	Madde 16	Mesleki Gelişim	YZ mentor, öğretmenlik hedeflerime uygun atölye ve seminerlere katılmam için yönlendirme yapabilir.
16	Madde 17	Mesleki Gelişim	YZ mentor, branşımdaki uzman öğretmen ve akademisyenlerle iletişim kurmam için yönlendirme yapabilir.
17	Madde 18	Mesleki Gelişim	YZ mentor, öğretmenlik gelişimime uygun fırsatları (örn. atölye, sertifika, yarışma) zamanında bildirebilir.