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Latent Profiles of Turkish Pre-Service Teachers' Attitudes Toward Artificial Intelligence

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Abstract

The rapid proliferation of artificial intelligence technologies in educational contexts demands a nuanced understanding of how future educators perceive and position themselves in relation to these tools. This study adopts a person-centred approach to identify latent attitudinal profiles of Turkish pre-service teachers concerning AI integration in education. Utilizing a cross-sectional survey design, data were collected from 529 participants and analysed through Latent Profile Analysis, complemented by confirmatory factor analysis, ANOVA, and chi-square tests. The results uncovered three distinct profiles: Artificial Intelligence (AI)-Confident Advocates, Balanced Readiness, and Low-Readiness Sceptics. Each profile demonstrated unique patterns of AI-related self-efficacy, pedagogical technology engagement, and attitudinal orientation, indicating substantial intra-group variation. While the majority exhibited moderate openness to AI, only a small subgroup reported the confidence and practical readiness necessary for meaningful classroom integration. Notably, demographic predictors such as gender, and programme type did not significantly influence profile membership, whereas academic seniority emerged as a differentiating factor. These findings underscore the limitations of one-size-fits-all approaches in teacher education and highlight the necessity of differentiated, profile-sensitive training models, as pre-service teachers differ in AI confidence and readiness, making uniform training unable to address their diverse learning needs. Furthermore, the study suggests that fostering AI readiness requires not only technical proficiency but also the cultivation of pedagogical confidence and reflective engagement with emerging technologies. By mapping the attitudinal landscape of pre-service teachers, this research offers critical insights for curriculum developers, educational policymakers, and teacher educators seeking to align technological innovation with human-centred pedagogical capacity.

Keywords: Artificial intelligence, pre-service teachers, latent profile analysis, teacher readiness, educational technology

Türk Öğretmen Adaylarının Yapay Zekâya Yönelik Tutumlarının Örtük Profilleri

Öz

Yapay zekâ (YZ) teknolojilerinin eğitim bağlamlarında hızla yaygınlaşması, bu araçların etkili biçimde benimsenebilmesi için öğretmen adaylarının YZ'ye yönelik algılarının ve konumlanışlarının derinlemesine anlaşılmasını zorunlu kılmaktadır. Bu çalışma, öğretmen adaylarının YZ'nin eğitime entegrasyonuna ilişkin tutumsal eğilimlerini belirlemek amacıyla kişi-merkezli bir yaklaşım benimseyerek örtük profil analizini (Latent Profile Analysis) kullanmıştır. Kesitsel bir tarama modeliyle yürütülen araştırmada, 529 öğretmen adayından toplanan veriler doğrulayıcı faktör analizi, ANOVA ve ki-kare testleriyle desteklenerek analiz edilmiştir. Bulgular, üç farklı tutumsal profilin varlığını ortaya koymuştur: YZ'ye Güvenli Savunucular, Dengeli Hazır Gruplar ve Düşük Hazırlıklı Şüpheciler. Her bir profil, YZ'ye yönelik öz-yeterlik, pedagojik teknoloji kullanımı ve genel tutumlar açısından kendine özgü bir örüntü sergilemiş; bu da katılımcılar arasında anlamlı iç grup farklılıklarına işaret etmiştir. Katılımcıların büyük kısmı YZ'ye karşı temkinli bir açıklık sergilese de yalnızca küçük bir grup bu teknolojiyi sınıf ortamında etkili şekilde kullanabilecek özgüven ve hazırlık düzeyine sahiptir. Cinsiyet, yaş ve program türü gibi demografik değişkenler profil üyeliği üzerinde anlamlı bir etki göstermezken; akademik kıdem belirleyici bir unsur olarak öne çıkmıştır. Bu bulgular, öğretmen eğitiminde herkese aynı biçimde uygulanan yaklaşımların sınırlılıklarını ortaya koymakta ve öğretmen adaylarının yapay zekâya yönelik özgüven ve hazırlık düzeylerinin farklılık göstermesi nedeniyle, farklı profillere duyarlı, farklılaştırılmış eğitim modellerinin gerekliliğini vurgulamaktadır. Araştırma, yalnızca teknik becerilerin değil, aynı zamanda pedagojik özgüvenin ve eleştirel teknoloji etkileşiminin geliştirilmesi gerektiğini göstermektedir. Öğretmen adaylarının YZ'ye yönelik tutumsal yapısını haritalandırarak, eğitim programı geliştiricilerine, politika yapıcılara ve öğretmen eğitimcilerine kişi-merkezli teknolojik dönüşüm için önemli açılımlar sunmaktadır.

Anahtar Kelimeler: Yapay zekâ, öğretmen adayları, örtük profil analizi, öğretmen yeterliliği, eğitim teknolojisi

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INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force across diverse sectors, with education being one of the most profoundly affected domains. Through its capacity to support personalised instruction, intelligent tutoring systems, and gamified learning environments, AI is facilitating pedagogical innovations that redefine traditional teaching and learning paradigms (Dwivedi et al., 2021). As a result, the incorporation of AI into educational practices is accelerating, and the field of AI in education has gained prominence as a key subdiscipline within educational technology research (Zawacki-Richter et al., 2019). This development presents opportunities to improve teaching practices, learning outcomes, and educational management through AI technologies (Marino et al., 2023). Recent studies demonstrate that AI can redefine traditional educational practices, rendering them in a more efficient, adaptive, and personalised way to meet individual needs (Yu, 2021).

The application of AI in educational settings extends beyond traditional subjects to specialised fields, including physics and special education technologies (Kaestner, 2022; Mahligawati, 2023). By strategically integrating AI technologies, educators are empowered to design more dynamic, responsive, and learner-centred instructional environments that accommodate a broad spectrum of student needs and learning preferences (Chen et al., 2020). AI integration in education facilitates the development of intelligent teaching tools, automated feedback systems, and personalised learning platforms (Sultangazina et al., 2021). For instance, in medical and dental education, AI transforms how students engage with course materials, assessments, and career planning (Boscardin, 2023; Singh & Hiran, 2022).

As AI becomes more ubiquitous in education, it is essential to consider the challenges and opportunities associated with its integration (Lainjo & Tsmouche, 2023). Educators and academic leaders must address ethical considerations, diversity, equity, and inclusion to ensure AI is utilised responsibly and effectively (Park & Kwon, 2023). By cultivating a deeper understanding of AI technologies and their implications, educational institutions can optimise AI to improve teaching practices, student engagement, and overall learning outcomes (Fahimirad & Kotamjani, 2018). The evolving role of AI in education underscores the need for ongoing research, collaboration, and innovation to effectively harness its potential for the benefit of both learners and educators (Zheng & Badarch, 2022).

Despite the growing prevalence of AI in educational contexts, much of the current research has focused on the technical affordances and system-level implementations of AI (Dwivedi et al., 2021; Zawacki-Richter et al., 2019). At the same time, increasing attention has been directed toward the psychological dimension of AI integration, particularly how individuals perceive, react to, and form attitudes toward AI (Wang et al., 2022; Xu, 2023). As AI becomes an integral part of learning environments, understanding how diverse learner groups develop distinct attitudinal profiles that influence their readiness, engagement, and willingness to use AI-based tools becomes increasingly important (Yukhymenko-Lescroart et al., 2021).

Traditional variable-centred approaches are limited in capturing this nuanced heterogeneity because they average effects across individuals, masking meaningful subgroup differences. Therefore, person-centred methods such as Latent Profile Analysis (LPA) have emerged as valuable tools for identifying hidden subgroups based on response patterns (Ferguson et al., 2020; Spurk et al., 2020). This study addresses this research gap by employing LPA to investigate university students' attitudes toward AI in education. Using item-level data, the aim of this study is to uncover distinct psychological profiles and provide insights into how students meaningfully differ in their receptiveness to AI technologies. The findings can inform the design of more adaptive, inclusive, and psychologically responsive AI integration strategies in higher education.

AI Integration in Turkish Education

In recent years, the integration of AI into educational practices in Türkiye has gained significant momentum, reflecting a national commitment to modernising teaching methodologies and enhancing student learning outcomes (İçen, 2022). This shift within Türkiye's educational landscape is characterised by the increasing adoption of AI tools designed to create more dynamic and personalised learning environments (Taşkıran, 2023). Despite the limited incorporation of AI-specific content in the national curriculum, there is a noticeable increase in interest in AI. This emerging emphasis is largely motivated by the need to equip students with critical competencies for the digital age and to align educational outcomes with the dynamic requirements of the global workforce (Taşkıran, 2023).

Developing teachers' techno-pedagogical competencies has therefore become a cornerstone of modern education, as the effective integration of AI and digital tools relies on educators' ability to design, implement, and evaluate technology-enhanced learning. The European Framework for the Digital Competence of Educators

(DigCompEdu) provides a comprehensive model for this purpose, identifying six key areas that encompass professional engagement, digital resource use, teaching and learning, assessment, learner empowerment, and the facilitation of learners' digital competence (Redecker & Punie, 2017). These competencies are essential for fostering inclusive, innovative, and student-centred learning environments, enabling teachers to act not only as transmitters of knowledge but also as facilitators who empower learners to use technology creatively and critically in a digital society (Redecker & Punie, 2017).

Türkiye's commitment to educational innovation is further bolstered by a robust private education sector and increasing international collaboration, both of which underscore the country's strategic focus on leveraging AI for educational advancement (İçen, 2022). Beyond traditional classroom instruction, AI is increasingly being employed within educational institutions for administrative purposes, streamlining operations, and enhancing institutional efficiency (Rane et al., 2023). The deployment of intelligent software programmes offers not only operational improvements but also the potential to deliver personalised educational experiences that cater to individual student needs. This approach promises to identify and address areas for pedagogical enhancement, stimulate talent development, and encourage educational innovation in response to the shifting needs of Turkish society (Çetin & Aktaş, 2021).

The integration of AI into teacher training programmes represents another critical area of development. In the Turkish educational context, various institutional efforts have been launched to integrate AI-enhanced technologies into conventional teaching methods (İçen, 2022). These initiatives encompass the deployment of intelligent tutoring systems and adaptive learning platforms aimed at enriching instructional practices and promoting personalised learning (İçen, 2022). These programmes extend beyond instructional methods to encompass administrative tasks such as curriculum design, examination management, and cybersecurity, thus equipping educators with the resources necessary to navigate an increasingly digital educational environment. By harnessing AI technologies, Turkish educators are better positioned to create personalised, learner-centred experiences that meet the diverse needs of students, ultimately contributing to the broader goal of improving educational quality across the country.

In alignment with the broader objectives outlined in Türkiye's IPA III Digital Transformation and Technology Project (IPA III, 2024), AI integration within the education sector is increasingly recognised as part of the country's strategic digital transformation agenda. The project emphasises the upskilling of educators and the development of AI-competent teaching personnel as foundational to achieving sustainable digital capacity in schools. It also highlights persistent challenges, including insufficient teacher training on digital pedagogy, limited infrastructure for AI-supported learning environments, and the need for continuous professional development to ensure equitable access and competence. Embedding AI competencies within teacher education curricula, as proposed in the project framework, is thus critical for realising the national vision of a digitally empowered education system capable of fostering innovation and inclusion.

Teacher Candidates' Attitudes towards AI

Teachers' attitudes and conceptual understanding of AI play a critical role in determining how effectively AI is integrated into educational environments. However, empirical evidence suggests that a significant proportion of educators possess limited knowledge of AI and its pedagogical applications (Kuleto et al., 2022). To address this, providing teacher candidates with opportunities to enhance their AI knowledge has been identified as essential for preparing them for the evolving educational landscape (Ferikoğlu & Akgün, 2022). Teacher candidates' perceptions of AI in education can significantly impact their attitudes towards technology integration, as well as their capacity to utilise AI tools to enhance student learning outcomes (Memon et al., 2023).

Research has demonstrated that teacher candidates' attitudes towards AI can strongly influence their readiness to integrate technology into teaching methodologies (Hussain, 2020). Positive attitudes towards AI have been linked to the creation of more engaging learning environments, which facilitate innovation and improve educational outcomes (Lin & Chen, 2024). Investigating teacher candidates' perceptions of AI provides valuable insights into their willingness to adopt AI tools in the classroom, which is crucial for the successful integration of technology in education (Hussain, 2020). Developing a supportive stance towards AI not only fosters innovative teaching practices but also enhances student engagement and learning outcomes, highlighting the importance of cultivating positive attitudes towards technological advancements in education (Tahir & Tahir, 2023). The attitudes of teacher candidates towards AI are shaped by multiple factors, including their previous experiences, training, and exposure to educational technology. Studies investigating the intersection of cultural intelligence and

attitudes towards the teaching profession reveal that cultural competencies can influence teacher candidates' perspectives on diverse student populations and teaching approaches (Karataş & Han, 2022).

Although empirical studies focusing on teacher candidates' attitudes toward AI are scarce, existing research on students and professionals offers important insights into general perceptions of AI (e.g., Al-Ayed & Al-Tit, 2024; Kim & Lee, 2024). Demographic factors, particularly gender, have been shown to significantly shape attitudes towards AI adoption and acceptance (Al-Ayed & Al-Tit, 2024). For instance, research by Kim and Lee (2024) highlights the role of socio-cultural factors, particularly gender, in shaping AI attitudes. Several studies, including those by Fietta et al. (2022), have found that females tend to exhibit more negative attitudes towards AI compared to males, particularly concerning legal and ethical implications. Similarly, Busch (2023) notes that male students often express more positive views of AI's efficiency, while females voice greater concerns about its broader implications. However, other studies, such as Ho et al. (2022), suggest that gender may not significantly influence AI attitudes in certain professional contexts, demonstrating that these effects can vary by domain and context.

In addition to gender, grade levels also play a role in shaping students' attitudes towards AI. Evangelou et al. (2022) emphasise the importance of grade level in shaping attitudes towards assessments and learning tasks, suggesting a complex relationship between educational advancement and technology adoption. Age-related factors also influence attitudes towards AI. While age may not be the primary determinant in some contexts, several studies have highlighted its impact on perceptions of AI. Research by Oh et al. (2019) and Abdullah and Fakieh (2020) suggests that older individuals tend to approach AI with more caution or scepticism, whereas younger individuals often hold more optimistic views. Findings by Moldt et al. (2023) further confirm this, demonstrating that younger individuals are usually more receptive to AI than their older counterparts. These studies collectively underline the impact of age on AI attitudes, with younger demographics typically exhibiting greater enthusiasm for AI integration. Overall, teacher candidates' attitudes towards AI play a critical role in fostering innovation, adaptability, and effective technology integration within educational settings. Positive attitudes towards AI contribute to more effective teaching practices, improved student engagement, and enhanced learning outcomes (Al-Abdallat & Alwraikat, 2020). By encouraging a supportive stance towards AI and offering teacher candidates opportunities to develop their knowledge and skills in this area, educational institutions are equipping future educators to meet the challenges of the digital age and to create dynamic, personalised learning environments.

Implementing AI in Teacher Training

The integration of AI into the teaching profession represents a profound and multifaceted transformation, reshaping pedagogical frameworks and redefining educators' roles within contemporary learning environments. Existing literature underscores AI's potential to revolutionise higher education by facilitating personalised instruction, adaptive tutoring systems, and data-informed pedagogical strategies (Zawacki-Richter et al., 2019). As these technologies become increasingly embedded across educational settings, their influence extends beyond efficiency gains, fostering adaptive learning environments, enhancing instructional responsiveness, and strengthening student engagement (Popenici & Kerr, 2017). Current empirical research also suggests a growing educator awareness of a paradigm shift toward more student-centred, interactive models of instruction, supported by AI tools capable of tailoring learning to individual needs (Jian et al., 2021). However, the extent to which teacher preparation programmes are equipped to respond to these structural and pedagogical shifts remains underexplored.

The adoption of AI into formal education is also projected to substantially reconfigure core instructional processes, including curriculum development, assessment strategies, and classroom management. Through the automation of administrative routines and deployment of real-time analytics, AI enables the delivery of differentiated learning pathways that accommodate diverse cognitive profiles and learner needs (Kshirsagar et al., 2022). Such transformations not only promise pedagogical efficiency but also foster environments that prioritise critical thinking, creativity, and learner autonomy (Shan & Yu, 2021). In this context, the role of the teacher is undergoing a fundamental redefinition, from that of a traditional content transmitter to a facilitator and designer of AI-mediated learning experiences (Lei & Liu, 2022). This evolution underscores the necessity for educators to develop new professional competencies, particularly digital fluency and technological pedagogical content knowledge. Recent research has also shown that pre-service teachers differ substantially in their diagnostic engagement, knowledge structures, and motivational orientations (Radkowitsch et al., 2023), highlighting the need for adaptive, AI-supported teacher education programmes that effectively address such learner diversity. It also points to an urgent need for systemic reform within teacher education systems, aligning them with the skills required for the 21st-century AI-driven classroom (Huang et al., 2022; Yang & Wang, 2020).

Simultaneously, expectations surrounding AI-supported teacher education programmes have intensified, driven by the intersection of technological advancement, pedagogical innovation, and workforce readiness. Pre-service and in-service educators increasingly anticipate that such programmes will not only improve teaching quality and student outcomes but also alleviate administrative burdens and streamline instructional design (Oh et al., 2019). Beyond operational improvements, these initiatives are expected to cultivate educators' capacities to integrate AI into everyday teaching practices, fostering a sustainable culture of innovation and continuous adaptation (Chen et al., 2020). Nevertheless, these aspirations raise critical questions about the current readiness of teacher education systems to deliver on this promise. As such, this study responds to a pressing gap in the literature by empirically examining how future educators perceive, interpret, and position themselves in relation to AI in education, thereby contributing to a more grounded understanding of what meaningful AI integration in teacher preparation might require.

Latent Profiles of Teacher Candidates' Attitudes Towards Artificial Intelligence

Traditional variable-centred approaches, such as regression and correlation analysis, are limited in their ability to capture the complexity of individual differences in psychological constructs like attitudes toward AI. These methods tend to assume a homogeneous population and focus on average effects, which may obscure meaningful subgroups within the sample (Ferguson et al., 2020). In the context of education, learners and teacher candidates often exhibit diverse and nuanced perspectives on AI, shaped by varying levels of digital literacy, emotional responses, and pedagogical readiness (Yukhymenko-Lescroart et al., 2021). Understanding these differences is critical, particularly in contexts such as Türkiye, where educational systems are actively undergoing technological transformation. Consequently, there is a growing need for analytical techniques that can uncover distinct psychological profiles and better reflect the heterogeneity of learners' attitudes.

LPA is a person-centred statistical method designed to identify unobserved subgroups within a population based on individuals' response patterns to a set of continuous variables (Spurk et al., 2020). LPA has been increasingly adopted in educational psychology to classify learners according to their motivational profiles, emotional regulation strategies, or technology acceptance orientations (Howard & Hoffman, 2018; Thurm, 2018). For example, a recent person-centred study identified three distinct latent profiles of student teachers' intra- and interindividual emotion-regulation strategies, and showed that grit predicted profile membership, demonstrating how LPA reveals meaningful heterogeneity in teacher populations (Methlagl & Vogl, 2022). These applications demonstrate the method's potential to offer insights into the diverse ways individuals relate to educational technologies.

Building on these methodological advances, the present study employs LPA to examine the latent attitudinal profiles of Turkish teacher candidates toward AI in education. Rather than relying on predefined subscales or global mean scores, this study uses item-level responses to identify naturally occurring patterns of perception, belief, and acceptance. This approach enables a more nuanced understanding of how future educators position themselves in relation to AI technologies, beyond simple positive or negative categorisations. Previous studies have begun to address teacher candidates' psychological readiness for AI integration (Ferikoğlu & Akgün, 2022; Kuleto et al., 2022); however, research in this area is still emerging. In doing so, the present study contributes to this emerging body of research by providing a person-centred analysis of attitudinal profiles. By revealing distinct profiles, the findings can provide valuable insights for the development and improvement of AI-focused teacher training programmes, support evidence-based policy development, and encourage the design of more adaptive and personalised AI strategies in teacher education.

Research Aims and Objectives

The growing integration of AI into education has drawn increasing attention to its implications for teaching and learning. However, the psychological readiness and attitudinal dispositions of teacher candidates have received comparatively less empirical attention. While prior research has largely focused on the technical affordances and implementation challenges of AI, limited attention has been paid to how teacher candidates conceptualise and emotionally respond to AI within their anticipated professional roles. Addressing this gap, the present study adopts a person-centred approach to identify distinct attitudinal profiles toward AI in education. This approach enables a nuanced understanding of teacher candidates' beliefs, anxieties, competencies, and openness to innovation, providing insights that can inform the design of targeted professional development programmes, AI literacy initiatives, and evidence-based teacher education curricula.

To guide this investigation, the following research questions have been formulated:

1. Which latent attitudinal profiles can be identified among Turkish pre-service teachers toward AI?

2. Do the identified latent profiles significantly differ in terms of AI-related self-efficacy, pedagogical technology use, and general attitudes toward AI?
3. Are demographic variables such as gender, grade level, and teacher education programme significantly associated with latent profile membership?

METHOD

Research Design and Participants

This study employed a quantitative, cross-sectional survey design aimed at exploring the attitudinal profiles of Turkish pre-service teachers toward AI in education. The selection of this design aligns with best practices in educational psychology and technology integration research, where survey-based approaches allow for the systematic measurement of perceptions and latent dispositions across a large sample (Creswell & Clark, 2018). A person-centred analytical framework was adopted through LPA, which enables the identification of unobserved subpopulations based on individuals' response patterns (Lubke & Muthén, 2005; Spurk et al., 2020). Unlike cluster analysis, LPA provides statistical indicators for model fit, class separation, and classification accuracy, making it a robust technique for theory-driven exploration. In recent years, LPA has been successfully used to study attitudes toward digital learning, AI literacy, and mobile technology integration among students and faculty (Kırksekiz et al., 2024; Yukhymenko-Lescroart et al., 2021). This method has gained increasing traction in educational research for tailoring interventions and informing differentiated professional development strategies (Howard & Hoffman, 2018). To ensure construct validity, a Confirmatory Factor Analysis (CFA) was conducted in RStudio (version 2025.09.1+401) using R (version 4.3.2; R Core Team, 2025) and the lavaan package (Rosseel, 2012) prior to the LPA to test the hypothesised three-factor structure of the adapted attitude scale. This approach follows recommendations for validating measurement models before applying mixture modelling techniques (Geiser, 2013).

A purposive criterion sampling strategy was employed to recruit participants who met the inclusion criterion of being prospective teachers enrolled either in education faculties or pedagogical formation programmes. These two groups were considered comparable, as both receive formal teacher training and share similar pedagogical competencies, course content, and professional goals. This approach ensured the inclusion of participants who were equally positioned within pre-service teacher education while allowing for natural variation in demographic and experiential factors. Such purposive sampling aligns with the principle of selecting information-rich cases relevant to the study purpose (Patton, 2015). A total of 550 teacher candidates were recruited for participation from two universities in Türkiye. However, 21 respondents were excluded from the analysis due to providing uniform responses across all questionnaire items. The final sample comprised 529 participants, with no missing data, offering a comprehensive overview of their demographic characteristics. The distribution of participants by gender, grade level, age, and programme type is presented in Table 1.

Table 1. Model Demographic Characteristics of the Participants (N = 529)

Variable	Category	*n*	%
Gender	Male	273	51.6
	Female	256	48.4
Grade level	2nd year	203	38.4
	3rd year	76	14.4
	4th year	250	47.3
Age (years)	20	85	16.1
	21	101	19.1
	22	122	23.1
	23	121	22.9
	24	52	9.8
	25	37	7.0
	26	11	2.1
Programme type	Pedagogical Formation	273	51.6
	Faculty of Education	256	48.4

Measures

The development of the 16-item scale used in this study was based on the adaptation of the instrument developed by Almaraz-López et al. (2023), originally designed to measure attitudes toward AI in education. The adaptation process involved careful linguistic and contextual modifications to align the items with the Turkish educational setting and the experiences of pre-service teachers. While the conceptual framework of the original scale was preserved, certain items were refined to enhance their relevance to the local context, particularly in relation to digital pedagogy and AI-supported instructional practices.

Language equivalence studies are a critical step in the adaptation of measurement instruments, as they ensure that the translated version of a scale maintains the same semantic, conceptual, and contextual meaning as the original. This process is particularly important in cross-cultural educational research, where linguistic inconsistencies can compromise construct validity and measurement invariance (Hambleton et al., 2004). To ensure that the adapted scale measured the intended constructs in a manner equivalent to the original, this study followed the guidelines set forth by the World Health Organization's (WHO) "Process of Translation and Adaptation of Instruments" (WHO, 2015).

After obtaining formal permission to adapt and use the original scale, the translation process was initiated with independent forward translation. First, the original English version of the scale was translated into Turkish by a bilingual linguist and three field experts in educational technology and AI. These individuals worked independently to ensure diverse linguistic and conceptual perspectives. Following this, the translations were reviewed collectively, and a consensus version was produced, integrating the most accurate and culturally appropriate item formulations.

Following the initial forward translation, the Turkish draft of the scale underwent a rigorous multi-phase evaluation process to ensure both linguistic equivalence and content validity. First, the draft was reviewed for semantic integrity and conceptual consistency by two additional bilingual experts who were not involved in the original translation phase. This review ensured that the items retained alignment with the original constructs while maintaining clarity for the Turkish pre-service teacher population. To verify backward compatibility, a back-translation was conducted by an independent linguist and two academic researchers fluent in both English and Turkish, all of whom were blind to the original version. The back-translated scale was then systematically compared with the original English version by a panel of three experts in artificial intelligence and educational measurement.

In the next phase, expert judgment was used to evaluate the content validity of each item. The Content Validity Ratio (CVR) was calculated for all 16 items based on the method established by Lawshe (1975). CVR is a statistical index used to quantify the degree of agreement among subject matter experts on whether an item is essential to the construct being measured (Lawshe, 1975). In this study, the CVR method was used to ensure that each item reflected essential content aligned with the construct, thereby enhancing the instrument's content validity before empirical testing. A panel of five domain experts, including scholars in educational psychology, AI in education, and psychometrics, rated each item's necessity using a three-point scale. All items met or exceeded the acceptable threshold for five experts (CVR ≥ .62), reflecting a strong consensus on their relevance. Consequently, no items were eliminated. However, in line with qualitative feedback from the panel, minor linguistic adjustments were made to enhance clarity and ensure alignment with Turkish academic discourse and cultural norms. This multi-step validation procedure strengthened both the linguistic fidelity and construct validity of the adapted instrument. Subsequently, a pilot test was conducted with 30 teacher candidates. The pilot results confirmed the instrument's overall clarity and internal coherence, with no major comprehension issues reported. Internal reliability, assessed via Cronbach's alpha, yielded a coefficient of 0.76, indicating acceptable internal consistency for early-stage implementation (George & Mallery, 2024).

The final CFA model consisted of three latent dimensions. The first factor, *technological self-efficacy*, included three items (e.g., "I consider myself skilled and knowledgeable about AI") and demonstrated acceptable internal consistency (Cronbach's α = .71). The second factor, *attitudes toward AI in education*, comprised nine items (e.g., "AI will play an important role in education" and "All pre-service teachers should receive training on AI") and showed good reliability (Cronbach's α = .85). The third factor, *pedagogical use of educational technologies*, contained four items (e.g., "I have considerable experience in using educational technologies to support student learning") with good internal consistency (Cronbach's α = .81).

The CFA conducted on the full sample (n=529) demonstrated that the three-factor model adequately fit the observed data, supporting the structural validity of the adapted scale. Specifically, the fit indices indicated acceptable to good model fit ($\chi^2/df = 2.88$; RMSEA = .060; CFI = .938; TLI = .924; SRMR = .044). These values

fall within the recommended thresholds (e.g., RMSEA < .08, CFI/TLI > .90, SRMR < .08), suggesting that the hypothesised factor structure reflects the underlying data well (Hu & Bentler, 1999).

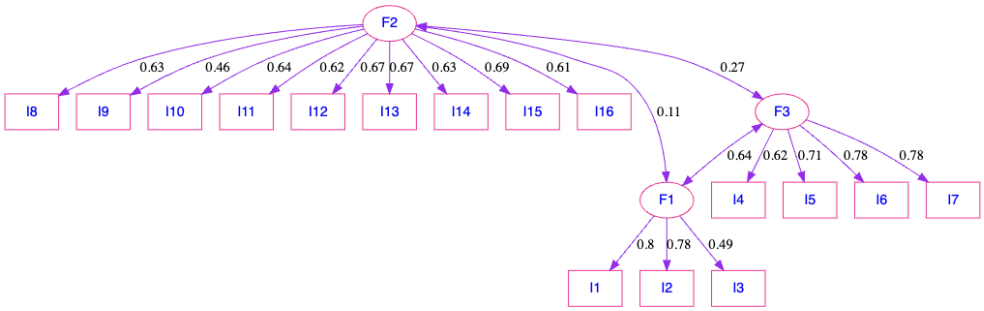


Figure 1. *Standardised Path Diagram of the CFA Model*

The standardised factor loadings for the items ranged from .49 to .80, all statistically significant at $p < .001$, indicating adequate item reliability (see Figure 1). Composite Reliability (CR) was used to assess internal consistency, as it provides a more precise estimate of construct reliability than Cronbach's alpha by incorporating standardised loadings and measurement error (Hair et al., 2010). The CR values for Technological Self-Efficacy, Attitudes toward AI in Education, and Pedagogical Use of Educational Technologies were .81, .87, and .86, respectively, exceeding the recommended .70 threshold (Fornell & Larcker, 1981). These results provide strong evidence of internal consistency and support the reliability of the three-factor measurement model. The final version of the instrument consisted of 16 Likert-type items focused on various aspects of AI-related attitudes, competencies, and expectations in education, without being pre-organised into subscales. This allowed for item-level person-centred modelling using LPA, enabling the identification of distinct attitudinal patterns among participants. The scale represents a context-sensitive, pedagogically grounded, and methodologically sound tool for assessing teacher candidates' engagement with AI in education.

Data Analysis

Quantitative analyses were conducted to examine Turkish pre-service teachers' attitudes toward AI. Initially, descriptive statistics were computed using SPSS version 29.0.2 to summarise participants' demographic characteristics and response distributions. Prior to modelling, data were screened for outliers and missing values; no missing data were found. To standardise scale differences and ensure equal weighting, all three AI-related variables were transformed into standardised z-scores before further analysis. To verify the factor structure of the adapted instrument, CFA was conducted using R (version 4.3.2; R Core Team, 2025), employing the Maximum Likelihood (ML) estimation method. Model fit was evaluated using multiple indices, including χ^2/df, RMSEA, CFI, TLI, and SRMR, in accordance with conventional thresholds (e.g., Hu & Bentler, 1999).

Following the validation of the measurement model, LPA was performed using Mplus 8.9 - ML estimation on the standardised (Z-score) total scores of the three dimensions: AI self-efficacy, pedagogical use of educational technologies, and attitudes toward AI in education. Competing models with two to six latent profiles were tested and compared using a combination of statistical indicators, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), entropy values, and likelihood-based tests such as the Lo–Mendell–Rubin adjusted likelihood ratio test (LMR-LRT) and Bootstrap Likelihood Ratio Test (BLRT). The optimal number of profiles was determined based on both statistical fit and theoretical interpretability. To examine group differences across the latent profiles, one-way ANOVAs were conducted on the original AI-related scale scores, followed by

Tukey HSD post-hoc comparisons. Additionally, chi-square tests were used to investigate whether demographic variables (gender, programme type, and grade level) were significantly associated with latent profile membership. Effect sizes (e.g., η^2, ω^2, and Cramer's V) were reported to complement the significance tests. This multistep analytic strategy allowed for a comprehensive examination of both individual variation and group-level patterns in AI-related attitudes.

Research Ethics

The present study adhered to established ethical guidelines governing research with human participants, ensuring the protection of participants' rights, confidentiality, and informed consent throughout the research process. Prior to data collection, ethical approval was obtained from the Çankırı Karatekin University Ethics Committee for Science, Mathematics and Social Sciences (Meeting No: 38, Approval Date: 23 February 2024). The study adhered to the principles outlined in the Declaration of Helsinki and complied with institutional and national ethical guidelines for research with human subjects.

FINDINGS

Latent profile models ranging from two to six classes were estimated using participants' standardised scores on three AI-related dimensions. Model adequacy was evaluated based on multiple statistical indices, including the AIC, BIC, entropy, LMR-LRT and BLRT. The fit statistics are summarised in Table 2. AIC and BIC were used to compare model parsimony, with lower values indicating better fit. Entropy, which ranges from 0 to 1, provides an index of classification precision and is often interpreted similarly to a reliability coefficient for profile assignment. Values of .80 or higher suggest strong classification quality, whereas values above .60 are generally considered acceptable (Asparouhov & Muthén, 2014). While not a primary selection criterion, entropy can offer valuable insight when competing models yield similar fit indices, as it reflects how accurately the established model classifies individuals into latent classes (Rost, 2006).

Table 2. Model Fit Indices for Competing Latent Profile Solutions (Two- to Six-Class Models)

Classes	AIC	BIC	Entropy	LMR-LRT p	BLRT p	Best Loglik
2	8337.62	8380.33	0.765	<.001	<.001	-4158.81
3	8302.13	8371.92	0.792	0.032	<.001	-4126.07
4	8288.32	8385.19	0.768	0.136	<.001	-4116.16
5	8295.40	8419.35	0.757	0.311	0.210	-4111.70
6	8311.24	8462.27	0.710	0.548	0.410	-4105.62

Model fit improved considerably from the two- (AIC = 8337.62, BIC = 8380.33, entropy = .765) to the three-class solution (AIC = 8302.13, BIC = 8371.92, entropy = .792), with a statistically significant LMR-LRT (p = .032) and high entropy, indicating good classification precision. While the four-class model yielded slightly better AIC (8288.32) and BIC (8385.19) values, the LMR-LRT became non-significant (p = .136), and entropy decreased (0.768). The five- and six-class models also showed further declines in model fit and classification quality, with LMR-LRT p-values > .30 and entropy values below .76. Based on statistical criteria and interpretability of the profiles, the three-profile solution was retained as the most parsimonious and theoretically meaningful model. Posterior classification probabilities for the three classes ranged between .87 and .94, and the entropy value (0.792) suggested satisfactory separation between profiles.

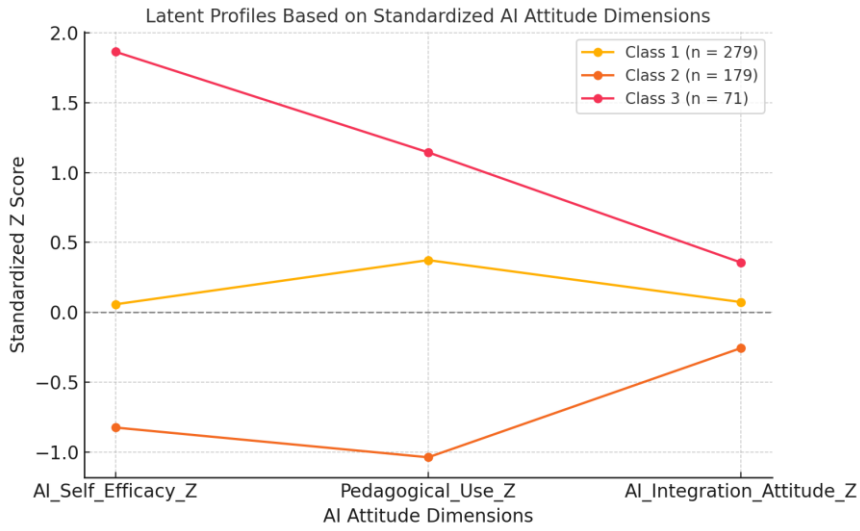


Figure 2. *Latent profiles based on standardised AI attitude dimensions*

As illustrated in Figure 2, the latent profile analysis identified three distinct groups of pre-service teachers based on their standardised scores across AI-related dimensions. The first and largest group (Class 1, Balanced Readiness, n = 279, 52.7%) exhibited moderate levels of AI self-efficacy, pedagogical technology use, and attitudes toward AI integration. The second group (Class 2, Low-Readiness Sceptics, n = 179, 33.8%) reported consistently low scores across all three dimensions, indicating limited confidence in AI-related competencies and less favourable attitudes toward the educational use of AI. The third and smallest group (Class 3, AI-Confident Advocates, n = 71, 13.5%) demonstrated the highest standardised scores on all three dimensions, suggesting strong self-efficacy, frequent pedagogical use of technology, and strong support for AI integration in education. These profiles reflected both level-based (quantitative) and shape-based (qualitative) differentiation, offering nuanced insight into pre-service teachers' readiness for AI-enhanced teaching contexts.

The labelling of the three profiles was based on the standardised mean scores across the three latent dimensions rather than on individual items. Participants in the Low-Readiness Sceptics group showed consistently low Z-scores on AI self-efficacy, pedagogical technology use, and AI integration attitude, reflecting limited confidence and cautious perceptions towards AI in education, hence the "Sceptic" label. In contrast, the Balanced Readiness group displayed moderate, balanced levels across all three dimensions, indicating a stable but developing readiness, while the AI-Confident Advocates demonstrated strong positive scores on each factor, representing high confidence, pedagogical engagement, and strong support for AI integration.

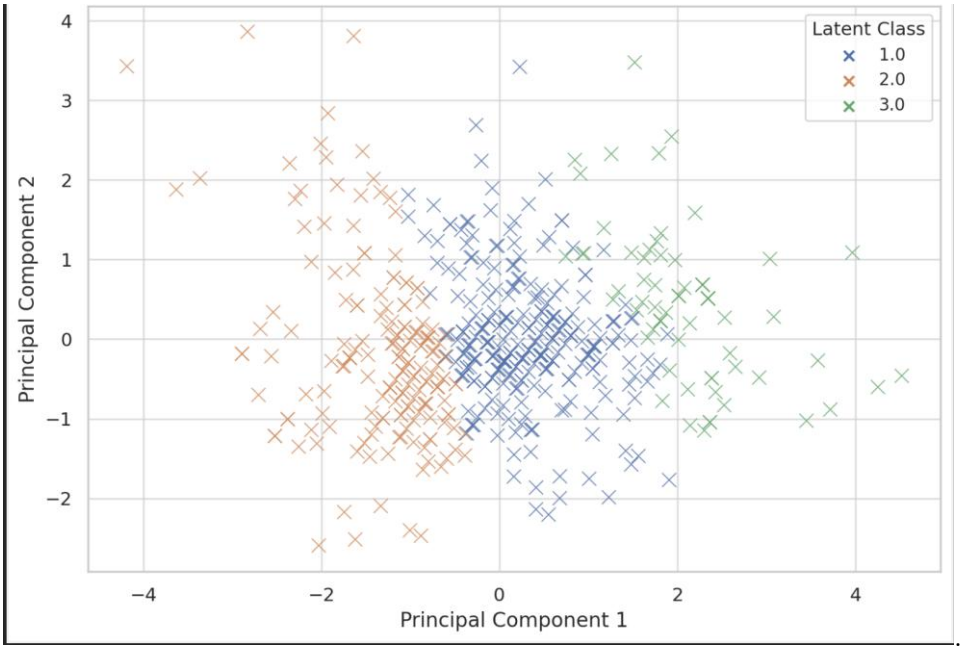


Figure 3. *2D scatter plot of participants by latent class*

To visually examine and validate the distinctiveness of the latent profiles derived from the LPA, a two-dimensional scatter plot was generated using principal component analysis (PCA) based on the standardised scores of the three AI attitude dimensions (see Figure 3). Each point in the plot represents an individual participant, positioned according to their values on the first two principal components, which together accounted for the majority of the variance in the original data. Colour coding was used to indicate class membership. This scatter plot complements the profile structure by providing a visual confirmation of the separation between latent classes, based on the overall variance captured from the standardised attitude dimensions. While some degree of overlap was expected due to the continuous nature of the latent traits, the spatial clustering observed in the plot aligns closely with the Z-score patterns observed across profiles. This visual representation further supports the robustness and interpretability of the three-profile solution identified in the analysis.

Table 3. Distribution of Demographic Characteristics Across Latent Profiles

Demographic Variable	Category	Class 1 (n=279)	Class 2 (n=179)	Class 3 (n=71)
Gender	Female	187 (67.0%)	131 (73.2%)	45 (63.4%)
	Male	92 (33.0%)	48 (26.8%)	26 (36.6%)
Age	20	43 (15.4%)	34 (19.0%)	8 (11.3%)
	21	56 (20.1%)	34 (19.0%)	11 (15.5%)
	22	64 (22.9%)	44 (24.6%)	14 (19.7%)
	23	63 (22.6%)	39 (21.8%)	19 (26.8%)
	24	28 (10.0%)	12 (6.7%)	12 (16.9%)
	25	21 (7.5%)	11 (6.1%)	5 (7.0%)
	26	4 (1.4%)	5 (2.8%)	2 (2.8%)
Programme Type	Pedagogical Formation	141 (50.5%)	97 (54.2%)	35 (49.3%)
	Faculty of Education	138 (49.5%)	82 (45.8%)	36 (50.7%)
Grade Level	2	94 (33.7%)	88 (49.2%)	21 (29.6%)
	3	42 (15.1%)	22 (12.3%)	12 (16.9%)
	4	143 (51.3%)	69 (38.5%)	38 (53.5%)

Table 3 presents the distribution of participants across the three latent profiles in terms of gender, programme type, and grade level. In terms of gender, females were slightly more prevalent across all profiles, although the differences were not statistically significant. Programme type (i.e., faculty of education vs. pedagogical formation) was also evenly represented within each profile. However, a noticeable pattern emerged in grade level: higher-grade students (3rd and 4th year) appeared more frequently in the highly engaged profile, while earlier-grade students were more concentrated in the moderately engaged group.

Table 4. Chi-Square Test Results for Differences in Latent Profile Membership Across Demographic Variables

Demographic Variable	χ^2 (df)	p-value	Cramer's V
Gender	2.97 (2)	.227	.075
Programme Type	0.76 (2)	.685	.038
Grade Level	13.81 (4)	.008	.114

Chi-square tests were conducted to examine whether latent profile membership varied according to participants' demographic characteristics, including gender, programme type, and grade level (see Table 4). The results showed no statistically significant differences in profile membership by gender ($\chi^2(2) = 2.97$, $p = .227$, Cramer's $V = .075$), or programme type ($\chi^2(2) = 0.76$, $p = .685$, Cramer's $V = .038$), suggesting that these characteristics were evenly distributed across the latent classes. However, grade level was significantly associated with profile membership ($\chi^2(4) = 13.81$, $p = .008$, Cramer's $V = .114$), indicating that students in more advanced grades were more likely to belong to the higher-readiness profiles. This suggests that as teacher candidates progress through their programmes, their pedagogical experience, exposure to educational technologies, and opportunities

to engage with AI-related discussions may enhance both their confidence and openness to AI integration. Although the effect size was small (Cramer's V = .114; values below .20 are considered small for three-category variables; Cohen, 1988), the finding underscores the importance of considering academic seniority when interpreting latent profiles in pre-service teacher populations.

Table 5. Differences in AI Attitude Dimensions Across Latent Profiles

AI Attitude Variable	F (df)	p-value	η^2 (Effect Size)	Significant Differences (Tukey HSD)
AI Self-Efficacy	613.21 (2,526)	<.001	.700	All groups differ: Low-Readiness Sceptics < Balanced Readiness < AI-Confident Advocates
Pedagogical Tech Use	420.61 (2,526)	<.001	.615	All groups differ: Low-Readiness Sceptics < Balanced Readiness < AI-Confident Advocates
AI Integration Attitude	11.59 (2,526)	<.001	.042	Low-Readiness Sceptics < Balanced Readiness ≈ AI-Confident Advocates

One-way ANOVAs were conducted using standardised total scores to assess whether the latent profiles differed significantly across AI-related attitudes (see Table 5). The results indicated robust group differences across all three dimensions. For AI self-efficacy, the analysis yielded a large and statistically significant effect ($F_{(2, 526)}$= 613.21, $p < .001$, $\eta^2 = .700$), indicating substantial differences among the latent profiles. According to conventional benchmarks (Cohen, 1988), η^2 values above .14 represent large effects, suggesting that AI self-efficacy was a key discriminating dimension among the groups. Post-hoc Tukey tests revealed that Low-Readiness Sceptics reported the lowest self-efficacy scores, followed by Balanced Readiness, while AI-Confident Advocates had the highest scores, with all pairwise comparisons reaching significance. A similarly strong effect was observed for pedagogical technology use ($F_{(2, 526)}$= 420.61, $p < .001$, $\eta^2 = .615$), again indicating a large magnitude of difference among the profiles (Cohen, 1988) with the same ordering of group means: Low-Readiness Sceptics < Balanced Readiness < AI-Confident Advocates. Again, all groups differed significantly from one another. Lastly, a smaller but statistically significant group difference emerged for attitudes toward AI integration ($F_{(2, 526)}$ = 11.59, $p < .001$, $\eta^2 = .042$). In this case, although Low-Readiness Sceptics scored significantly lower, the difference between Balanced Readiness and AI-Confident Advocates was not statistically significant, suggesting a shared openness to AI integration despite varying levels of confidence and pedagogical application. This pattern may reflect a conceptual endorsement of AI's potential benefits among both groups, even though only the latter may possess the pedagogical confidence and practical readiness to implement it effectively. In other words, while attitudes may reflect willingness or ideological support, actual classroom integration likely depends more on perceived self-efficacy and technological fluency, factors that distinguish the two groups. These findings support both the statistical distinctiveness and theoretical interpretability of the three-profile solution.

The qualitative labelling of the three latent profiles was informed by both the relative mean levels and the interpretive patterns observed across the AI-related dimensions. Specifically, the first group was labelled Balanced Readiness as members demonstrated moderate and consistent scores on all dimensions, indicating a balanced but not advanced preparedness for AI integration. The second group, characterised by the lowest scores in AI self-efficacy, pedagogical technology use, and attitudes toward AI, was defined as Low-Readiness Sceptics to reflect their limited confidence and cautious stance toward AI in education. In contrast, the third group, exhibiting the highest scores across all variables, was termed AI-Confident Advocates, representing participants with strong self-efficacy, frequent pedagogical technology use, and positive orientations toward AI adoption. These labels thus capture both the quantitative level differences (low, moderate, high) and the qualitative attitudinal orientations distinctive to each latent class.

DISCUSSION & CONCLUSION

The present study investigated the attitudinal orientations of Turkish pre-service teachers toward AI in education using LPA, identifying three distinct psychological profiles: AI-Confident Advocates, Balanced Readiness, and Low-Readiness Sceptics. These profiles revealed a substantial heterogeneity in the participants' AI-related self-efficacy, pedagogical technology use, and general attitudes toward AI integration. Unlike variable-centred approaches that assume a uniform pattern across the sample, the person-centred LPA enabled the identification of meaningful subgroups based on item-level response patterns, allowing for a more differentiated understanding of teacher candidates' dispositions. This methodological approach aligns with recent research advocating for individualised analyses to capture latent psychological diversity, especially in technology

acceptance studies (Howard & Hoffman, 2018; Spurk et al., 2020). The three-profile solution demonstrated both statistical adequacy and theoretical coherence, suggesting that the attitudinal readiness of teacher candidates toward AI is far from monolithic.

The AI-Confident Advocates, though the smallest group, represented a highly engaged cluster characterised by elevated self-efficacy, frequent use of educational technologies, and strong positive attitudes toward AI integration. Their psychological profile is consistent with the concept of "early adopters" in diffusion theory, individuals who are not only open to innovation but often serve as agents of change within educational systems (Rogers, 2003). From the perspective of the Technology Acceptance Model (Davis, 1989), this group also reflects high perceived usefulness and perceived ease of use, which may explain their positive orientation and confidence in integrating AI tools into teaching practice. This group's presence is particularly notable given the still-developing infrastructure of AI integration in Türkiye's educational institutions, suggesting that some teacher candidates are already poised to lead AI-based pedagogical transformations. The high self-efficacy, frequent pedagogical technology use, and positive attitudes observed in this profile indicate a stronger readiness to use AI as an active component of lesson planning, assessment, and adaptive instruction, beyond purely administrative tasks. While prior research has linked digital fluency and technology exposure with greater confidence toward educational technologies (e.g., Lei & Liu, 2022), we did not directly measure these constructs here; therefore, we refrain from attributing the observed differences to prior exposure. Instead, our interpretation emphasises the central role of self-efficacy, pedagogical engagement, and positive attitude as the key characteristics distinguishing this group.

The largest group, Balanced Readiness, comprised more than half of the sample and exhibited moderate levels across all three measured dimensions. While not as confident as the advocate group, they expressed relatively positive attitudes toward AI's role in education. This group may represent an ambivalent yet open cohort who could potentially transition into confident users with proper institutional support and structured exposure to AI tools. Their moderate positioning mirrors findings in international literature where educators express conceptual support for AI but simultaneously report uncertainty or low implementation due to lack of training or contextual barriers (Yu, 2021; Zawacki-Richter et al., 2019). In the Turkish context, this pattern may also reflect structural gaps in AI-specific teacher education curricula, which tend to prioritise general ICT competencies while overlooking the pedagogical integration, ethical implications, and classroom applications of AI technologies (IPA III, 2024). The Balanced Readiness group, therefore, underscores the importance of strengthening pedagogical and reflective components within current teacher education frameworks to bridge this gap. Although these participants showed openness toward AI integration, their moderate positioning suggests that their engagement may not yet be supported by sufficient AI-specific training, consistent with national reports on teacher preparation practices (IPA III, 2024; İçen, 2022).

Conversely, the Low-Readiness Sceptics profile presented a more challenging picture. These individuals reported the lowest levels of AI self-efficacy, minimal pedagogical use of educational technology, and overall sceptical attitudes toward AI in education. Their resistance appears both attitudinal and behavioural and may stem from negative emotional responses, lack of institutional encouragement, or broader concerns about AI's implications. Consistent with previous research (Busch, 2023; Fietta et al., 2022), the scepticism observed among this group aligns with self-reported concerns such as fears of being replaced, ethical uncertainties, and difficulties in managing technological complexity. In the Turkish context, such scepticism may also be shaped by systemic conditions, including the relatively recent emphasis on AI in education and limited opportunities for teacher candidates to engage with AI-focused pedagogical practices or ethical discussions. Although this interpretation remains tentative, it corresponds with broader observations that national teacher education frameworks have only begun to incorporate AI-related competencies. Importantly, their scepticism is not necessarily fixed but may be amenable to change through sustained, supportive exposure and targeted professional development initiatives. Addressing this group's concerns requires both emotional scaffolding and opportunities to engage with AI in low-risk, pedagogically meaningful ways. This pattern may also reflect structural limitations within current teacher education programmes in Türkiye, where courses rarely incorporate AI-specific content or practice-based digital pedagogy components. The absence of systematic exposure to AI applications, critical discussions on ethics, and experiential learning opportunities may contribute to the limited confidence and scepticism observed among this group. Embedding AI literacy and pedagogical technology integration into pre-service teacher curricula could therefore play a crucial role in transforming scepticism into informed engagement and readiness for AI-enhanced teaching.

The comparison across profiles revealed significant differences in all three measured constructs, particularly in AI self-efficacy and pedagogical technology use. Post-hoc analyses confirmed that each group differed significantly from the others on these variables, following a clear linear progression. Interestingly, attitudes toward AI integration, while statistically different between the Sceptics and the other groups, did not significantly differ between Balanced Readiness and AI-Confident Advocates. This suggests that while belief in the value of AI may be increasingly shared, the capacity to act on those beliefs diverges significantly based on individual levels of confidence and technological competence. This finding is supported by Bandura's (1986) social cognitive theory, which emphasises the mediating role of self-efficacy between beliefs and actions in technology-related behaviour. Empirical research similarly confirms that teachers' beliefs about their technological competence strongly predict their intention and ability to integrate technology into teaching (Sang et al., 2010; Teo, 2009; Tondeur et al., 2017). This underscores that positive attitudes alone are insufficient for meaningful pedagogical transformation; educators also require confidence in their capacity to translate these beliefs into effective practice.

Although demographic characteristics such as gender, and programme type did not significantly predict latent profile membership, this finding should be interpreted carefully in light of previous research. Previous studies have often reported that gender plays a significant role in shaping attitudes toward AI, with males typically exhibiting more favourable dispositions and females expressing greater concern over ethical and practical issues (Fietta et al., 2022; Kim & Lee, 2024). Additionally, the near-equal gender distribution and the standardisation of teacher education programmes across faculties and pedagogical formation routes in Türkiye may have contributed to this statistical non-significance. Another plausible explanation lies in the possibility that traditional gender-based attitudinal gaps are gradually narrowing among newer cohorts of teacher candidates, especially as digital literacy becomes increasingly integrated into both formal education and daily life. This shift may reflect broader sociocultural transformations in Türkiye, where access to technology has expanded and digital competencies are no longer disproportionately distributed by gender or academic track. Nonetheless, the significant effect of grade level suggests that pedagogical maturity and accumulated exposure to educational technologies are critical factors in shaping AI readiness, potentially overriding the influence of static demographic traits. These findings underscore the importance of considering developmental and contextual variables over purely demographic ones when designing interventions aimed at fostering AI integration in teacher education.

The study's results have important implications for policy and practice. First, the identification of attitudinal subgroups allows for the design of differentiated professional development pathways, where interventions are tailored according to psychological readiness. One-size-fits-all approaches risk alienating both the most sceptical and the most advanced users. Institutions might consider implementing diagnostic instruments at the beginning of teacher education programmes to assign students to training tracks that align with their attitudinal profile. Second, the findings highlight the need for curriculum developers to move beyond surface-level digital skills and incorporate critical engagement with AI, including discussions of ethical dilemmas, algorithmic bias, and AI's limitations in human-centric learning. In parallel, teacher education programmes should actively promote AI-related self-efficacy and pedagogical application by embedding hands-on practice, modelling successful AI use in instructional contexts, and providing mentorship or peer-supported learning opportunities. Such experiential and reflective components have been shown to strengthen confidence and willingness to integrate AI in teaching (Teo, 2009; Tondeur et al., 2017). Finally, the results suggest that grade-level interventions might be especially timely; upper-year students appear more prepared, which implies that earlier integration of AI literacy in the curriculum may accelerate readiness across the board.

In conclusion, this study contributes to a growing body of literature exploring the human dimensions of AI integration in education by revealing the presence of psychologically distinct attitudinal profiles among Turkish pre-service teachers. These findings emphasise the necessity of adopting person-centred approaches in both research and practice, as educators' readiness for AI is shaped not only by structural access or institutional mandates but by their individual confidence, beliefs, and pedagogical habits. As education systems increasingly turn to AI for solutions to complex challenges, understanding and supporting the human element will be critical to ensuring that these technologies are used in ways that are inclusive, ethical, and genuinely transformative for teaching and learning.

Limitations

Despite its contributions, this study is not without limitations. Its cross-sectional design precludes any causal inferences about how attitudes toward AI develop over time; longitudinal research could offer greater insight into the stability and evolution of these attitudinal profiles. Additionally, the reliance on self-reported data

may introduce biases, including social desirability effects, although anonymity and voluntary participation were ensured. The sample consisted of Turkish pre-service teachers drawn from two distinct programmes, education faculties and pedagogical formation courses, which may have introduced unobserved group differences influencing the latent profiles. Future studies should aim to examine these subgroups separately or statistically control for potential programme-level effects. Furthermore, while the adapted attitude scale demonstrated good psychometric properties, it may not capture all dimensions of AI perception, such as ethical concerns or privacy-related anxieties. Incorporating qualitative components or adopting a mixed-methods design could help triangulate and validate the present findings by revealing deeper motivational and contextual factors underlying participants' responses. Finally, as the data were collected within the Turkish higher education context, the findings may not be generalisable to other educational systems. Future research should consider more diverse sampling, behavioural measures, and cross-cultural comparisons to enhance the robustness and applicability of the results.

Statements of Publication Ethics

Ethical approval was obtained from the Çankırı Karatekin University Ethics Committee for Science, Mathematics and Social Sciences (Meeting No: 38, Approval Date: 23 February 2024).

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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