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The Role of ICT Self-Efficacy, Technostress, Individual Innovativeness and Mindset on Artificial Intelligence Literacy

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Abstract

This study examines the various factors that influence the development of artificial intelligence (AI) literacy among pre-service teachers. The research delves into the intricate interrelations among Information and Communication Technologies (ICT) self-efficacy, technostress, individual innovativeness, mindset orientation, and AI literacy, utilizing a sample of 620 pre-service teachers from diverse educational faculties throughout Turkiye. Empirical data were amassed employing validated measurement instruments, which include the ICT Self-Efficacy Scale, Teachers' Technostress Level Scale, Individual Innovativeness Scale, Mindset Theory Scale, and Generative AI Literacy Scale. The results indicate that ICT self-efficacy is identified as the most substantial predictor of AI literacy, whereas technostress is found to exert a significant detrimental effect. Furthermore, individual innovativeness alongside growth mindset dimensions—comprising effort and belief in personal development—also serve as significant predictors of AI literacy. The holistic model accounts for 28.8% of the variance associated with AI literacy. These findings furnish critical evidence-based insights for educational institutions, policymakers, and teacher education programs aimed at promoting the advancement of AI literacy by addressing psychological impediments and capitalizing on enabling factors within the framework of educational technology integration.

Keywords: Artificial intelligence literacy; ICT self-efficacy; technostress; individual innovativeness; mindset; university students

1. Introduction

The quick development of artificial intelligence (AI) applications in academic frameworks has generated an unparalleled necessity for instructors to gain substantial knowledge in AI literacy (Luckin & Holmes, 2016). As AI-enhanced educational instruments, individualized learning frameworks, and intelligent tutoring systems are increasingly assimilated into academic settings, pre-service educators are required to

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attain not merely technical expertise but also a profound comprehension of AI's pedagogical ramifications, ethical dilemmas, and societal consequences (Holmes, Bialik, & Fadel, 2023). This technological evolution signifies a fundamental transformation that fundamentally contests conventional pedagogical methodologies and compels a thorough reassessment of teacher training programs (Chen, Chen, & Lin, 2020).

As described by Long and Magerko (2020), AI literacy involves "the proficiency to comprehend, use, and evaluate AI systems critically, while addressing their ethical and societal implications." This diverse capability reaches past standard digital literacy to merge algorithmic thought, data skills, and qualifications associated with human-AI interactions (Touretzky, Gardner-McCune, Martin, & Seehorn, 2019). Differing from conventional technology integration, fostering AI literacy compels educators to comprehend elaborate decision-making frameworks, analyze algorithmic outputs, and navigate the intricate dynamics of human cognition alongside artificial systems (Ng, Leung, Chu, & Qiao, 2021).

Nevertheless, the development of artificial intelligence literacy among pre-service educators is influenced by a complex interplay of psychological, technological, and cognitive factors that engage in sophisticated dynamics. Empirical research indicates that individuals' perceptions of their technological competencies, their affective responses to the adoption of technology, their openness to innovative methodologies, and their fundamental beliefs regarding skill development significantly affect their engagement with emerging technologies (Dweck, 2006; Rogers, 2003; Scherer, Siddiq, & Tondeur, 2019; Tarafdar, Pullins, & Ragu-Nathan, 2014). Despite the critical importance of understanding these interconnections, there exists a notable gap in the academic literature pertaining to comprehensive frameworks that examine the simultaneous and interactive effects of these elements on the enhancement of AI literacy.

1.1. *The Educational Technology Landscape and AI Integration*

The present educational structure is lauded for its quick technological upgrades and a rising digital evolution in instructional approaches. The pandemic-related health situation has sped up this change, requiring that learning organizations everywhere urgently incorporate technological progress and seek out inventive instructional techniques (Hodges, Moore, Lockee, Trust, & Bond, 2020). In this milieu, advancements in artificial intelligence have surfaced as significantly advantageous instruments for augmenting educational effectiveness, personalizing learning pathways, and aiding both instructors and learners in attaining elevated educational achievements (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019).

The deployment of artificial intelligence applications within the educational domain encompasses an extensive array of tools and frameworks, including individualized learning environments, advanced tutoring systems, automated assessment instruments, virtual assistants for learner support, and predictive analytics designed to identify students who may be at risk of academic underperformance (Zhai et al., 2021). Emerging technologies create vast opportunities for shaping personalized educational routes that address the specific demands, interests, and approaches to learning of every learner (Hwang, Xie, Wah, & Gašević, 2020). Findings demonstrate that educational frameworks refined by artificial intelligence can amplify student participation, enhance scholarly achievement, and deliver significant viewpoints on instructional methods that were formerly tough to grasp (Roll & Wylie, 2016).

Yet, the fruitful blending of artificial intelligence tools in teaching contexts hinges primarily on the preparedness, knowledge, and willingness of instructors to welcome these developments (Celik, Dindar, Muukkonen, & Järvelä, 2022). Teachers in training, acknowledged as the forthcoming leaders responsible for impacting the next cohort of learners, carry a remarkably crucial duty in this online advancement. Their proficiency in artificial intelligence will significantly influence the effectiveness of AI technologies' assimilation into educational methodologies and the degree to which learners are prepared for an AI-oriented society (Chiu & Chai, 2020).

1.2. *. Theoretical Framework: ICT Self-Efficacy and Technology Adoption*

As per Bandura's social cognitive theory (Bandura, 1997), ICT self-efficacy signifies the beliefs that individuals carry regarding their adeptness in applying and merging information and communication technologies within the sphere of education. This framework includes three essential aspects: technical skills (the capacity to handle technological tools), pedagogical application (the talent to utilize technology for learning goals), and troubleshooting skills (the proficiency to resolve issues and adjust when encountering technological obstacles) (Hatlevik & Christophersen, 2013).

The empirical evidence derived from a multitude of scholarly investigations indicates that the degree of trust educators possess in their own information and communication technology (ICT) proficiencies profoundly influences their engagement with and adoption of technological advancements (Tondeur, Van Braak, Siddiq, & Scherer, 2016). Educators who demonstrate heightened self-efficacy in their ICT skills are typically more predisposed to engage in innovative methodologies that incorporate emerging technologies, confront implementation challenges, and adeptly integrate technological tools into their pedagogical frameworks (Ertmer & Ottenbreit-Leftwich, 2010). The link is notably important in the realm of advancing artificial intelligence (AI) abilities, since developments in AI generally include sophisticated interfaces and demand a full comprehension of vital algorithms and data frameworks (Koehler & Mishra, 2009).

The connection that exists between one's confidence in ICT abilities and understanding of AI can be clarified using different theoretical models. Initially, persons who demonstrate a high degree of ICT self-efficacy reveal increased certainty in their potential to integrate new technologies, thereby easing worries and improving their readiness to use AI tools (D. R. Compeau & Higgins, 1995). Furthermore, heightened ICT self-efficacy is associated with more proficient problem-solving approaches when confronted with technological obstacles, thereby empowering individuals to navigate the learning curve inherent in AI technologies (Agarwal, Sambamurthy, & Stair, 2000). To encapsulate, the measure of assurance that individuals possess in their ICT proficiency influences their opinions about the practicality and functionality of novel technologies, which are crucial in models that interpret technology adoption (Venkatesh, Morris, Davis, & Davis, 2003).

1.3. *Technostress as a Psychological Barrier*

Initially articulated by Brod (1984) as "a modern adaptation disease caused by an inability to cope with new technologies in a healthy manner," technostress has evolved into a complex construct that encompasses a variety of technology-induced stressors and anxieties. In accordance with current scholarly discussions, there exist five essential dimensions of technostress: techno-overload (the compulsion to expedite work processes as a result of technological advancements); techno-invasion (the incessant pressure associated with constant connectivity); techno-complexity (challenges encountered in comprehending and utilizing sophisticated technologies); techno-insecurity (anxiety regarding the risk of obsolescence due to rapid technological evolution); and techno-uncertainty (ongoing fluctuations in technological landscapes) (Ragu-Nathan, Tarafdar, Ragu-Nathan, & Tu, 2008).

In the field of academic conversation, signs of technostress emerge as reflections of psychological pressure, irritation, and hesitance when educators engage with cutting-edge technologies or must weave technological resources into their teaching practices (Çoklar, Efilti, & Şahin, 2017). The intricate and at times unpredictable characteristics of artificial intelligence systems may exacerbate technostress, as these technologies typically employ 'black box' algorithms that are challenging for users to comprehend or exert control over (Burrell, 2016). Such vagueness might stir emotions of insecurity and apprehension, mainly for instructors who emphasize comprehension and proficiency in their teaching aids (Shin, 2021).

Investigative studies emphasize that technostress profoundly limits the crafting and successful utilization of technology (Ayyagari, Grover, & Purvis, 2011). Individuals subjected to substantial levels of technostress frequently engage in the avoidance of novel technological innovations, demonstrate diminished performance in the application of technological tools, and encounter a decline in job satisfaction and overall life quality (Maier, Laumer, Weinert, & Weitzel, 2015). Within the context of AI literacy enhancement, technostress may represent considerable barriers to both learning and active participation, thereby impeding pre-service educators from developing the necessary competencies essential for the successful integration of AI within their future educational environments (Joo, Lim, & Kim, 2011).

1.4. *Individual Innovativeness and Change Adoption*

Individual innovativeness, as delineated within Rogers' Diffusion of Innovation Theory (Rogers, 2003), pertains to the extent to which individuals exhibit a propensity to experiment with novel concepts and embrace innovations more swiftly than their peers within the social framework. This design features multiple critical traits: a capacity to welcome risk, an openness to new situations, an allowance for uncertainty, and a desire to find original solutions to difficulties (Hurt, Joseph, & Cook, 1977).

Empirical evidence indicates that individual innovativeness exerts a substantial impact on technology adoption behaviors, whereby individuals characterized by high levels of innovativeness are more inclined to engage in experimentation with new technologies, explore imaginative applications, and assume the role of opinion leaders who affect others' decisions regarding adoption (Agarwal & Prasad, 1998). Within educational settings, teachers who are innovative are more prone to incorporate new technologies into their instructional methodologies and exhibit enhanced success in pedagogical approaches that are technology-enhanced (Kılıçer & Odabaşı, 2010).

Different pathways reveal how individual creativity interacts with the advancement of AI literacy. First off, those who are pioneering are typically more likely to delve into information about AI technologies and get involved in experimenting with AI tools in educational scenarios (Thong, Hong, & Tam, 2002). Additionally, they portray an enhanced tolerance for the unpredictability and complexity tied to advancing technologies, allowing them to continue through the educational path even when challenges arise (Lu, Yao, & Yu, 2005). Finally, forward-thinking people are generally more ready to appreciate the upcoming perks of AI tech and promote inventive uses that enhance their instructional impact (Yi, Fiedler, & Park, 2006).

1.5. *Mindset Theory and Learning Orientation*

Mindset theory, as articulated by Dweck (2006), delineates two fundamental orientations regarding the essence of human capabilities: the fixed mindset (a conviction that abilities represent immutable characteristics that are not subject to substantial modification) and the growth mindset (the assertion that abilities can be cultivated through diligence, education, and perseverance). This framework of ideas results in important outcomes regarding how individuals manage educational hurdles, react to challenges, and uphold their commitment during tough times (D. S. Yeager & Dweck, 2012).

Findings from hands-on investigations reveal that a person's perspective greatly influences their success in education, trends in motivation, and capacity for resilience across multiple areas (Blackwell, Trzesniewski, & Dweck, 2007). People who nurture a growth-focused attitude frequently reveal a stronger inclination to embrace challenges, understand failures as crucial teachings, and maintain their resolve when confronting barriers (Mueller & Dweck, 1998). In a different light, those embracing a static mindset often evade challenges, consider failures as markers of insufficient ability, and manifest a stronger tendency to quit their efforts when they run into hindrances (Hong, Chiu, Dweck, Lin, & Wan, 1999).

Within the landscape of boosting AI insight, one's perspective could carry a particularly crucial importance considering the complex and swiftly transforming character of AI breakthroughs. Fully understanding the principles of AI usually calls for sustained dedication, a realization of the unexplored, and an openness to tackle complex thoughts (Ali, Kumar, & Breazeal, 2023). Those with a growth-oriented perspective seem to manage these hurdles more adeptly, interpreting early setbacks as vital components of their learning experience instead of markers of inadequate proficiency (Elçiçek, 2024).

2. Literature Review

2.1. *Artificial Intelligence Literacy in Educational Contexts*

The grasp of AI has turned into an indispensable expertise for contemporary society, incorporating the essential information, competencies, and outlooks vital for understanding, applying, and judiciously reviewing AI advancements (Long & Magerko, 2020). Grasping AI literacy is not limited to just essential digital skills; it involves an understanding of how algorithms function, a firm grounding in machine learning basics, proficiency in analyzing data, and an insight into the ethical issues tied to AI technologies (Touretzky et al., 2019).

Recent investigations by scholars have outlined multiple core features of AI literacy. Apprehending the practical facets of AI frameworks is important, intertwining foundational notions about machine learning, neural networks, and data manipulation (Brennan & Resnick, 2012). Skills in practical application encompass the proficiency to utilize AI tools effectively for designated objectives, such as the creation of educational content, assessment methodologies, or personalized learning experiences (Lowyck, 2014). Sharpening the talent for critical evaluation means inspecting the dependability, subjective biases, and restrictions of AI technologies (Floridi et al., 2018). In the scope of ethical evaluation, it is vital to stress topics related to confidentiality, justice, lucidity, and the duties linked to the use of AI (Verma, 2019).

In the context of educational structures, the notion of AI literacy encompasses broader elements that are linked to instructional approaches and the subsequent learning effects for pupils. For teachers, it is paramount to understand the role of AI innovations in enhancing educational practices, supporting customized teaching methods, and shedding light on student performance and requirements (Holmes, Bialik, & Fadel, 2019). In addition, they should be equipped to help learners develop their own abilities in understanding AI and addressing the ethical and societal consequences of AI in today's world (Dai & Ke, 2022).

2.2. *Factors Influencing Technology Adoption in Education*

The assimilation and expert application of educational changes are dictated by a vibrant mosaic of influences that connect through personal, institutional, and societal layers (Ertmer, 1999). At the individual stratum, empirical studies have consistently delineated several pivotal predictors of technology assimilation among educators, encompassing perceived utility, perceived simplicity of use, self-efficacy beliefs, attitudes towards technology, and personal innovativeness (Davis, 1989).

The Technology Acceptance Model (TAM), when utilized with its modifications, has been vital in shaping models that aim to evaluate projects related to technology acceptance (Venkatesh et al., 2003). As per TAM, the propensity of people to accept technology is predominantly influenced by their judgment of the technology's operational effectiveness and ease of use (Davis, Bagozzi, & Warshaw, 1989). To wrap up, repeated evaluations have uncovered extra elements that profoundly impact technology acceptance, involving community factors, favorable settings, and unique individual attributes (Venkatesh & Davis, 2000).

In the realm of education, the impact of technology is distinctly essential to cater to the immediate necessity for harmonizing tech assets with pedagogical approaches and aspirations (Mishra & Koehler, 2006). The TPACK (Technological Pedagogical Content Knowledge) principle reveals the key obligation to understand the sophisticated dynamics that exist between technology, teaching strategies, and knowledge content to advance worthwhile technology deployment (Koehler & Mishra, 2009). The viewpoint maintains that maximizing the potential of technology requires a dual focus on technical expertise and a clear insight into how it can elevate targeted educational strategies and subject areas (Chai, Koh, & Tsai, 2013).

2.3. *Psychological Factors in Technology Learning*

The process of acquiring proficiency in new technological tools encompasses substantial psychological dimensions that can either promote or obstruct effective adoption and application (D. Compeau, Higgins, & Huff, 1999). Empirical investigations have delineated several pivotal psychological determinants that shape technology learning outcomes, such as self-efficacy beliefs, anxiety and stress responses, motivation and goal orientation, as well as metacognitive awareness (Bandura, 1991).

The beliefs surrounding self-efficacy take on a notably crucial role within the domain of technology learning, as they substantially impact individuals' willingness to engage with emerging technologies, their endurance in confronting hurdles, and their eventual proficiency in gaining technological skills (D. R. Compeau & Higgins, 1995). Individuals with pronounced confidence frequently reveal an increased zeal for hitting ambitious targets, invest more energy, and preserve their persistence longer through adversities (Bandura, 1997).

Responses of anxiety and stress can profoundly hinder technology learning by diminishing the cognitive resources accessible for the assimilation of new information and skills (Saadé & Kira, 2009). Anxiety concerning technology is especially common among those who have had unfavorable encounters with tech or see themselves as lacking in technological skills (Brosnan & Lee, 1998). This anxiety can engender a detrimental cycle wherein negative emotional states give rise to avoidance behaviors, consequently obstructing the progression of competence and self-assurance (Heinssen Jr, Glass, & Knight, 1987).

2.4. *The Role of Mindset in Technology Learning*

The theoretical framework of mindset has garnered heightened scrutiny within the realm of educational technology research, attributable to its profound implications regarding the manner in which individuals navigate learning challenges and respond to adversities (Dweck, 2006). Data collected from empirical studies underscores the significant impact of mindset on learning effectiveness in technology-driven fields, with a growth mindset correlated with increased grit, the adoption of more useful learning tactics, and improved performance statistics.

In terms of technological uptake, the way we think impacts several key procedures. Mainly, it dictates how persons regard trials and setbacks they confront as they progress through their educational experience (Dweck & Leggett, 1988). Those with a growth mindset typically interpret struggles as opportunities for advancement and development, whereas those with a fixed mindset may see these struggles as an indication of their limited capabilities (Diener & Dweck, 1978). Furthermore, an individual's cognitive processes greatly affect the goals they set themselves and the strategies they implement (Elliott & Dweck, 1988). Those who have a growth mindset usually emphasize their desire to learn and apply successful educational techniques, unlike their fixed mindset associates, who might fixate on meeting performance benchmarks and use ineffective strategies.

Investigations specifically addressing mindset within technological contexts have ascertained that a growth mindset is linked to an increased propensity to engage with novel technologies, more favorable attitudes towards technology-based learning, and improved outcomes in technology-related academic settings (Claro, Paunesku, & Dweck, 2016). These findings imply that interventions aimed at fostering a growth mindset may hold significant potential for enhancing educational outcomes in technology and mitigating anxiety and avoidance associated with technology engagement (David S Yeager et al., 2019).

3. Methodology

3.1. *Research Design*

This study took a quantitative approach, using a relational survey model to investigate the links between ICT self-efficacy, technostress, individual innovativeness, mindset and AI literacy among pre-service teachers. This framework is especially advantageous for exploring the interrelations of numerous variables within an educational environment without the necessity for manipulation, thereby facilitating the analysis of organically occurring correlations (Fraenkel, Wallen, & Hyun, 2006).

3.2. *Participants and Sampling*

The study sample consisted of 620 pre-service teachers from education faculties across Turkiye. To achieve a comprehensive representation from multiple geographic locations and institutional forms, we opted for a cluster sampling strategy to pick our participants. The sampling approach included organizing Turkish universities based on geographic locations (seven distinct areas) and institution types (public and private), followed by a random choice of universities within each category and subsequently a random choice of participants from these universities.

The demographic examination disclosed that an overwhelming majority of participants were women (79.7%, n = 494), consistent with the usual gender distribution recognized in Turkish education areas. Examining participation according to academic years shows that second-year students dominate with 37.4% (n = 232), with first-year students next at 30.5% (n = 189), fourth-year students at 19.5% (n = 121), and lastly, third-year students at 12.6%

(n = 78). Such a distribution suggests the noted enrollment behaviors identified in Turkish teacher education projects (YÖK, 2023).

In relation to the participants' familiarity with artificial intelligence, a substantial 94% (n = 583) acknowledged their acquaintance with AI concepts, whereas a mere 6% (n = 37) indicated that they had not previously engaged with AI-related materials. Additionally, 79.2% of the respondents (n = 491) affirmed having utilized generative AI tools at least once, in contrast to 20.8% (n = 129) who reported a lack of experience with such technological instruments. These findings underscore a pronounced level of awareness concerning artificial intelligence as well as a moderate degree of practical engagement among pre-service educators in Turkiye (Güler & Polatgil, 2025).

3.3. *Data Collection Instruments*

Data collection employed five validated instruments, each measuring specific constructs relevant to the research questions:

ICT Self-Efficacy Scale: Initially created by Fraillon et al. (2014) for the International Computer and Information Literacy Study (ICILS) and adapted to Turkish by Esiyok, Gökçearslan, and Küçükergün (2025), focusing on how well individuals feel they can use information and communication technologies. The scale consists of 6 items rated on a 6-point Likert scale ranging from "I don't know how to do this" to "I know very well how to do this." The scale exhibits robust psychometric attributes, evidenced by a Cronbach's alpha reliability coefficient of .88 in the present investigation.

Teachers' Technostress Level Scale: Çoklar, Efilti, and Şahin (2017) designed the Teachers' Technostress Level Scale to analyze five specific dimensions of stress arising from technology among teachers. The instrument comprises 28 items systematically categorized into five factors: Learning-Teaching Process Oriented (7 items), Professional Oriented (5 items), Technical Issue Oriented (6 items), Personal Source (5 items), and Social Oriented (5 items). The evaluation process utilizes a 5-point Likert scale, extending from 'Strongly Disagree' to 'Strongly Agree.' The scale exhibited exceptional reliability in the current investigation, evidenced by a Cronbach's alpha of .91.

Mindset Theory Scale: The Mindset Theory Scale, conceptualized by Yılmaz (2022) for individuals within the age range of 14 to 22 years, assesses the convictions regarding the inherent nature of intelligence and capabilities. The scale comprises 19 items categorized into four distinct dimensions: Inertia (4 items), Belief in Unchangeability (4 items), Belief in Development (6 items), and Effort (5 items). Respondents evaluate items utilizing a 5-point Likert scale, ranging from "Not at all aligned with my thoughts" to "Highly aligned with my thoughts." The scale demonstrated an acceptable level of reliability, exhibiting a Cronbach's alpha coefficient of .78 in the present investigation.

Individual Innovativeness Scale: he Individual Innovativeness Scale, initially conceptualized by Hurt, Joseph, and Cook (1977) and subsequently adapted for the Turkish context by Kılıçer and Odabaşı (2010), evaluates the propensity of individuals towards the adoption of innovations. The instrument comprises 20 items that are assessed using a 5-point Likert scale, which includes 12 items articulated in a positive manner and 8 items articulated in a negative manner. This scale classifies individuals into five distinct categories of innovation adoption: Innovators (80+ points), Early Adopters (69-80 points), Early Majority (57-68 points), Late Majority (46-56 points), and Laggards (below 46 points). In the present study, the reliability coefficient, as indicated by Cronbach's alpha, was determined to be .85.

Generative AI Literacy Scale: he Generative AI Literacy Scale, which was conceived by Wang, Rau, and Yuan (2023) and subsequently adapted into Turkish by Gökçearslan et al. (2024), evaluates competencies pertinent to generative artificial intelligence technologies. This scale comprises 10 items, which are systematically allocated across four distinct dimensions: Awareness (2 items), Usage (3 items), Evaluation (3 items), and Ethics (2 items). Each item is assessed using a 7-point Likert scale that ranges from "Strongly Disagree" to "Strongly Agree." The scale exhibited notable reliability, achieving a Cronbach's alpha of .81 in the present investigation.

3.4. *Data Collection Procedure*

The interval from July 12, 2025, to August 12, 2025, involved data acquisition performed exclusively through a secure web survey interface. Prior to the initiation of data collection, the research obtained ethical endorsement from the Research Ethics Committee of the Hacettepe University Educational Sciences Institute (Protocol No: 2025/07). Participants were enlisted through formal channels at the collaborating universities, wherein faculty administrators disseminated survey invitations to students who met the eligibility criteria.

All engaged individuals gave their informed approval through digital means prior to entry into the survey tools. The survey was artfully put together to span approximately 20 to 25 minutes for completion, allowing participants the freedom to save their progress and return to finalize the survey as necessary. In order to uphold data integrity, multiple attention check items were strategically incorporated throughout the survey, and responses exhibiting conspicuous patterns (such as straight-lining) were flagged for further examination.

3.5. *Data Analysis Procedures*

Data analysis was executed utilizing the SPSS 28.0 software package in accordance with a methodical framework. Prior to engaging in the comprehensive analyses, careful data screening practices were executed to reveal outliers, scrutinize the normality premises, and competently tackle any missing data issues.

The analysis of missing data indicated that fewer than 3% of responses were absent for any given variable, and the observed pattern of missingness was determined to be entirely at random (Little's MCAR test: $\chi^2 = 45.23$, $p = .67$). Given the minimal proportion and stochastic nature of the missing data, listwise deletion was implemented, culminating in a final sample size of 620 participants with complete datasets.

The identification of outliers employed both one-variable and several-variable analytical approaches. Univariate outliers were recognized through standardized z-scores ($|z| > 3.29$), whereas multivariate outliers were identified using Mahalanobis distance with a $p < .001$ threshold (Tabachnick, Fidell, & Ullman, 2007). Ultimately, 11 cases were classified as multivariate outliers and subsequently excluded from the dataset.

Normality assessment involved examination of skewness and kurtosis values, with acceptable ranges defined as -1.5 to +1.5. All variables demonstrated acceptable normality, with skewness values ranging from -0.958 to 0.428 and kurtosis values ranging from -0.536 to 1.327.

Internal consistency reliability was assessed using Cronbach's alpha coefficients, with values above .70 considered acceptable (Nunnally & Bernstein, 1994). All scales demonstrated satisfactory reliability, with alpha values ranging from .78 to .91. Additionally, corrected item-total correlations were examined to ensure that all items contributed meaningfully to their respective scales, with all correlations exceeding .30.

Pearson correlation coefficients were calculated to examine bivariate relationships between all study variables. Prior to regression analysis, assumptions of linearity, independence, homoscedasticity, and absence of multicollinearity were verified. Multicollinearity was assessed using tolerance values (> .20) and Variance Inflation Factor (VIF) values (< 10), with all variables meeting these criteria.

A comprehensive multiple linear regression analysis was performed employing the enter methodology to investigate the concurrent influences of ICT self-efficacy, technostress, individual innovativeness, and the various dimensions of mindset on the construct of AI literacy. To establish the independence of the residuals assumption, the Durbin-Watson metric was used (Durbin & Watson, 1971).

4. Results

4.1. *Descriptive Statistics and Preliminary Findings*

Table 1 illustrates a broad selection of statistical descriptions related to all variables being examined. The analysis discloses that the participants exhibited comparatively elevated levels of artificial intelligence literacy (M = 4.88, SD = 0.92 on a 7-point metric) and information and communication technology self-efficacy (M = 4.86, SD = 0.78 on a 6-point metric). The levels of technostress were assessed as moderate (M = 2.79, SD = 0.65 on a 5-point metric), whereas the scores for individual innovativeness (M = 61.46, SD = 7.60) positioned the majority of participants within the "Early Majority" category as per Rogers'. Classification system.

Table 1: Descriptive Statistics for Study Variables

Variable	N	Min	Max	Mean	SD	Skewness	Kurtosis	α
AI Literacy (Total)	620	2.10	7.00	4.88	0.92	0.124	-0.333	.81
ICT Self-Efficacy	620	2.33	6.00	4.86	0.78	-0.431	-0.536	.88
Technostress (Total)	620	1.25	4.68	2.79	0.65	-0.147	0.017	.91
Individual Innovativeness	620	38.00	82.00	61.46	7.60	0.428	1.327	.85
Growth Mindset - Effort	620	2.20	5.00	4.12	0.58	-0.694	0.910	.76
Growth Mindset - Development	620	2.17	5.00	4.02	0.61	-0.958	0.978	.74
Fixed Mindset - Inertia	620	1.75	4.75	3.18	0.52	-0.207	-0.154	.72
Fixed Mindset - Unchangeability	620	1.50	4.75	3.24	0.58	-0.560	-0.225	.71

4.2. *Correlation Analysis Results*

4.2.1. *AI Literacy and ICT Self-Efficacy Relationships*

Investigating Pearson correlation provided insights into strong positive associations between ICT self-efficacy and every facet of AI literacy. The most pronounced relationship was identified between ICT self-efficacy and the cumulative AI literacy score (r = .454, p < .01), signifying a moderate to robust positive correlation. The outcome reveals that future educators with boosted confidence in their IT capabilities simultaneously show advanced levels of AI knowledge across different facets.

An investigation into the sub-dimensions of AI literacy indicated that ICT self-efficacy exhibited the most substantial correlation with the Usage dimension ($r = .442$, $p < .01$), succeeded by the Evaluation dimension ($r = .408$, $p < .01$), and the Awareness dimension ($r = .335$, $p < .01$). Importantly, the correlation with the Ethics dimension was notably weaker ($r = .176$, $p < .01$), implying that ethical considerations in the application of AI may be less intrinsically linked to beliefs regarding technical self-efficacy.

This information demonstrates the anticipated results grounded in self-efficacy theory, which asserts that those with higher confidence in their tech abilities are likely to engage with and adeptly employ new technologies (Bandura, 1997). The particularly robust association with the Usage dimension bolsters the assertion that the practical application of AI tools necessitates foundational ICT competencies (Scherer et al., 2019).

4.2.2. *AI Literacy and Technostress Relationships*

Research into the relationship between artificial intelligence knowledge and technostress showed considerable negative links throughout various factors. An observable negative relationship was detected between AI literacy levels and technology-induced stress, with statistical validation ($r = -.184$, $p < .01$), indicating that enhanced understanding of AI correlates with lower stress levels from technology.

A detailed examination of the sub-dimensions of technostress indicated that the most pronounced negative correlation was observed with Personal Source technostress ($r = -.263$, $p < .01$), implying that individuals possessing higher AI literacy encounter reduced stress concerning personal inadequacies in their utilization of technology. Furthermore, the Learning-Teaching Process Oriented technostress exhibited a noteworthy negative correlation with AI literacy ($r = -.139$, $p < .01$), suggesting that those with substantial AI literacy experience less stress when incorporating technology into educational environments.

Notably, the Ethics dimension of AI literacy did not demonstrate a significant correlation with overall technostress ($r = -.027$, $p > .05$), indicating that ethical awareness in the application of AI functions independently from stress-related reactions to technology. This finding could imply that ethical factors represent a distinct cognitive sphere that shows reduced vulnerability to emotional impulses tied to technology (Floridi et al., 2018).

4.2.3. *AI Literacy and Individual Innovativeness Relationships*

The evaluation illustrated striking positive ties between personal originality and familiarity with artificial intelligence in all considered dimensions. The overarching correlation between individual innovativeness and AI literacy was found to be moderate and statistically significant ($r = .240$, $p < .01$), thereby reinforcing the theoretical postulation that individuals characterized by innovative tendencies are more inclined to cultivate competencies associated with emergent technologies.

Among the various sub-dimensions of AI literacy, the most significant correlations with individual innovativeness were observed in the Evaluation dimension ($r = .196$, $p < .01$) and the Awareness dimension ($r = .203$, $p < .01$). The correlation identified within the Usage dimension exhibited a significant reduction ($r = .191$, $p < .01$), whereas the Ethics dimension revealed the least notable association ($r = .130$, $p < .01$).

The findings resonate with Rogers' Diffusion of Innovation Theory, suggesting that individuals who are particularly innovative tend to embrace new technologies quickly, thereby cultivating a more refined understanding of how they function and their constraints (Rogers, 2003). The pronounced association with the Evaluation dimension is particularly significant, as it implies that innovative individuals possess a superior capacity to critically evaluate AI technologies and their respective applications (Agarwal & Prasad, 1998).

4.2.4. *AI Literacy and Mindset Relationships*

Correlation analysis revealed significant positive relationships between AI literacy and growth mindset dimensions, while showing weaker or non-significant relationships with fixed mindset dimensions. The strongest correlations were observed between AI literacy and the Effort dimension of growth mindset ($r = .345$, $p < .01$) and the Developmental Self-Theory dimension ($r = .341$, $p < .01$).

The Belief in Development dimension also showed a significant positive correlation with AI literacy ($r = .259$, $p < .01$), while the Inertia dimension (representing aspects of fixed mindset) showed a weaker but still significant positive correlation ($r = .195$, $p < .01$). Notably, the Belief in Unchangeability dimension showed no significant relationship with AI literacy ($r = .122$, $p > .05$).

These findings strongly support Dweck's mindset theory in the context of technology learning, suggesting that individuals who believe abilities can be developed through effort are more likely to persist in learning complex technologies like AI (Dweck, 2006). The particularly strong relationship with the Effort dimension indicates that willingness to exert sustained effort is crucial for developing AI literacy competencies (D. S. Yeager & Dweck, 2012).

4.3. *Multiple Regression Analysis*

4.3.1. *Model Assumptions and Diagnostics*

Before undertaking the multiple regression analysis, all requisite assumptions were meticulously scrutinized and authenticated. The study of linearity was performed by reviewing scatterplots that displayed residuals against their predicted counterparts, showing no systematic patterns that would infer non-linear relationships. The independence of residuals was substantiated through the application of the Durbin-Watson test (DW = 2.009), which is situated within the acceptable interval of 1.5 to 2.5.

By evaluating standardized residuals plotted against standardized predicted values, the homoscedasticity assumption was carefully analyzed, showing a random dispersion pattern that lacked any indication of heteroscedasticity. The normality of the residuals was evaluated through histogram analysis in conjunction with the Kolmogorov-Smirnov test, both of which demonstrated satisfactory normality (K-S = .034, $p > .05$).

Multicollinearity diagnostics revealed no problematic relationships among predictor variables. All tolerance values exceeded .40 and all Variance Inflation Factor (VIF) values were below 3.0, well within acceptable limits (Hair, WC, BJ, & RE, 2019). These findings indicate that the regression model meets all necessary assumptions for valid interpretation.

4.3.2. *Overall Model Performance*

The multiple regression model examining the simultaneous effects of ICT self-efficacy, technostress, individual innovativeness, and mindset dimensions on AI literacy demonstrated significant explanatory power. The model accounted for 28.8% of the variance in AI literacy ($R^2 = .288$, Adjusted $R^2 = .280$), which represents a medium to large effect size according to Cohen's conventions (Cohen, 2013).

The comprehensive model exhibited statistical significance ($F(7,612) = 34.437$, $p < .001$), thereby demonstrating that the amalgamation of predictor variables substantially accounts for the variance in AI literacy beyond what could be anticipated through random occurrence. It was determined that the standard error of the estimate stands at 0.78, reflecting a noteworthy precision in the forecasts provided.

Table 2: Multiple Regression Analysis Results

Predictor Variable	B	SE B	ß	t	p	95% CI
(Constant)	1.018	0.386	-	2.642	.009	[0.260, 1.776]
ICT Self-Efficacy	0.426	0.043	.364	9.913	< .001	[0.342, 0.510]
Technostress	-0.136	0.054	-.096	-2.506	.012	[-0.242, -0.030]
Individual Innovativeness	0.012	0.005	.099	2.537	.011	[0.003, 0.021]
Mindset - Effort	0.089	0.021	.180	4.187	< .001	[0.047, 0.131]
Mindset - Development	0.039	0.019	.103	2.106	.036	[0.002, 0.076]
Mindset - Inertia	-0.009	0.015	-.027	-0.625	.532	[-0.038, 0.020]
Mindset - Unchangeability	-0.005	0.010	-.015	-0.319	.750	[-0.025, 0.018]

Note: $R^2 = .288$, Adjusted $R^2 = .280$, $F(7,612) = 34.437$, $p < .001$

4.4. *Additional Analyses*

4.4.1. *Demographic Differences*

Supplementary evaluations were executed to delve into potential fluctuations in the study variables as shaped by demographic characteristics. Independent samples t-tests indicated the presence of statistically significant gender disparities across several variables. The analysis indicated that female participants faced notably higher technostress levels ($M = 2.83$, $SD = 0.64$) compared to males ($M = 2.64$, $SD = 0.68$), $t(618) = 2.89$, $p = .004$, $d = 0.29$. In opposition, there were no substantial gender discrepancies identified concerning AI proficiency, ICT self-esteem, personal inventiveness, or dimensions of mentality.

One-way ANOVA revealed significant differences across class levels for AI literacy, $F(3,616) = 4.23$, $p = .006$, $\eta^2 = .02$. Post-hoc analyses using Tukey's HSD indicated that fourth-year students reported significantly higher AI literacy levels compared to first-year students ($p = .003$), suggesting that AI literacy may develop progressively throughout teacher education programs.

4.4.2. *Mediation Analysis*

A detailed mediation analysis was conducted to explore if ICT self-efficacy acts as a mediating factor in the connection between mindset and AI literacy. Utilizing the macro for SPSS, the findings revealed significant indirect effects of growth mindset on AI literacy through ICT self-efficacy (indirect effect = 0.087, 95% CI [0.052, 0.125]), indicating partial mediation. This result suggests that growth mindset affects AI literacy in both direct and indirect manners via its influence on beliefs regarding ICT self-efficacy

5. **Discussion**

5.1. *Principal Findings and Theoretical Implications*

The findings from this research significantly bolster a holistic framework of variables that shape the growth of AI literacy among aspiring educators. The findings indicate that AI literacy is considerably forecasted by an interplay of technological, psychological, and motivational elements, with the comprehensive model elucidating 28.8% of the variance in AI literacy results. This degree of elucidated variance signifies a substantial contribution to the comprehension of the intricate factors that affect technology acquisition within educational environments.

The emergence of information and communication technology (ICT) self-efficacy as the most significant predictor of artificial intelligence (AI) literacy ($\beta = .364$) provides compelling evidence in support of Bandura's self-efficacy theory within the realm of emerging technology education (Bandura, 1997). This discovery shows that the conviction people hold in their existing tech proficiency is a significant cornerstone for acquiring skills in more advanced technologies, including AI. The strength of this association indicates that pre-service educators who possess confidence in their ICT abilities are markedly more inclined to cultivate AI literacy competencies, thereby underscoring the critical need for the establishment of robust foundational technology skills within teacher education curricula (Ertmer & Ottenbreit-Leftwich, 2010).

The significant positive effects of growth mindset dimensions, particularly effort (β = .180) and belief in development (β = .103), provide compelling evidence for the relevance of Dweck's mindset theory in technology learning contexts (Dweck, 2006). These findings suggest that pre-service teachers who believe that abilities can be developed through effort and who value persistence in learning are more likely to successfully navigate the challenges associated with AI literacy development. This has important implications for teacher education programs, suggesting that fostering growth mindset beliefs may be as important as providing technical training (D. S. Yeager & Dweck, 2012).

The adverse influence of technostress (β = -.096) substantiates theoretical postulations regarding the harmful ramifications of technology-associated stress on educational outcomes (Tarafdar, Pullins, & Ragu-Nathan, 2015). Although the magnitude of the effect is relatively limited, the statistical significance of this association underscores the necessity of addressing psychological impediments to technology utilization for the effective advancement of AI literacy. This analysis corresponds with the literature regarding anxiety from technology and suggests that teacher training programs must incorporate features particularly focused on diminishing technology-related stress and nurturing confidence (Saadé & Kira, 2009).

The positive effect of individual innovativeness (β = .099) supports Rogers' Diffusion of Innovation Theory and suggests that openness to new ideas and willingness to experiment with emerging technologies facilitates AI literacy development (Rogers, 2003). This finding has implications for both selection and development of pre-service teachers, suggesting that fostering innovative attitudes and behaviors may enhance technology learning outcomes (Agarwal & Prasad, 1998).

5.2. *Practical Implications for Teacher Education*

The findings of this study have several important implications for the design and implementation of teacher education programs aimed at developing AI literacy among pre-service teachers.

Given the substantial predictive capacity of Information and Communication Technology (ICT) self-efficacy, it is imperative that teacher education programs prioritize the cultivation of fundamental technological competencies and self-assurance prior to the introduction of more sophisticated artificial intelligence (AI) concepts. This implies the necessity of a scaffolded pedagogical framework whereby pre-service educators initially acquire proficiency and confidence in basic educational technologies before advancing to applications specifically related to AI (Mishra & Koehler, 2006).

Practical strategies for building ICT self-efficacy include providing hands-on experiences with educational technologies, offering multiple opportunities for practice and mastery, providing supportive feedback and encouragement, and creating collaborative learning environments where pre-service teachers can learn from peers (Ertmer & Ottenbreit-Leftwich, 2010). Additionally, programs should include explicit instruction in troubleshooting and problem-solving strategies to help pre-service teachers develop confidence in their ability to overcome technological challenges (Koehler & Mishra, 2009).

The observable negative impacts of technostress stress the importance of teacher education structures to address the mental challenges related to technology engagement. In order to alleviate these obstacles, such curricula might integrate methodologies such as training in stress management, a phased approach to the adoption of new technologies, the provision of adequate support and resources, and the cultivation of constructive experiences with the assimilation of technology (Ragu-Nathan et al., 2008).

Programs may also gain advantages from the integration of mindfulness-based stress reduction methodologies, peer support networks, and personalized counseling services for pre-service educators who are encountering elevated levels of technology-related anxiety (Çoklar et al., 2017). Also, the effective demonstration of constructive technology by instructors, combined with clear expectations and detailed support, can help lessen stress and enhance confidence (Joo et al., 2011).

The significant implications of growth mindset characteristics indicate that educator preparation programs should engage actively in the investigation of concepts related to learning and skill development. This might entail the blend of growth mindset techniques, such as clarifying how neuroplasticity works and the adjustable nature of intelligence, presenting examples of learning success that arises from persistent work and dedication, and reimagining obstacles and failures as opportunities for further learning (Dweck, 2006).

Likewise, the positive influence of individual innovativeness indicates that educational programs should actively nurture innovative mindsets and practices. This can be achieved by incorporating creative problem-solving activities, promoting experimentation with emerging technologies, offering opportunities for innovation and entrepreneurship, and recognizing as well as celebrating creative and forward-thinking approaches to teaching and learning.

5.3. *Practical Implications for Teacher Education*

The findings obtained from this study carry substantial implications for the integration of artificial intelligence technologies within educational settings and the ensuing professional development of educators in preparation for a future enhanced by AI innovations.

The multifaceted characteristics of the determinants affecting AI literacy indicate that the successful incorporation of AI necessitates a methodical strategy that concurrently tackles various dimensions. In place of fixating only on technical education, schools should aim to construct detailed curricula that bring in psychological, motivational, and cognitive dimensions (Celik et al., 2022).

This might involve creating interdisciplinary teams that include technology specialists, educational psychologists, and curriculum experts to design holistic AI literacy programs. Such programs should include technical training, psychological support, mindset development, and opportunities for creative application and innovation (Fadel, Holmes, & Bialik, 2019).

The endeavor may necessitate the formulation of interdisciplinary collectives comprising technology experts, educational psychologists, and curriculum developers to construct comprehensive AI literacy initiatives. These initiatives ought to encompass technical instruction, psychological assistance, cognitive mindset enhancement, alongside avenues for creative implementation and innovation (Scherer et al., 2019).

Professional development programs should therefore include components designed to build ICT self-efficacy, address technostress, foster growth mindset, and encourage innovative attitudes. These programs should be designed with adult learning principles in mind and should provide ongoing support and resources for sustained development (Guskey, 2002).

5.4. *Limitations and Future Research Directions*

While this study provides valuable insights into factors influencing AI literacy development, several limitations should be acknowledged and addressed in future research. The cross-sectional nature of this study limits the ability to make causal inferences about the relationships between variables. While the theoretical framework suggests that factors like ICT self-efficacy and mindset influence AI literacy development, the current design cannot definitively establish causality (Campbell & Cook, 1979).

In upcoming endeavors, it is vital to utilize enduring structures to supervise the growth of artificial intelligence awareness through numerous timelines and to delve into the links between differences in forecasting signs and modifications in artificial intelligence awareness deliverables. Such empirical inquiries may yield more robust evidence for causal linkages and contribute to the formulation of more efficacious intervention (Ployhart & Vandenberg, 2010).

This study was conducted only with pre-service teaching candidates in Turkiye, which might constrain the applicability of the results across various cultural and educational settings. Distinct nations may exhibit heterogeneous degrees of technological infrastructure, disparate cultural perspectives regarding technology and innovation, and varied methodologies in teacher preparation (Hofstede, 2011).

Subsequent investigations should investigate these interrelations within diverse cultural and educational contexts to determine the extent to which the findings can be generalized to varied environments. Investigating cross-cultural disparities may additionally reveal cultural determinants that influence the evolution of psychological paradigms and the education of artificial intelligence (Peterson, 2004).

The research primarily hinged on self-reported tools, which are possibly at risk of social desirability bias and may not accurately capture genuine abilities and conduct (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Subsequent inquiries ought to integrate diverse assessment methodologies, encompassing performance-based evaluations of AI literacy, behavioral observations, and empirical indicators of technology utilization.

Following investigations must cover an array of assessment techniques, featuring performance-driven evaluations of AI knowledge, systematic observations of behavior, and metrics that can be quantified regarding technological participation (Venkatesh et al., 2003).

5.5. *Theoretical Contributions and Model Development*

This review offers vital theoretical discoveries that elevate our understanding of technology education and the advancement of AI literacy in scholarly environments. By combining and unifying different theoretical approaches—specifically self-efficacy theory, mindset theory, diffusion of innovation theory, and technostress theory—it grants a thorough outlook for assessing AI literacy. Such synthesis emphasizes the importance of utilizing multi-theoretical methodologies when tackling intricate educational issues.

The findings not only validate the significance of each discrete framework but also illuminate the intersections of these theories within the realm of AI literacy development. Consequently, this research establishes a crucial groundwork for both forthcoming theoretical enhancement and empirical investigation in this domain (Creswell & Clark, 2017).

The study's conclusions bolster the current technology acceptance models by underlining the significance of psychological and motivational factors that surpass ordinary constructs of usefulness and usability. The unification of components including mindset, technostress, and individual creativity facilitates a more detailed perspective on the operations of technology use and learning(Venkatesh et al., 2003).

This academic contribution bears significant weight in the field of novel technologies, particularly concerning artificial intelligence, which raises specific difficulties and chances insufficiently addressed by existing technology acceptance models (Davis, 1989).

5.6. *Policy Implications and Recommendations*

The research underscores vital viewpoints that might alter educational norms and strategies in various institutional, national, and global contexts. It is advised that teacher education structures focus on advancing extensive technological skills that should not only cover technical knowledge but also the mental preparedness important for the successful embedding of technology. Addressing this imperative may necessitate the revision of teacher education benchmarks to explicitly incorporate the advancement of AI literacy, alongside ensuring that educational institutions possess the requisite resources and support to execute robust and sustainable initiatives.

Policies must also encompass the imperative for continuous professional development and support for teacher educators, who are integral in exemplifying effective technology utilization and fostering the professional growth of pre-service teachers (Tondeur et al., 2016). The significance of ICT self-efficacy and the detrimental impacts of technostress indicate that educational institutions require sufficient technological infrastructure and support mechanisms to promote effective AI literacy advancement. This signifies more than mere technological and software elements, but also the inclusion of professional support, learning programs, and psychological care services (Ertmer, 1999). Policies ought to guarantee that institutions possess the requisite resources to deliver comprehensive technology education and support, inclusive of funding for equipment, training, and personnel (Cuban, 2001).

6. **Conclusion**

This investigation presents extensive empirical support for a multifaceted model of artificial intelligence literacy advancement among pre-service educators, illustrating that technological, psychological, and motivational elements interact synergistically to affect educational outcomes in this vital domain. The results indicate that information and communication technology self-efficacy emerges as the most significant predictor of AI literacy, whereas technostress imposes considerable obstacles to its progression. Also, qualities associated with a growth mindset and individual creativity are key in boosting the attainment of AI literacy.

The conclusions that were discussed earlier hold important consequences for programs targeting teacher development, reinforcing the demand for elaborate techniques that engage several spheres of technology within the educational landscape. A successful push for AI literacy is not merely about tech lessons; it involves a deliberate focus on psychological factors, motivational dynamics, and the establishment of vital tech expertise.

The research significantly enhances theoretical comprehension by effectively amalgamating various frameworks and broadening technology acceptance models to encompass psychological and motivational dimensions. The results establish a basis for subsequent inquiry and advancement in this swiftly progressing field.

The steady growth of artificial intelligence in learning spaces reveals the vital requirement to advance teachers' knowledge of AI. The results of this investigation provide empirically grounded insights for the formulation of efficacious programs and policies aimed at furthering this objective, consequently aiding in the preparation of educators who are adept at leveraging AI technologies in manners that enhance pedagogical practices and optimize educational outcomes.

The ramifications reach beyond the scope of individual educator training to include more extensive inquiries regarding educational reform in the context of the digital era. As society confronts the myriad opportunities and challenges introduced by artificial intelligence technologies, the training of educators capable of adeptly maneuvering through this intricate environment emerges as a paramount concern for educational institutions and policymakers on a global scale.

Future inquiries ought to explore these interrelations across a broader spectrum of contexts while utilizing longitudinal methodologies to enhance and clarify our comprehension of the progression of AI literacy. Likewise, strategies based on research that is rooted in these discoveries could present significant evidence regarding the impact of numerous methods designed to elevate AI literacy among educational staff.

The progression towards artificial intelligence literacy embodies both a formidable challenge and a significant opportunity for the educational domain. Through a comprehensive understanding and meticulous examination of the various elements that shape this evolution, we can enhance our preparedness of educators to effectively leverage the transformative capabilities of AI technologies while adeptly managing their inherent complexities and challenges in a responsible manner.

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