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# Lifelong learning predicting artificial intelligence literacy: A hierarchical multiple linear regression analysis

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✓ The author declares that there is no potential conflict of interest in this study.

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# Lifelong learning predicting artificial intelligence literacy: A hierarchical multiple linear regression analysis


## Abstract

This study investigated the relationship between preservice teachers' lifelong learning (LLL) tendencies and their artificial intelligence (AI) literacy. It aimed to understand whether a more substantial commitment to LLL contributes to developing essential AI competencies among future educators. A total of 318 preservice teachers from various universities and departments in Türkiye participated in the study. The results revealed significant positive correlations between LLL tendencies and overall AI literacy, as well as with each AI literacy subdimension, namely awareness, usage, evaluation, and ethics. The results suggested that preservice teachers with higher LLL tendencies tend to be more AI literate. Hierarchical multiple linear regression analysis was utilized to investigate whether demographic variables- gender, year of study, ICT competency, and AI tool usage- and LLL tendencies predicted AI literacy. ICT competency was found to be a significant predictor in the first model, and in the second model, LLL significantly improved the predictive power. As a result, ICT competency and LLL showed statistically significant predictive effects on preservice teachers' AI literacy. These findings indicate the importance of improving preservice teachers' LLL tendency to enhance AI literacy in their professional learning.


**Keywords:** Professional learning, Artificial intelligence, Lifelong learning, Preservice teachers

## EXTENDED ABSTRACT

### Introduction

In today's rapidly changing educational environment, it is crucial for preservice teachers (PSTs) to not only understand traditional teaching practices but also to grasp the emerging technologies. As generative AI tools become more common, PSTs are expected to integrate these technologies into their instruction effectively and to be AI literate. One potential way to promote AI literacy among them could be by examining their orientation toward lifelong learning (LLL). By cultivating LLL, PSTs can develop the skills necessary to adapt to technological advancements and employ AI-driven teaching methods (UNESCO, para. 1, 2025). This study explored the association between PSTs' LLL tendency and AI literacy. Various studies, such as Hagger et al. (2008), Sahin et al. (2010), and Sunthonkanokpong and Murphy (2019), highlighted the significance of LLL in adapting to the ever-evolving educational landscape. However, there is a gap in understanding the relationship between LLL and the PSTs' AI literacy. Furthermore, LLL research on AI literacy is still in its early stages and needs more investigation (Laupichler et al., 2022). Therefore, this study provided evidence for the hypothesis that PSTs who exhibit greater LLL tendencies are more likely to become AI literate, and the study aimed to put forth how cultivating LLL may support future educators' development of AI literacy by examining this relationship.

### Conceptual and Theoretical Framework

LLL is a broad concept that changes and evolves over time. It was first used in the late 1960s (Vislie, 2008). In its traditional usage, the term predominantly referred to the processes and structures designed to facilitate learning in adulthood and across the span of an individual's professional life. In time LLL policies and therefore its scope entails more holistic features that encompass formal, non-formal, and informal learning, each contributing to continuous personal and professional development across the lifespan (Laal, 2011). This perspective highlights the multifaceted nature of LLL which occurs not only in traditional educational settings but also through everyday experiences and workplace engagement. Therefore, the essential role of LLL in contemporary society cannot be overstated, particularly in navigating the complexities of a rapidly changing world in the age of AI. LLL serves not only to enhance PSTs' capabilities but also to foster active citizenship. As AI increasingly integrates into education, equipping future educators with the LLL mindset seems essential for improving growth, professional excellence, and overall well-being.

AI literacy is about competencies and abilities that enable individuals to understand, interact with, and critically evaluate AI technologies and their implications (Laupichler et al., 2022; Samoili et al., 2021; Shiri, 2024; Wang et al., 2023). Wang et al. (2023, 1324) conceptualized AI literacy through four core dimensions, as "awareness, usage, evaluation, and ethics". Overall, AI literacy is conceptualized as a multifaceted and evolving concept that encompasses understanding AI principles, being able to use and interact with AI technologies, critically evaluating their capabilities and limitations, and considering their ethical and societal implications.

The rise of digital technologies and AI has fostered highly interconnected learning ecosystems, where the integration of online and offline platforms enables continuous, personalized learning across diverse settings and timeframes (UNESCO, 2025). In coherence with this, the studies conducted in the literature primarily focus on how AI and AI literacy influence LLL. For instance, Pu et al. (2024) explored the influence of AI-related learning and digital literacy on LLL outcomes in China. They underscored the role of AI technologies in fostering effective LLL. In another study, the key factors influencing the adoption and effectiveness of AI tools—like ChatGPT—in supporting LLL in educational and workplace settings were analyzed (Ahn, 2024). The study results indicated that if AI tools are practical, individuals experience greater benefits, positively influencing academic and job performance. Similarly, Asad and Aijaz (2025) found that generative AI positively influences continuous learning and skill enhancement among students of higher education institutions in Pakistan. However, little is known about the PSTs' LLL tendency's role in AI literacy so far. Therefore, this study addressed a critical gap by investigating the predictive role of LLL tendencies on AI literacy among PSTs. These novel insight could reveal how initial teacher education programs can be designed to promote continuous professional learning and effectively integrate AI technologies into teaching practices.

**Method**

Employed as a quantitative research design, this study aimed to investigate the predictive role of LLL tendencies on AI literacy among PSTs. Accordingly, the subsequent hypotheses were formulated:

H1: PSTs with higher LLL tendencies will report significantly higher levels of AI literacy.

H2: Gender, year of study, ICT competency level, frequency of AI tool usage, and LLL tendencies will significantly predict AI literacy levels among PSTs.

H3: LLL tendency is a significant predictor of AI literacy even after controlling the demographic factors.

The sample of the current study was composed of 318 PSTs from various departments and universities in Türkiye. The convenience sampling strategy was adopted to select the participants of the study. The questionnaire used in this research consisted of three parts, which were demographic information form, the "Artificial Intelligence Literacy Scale (AILS)" developed by Wang et al. (2023), and the "Lifelong Learning Scale (WielkLLS)" produced by Wielkiewicz and Meuwissen (2014).

**Findings**

Following the validation of the data's suitability and examining the assumptions required for hierarchical multiple regression analysis the data analysis started. Accordingly, the skewness and kurtosis values of AILS and LLL suggested that the data distributions did not substantially deviate from normality. Following this, correlation analysis was conducted. The results showed that WielkLLS was positively and significantly correlated with the overall AILS score ($r = 0.398$, $p < .001$). Later, a hierarchical multiple linear regression analysis was conducted. Two models were tested. Model I included only demographic variables, which were gender, year of study, ICT competency, and AI tool usage. The first model explained 21% of the variance in AI literacy [$F$ (4, 313) =20.846, $p < .001$], indicating that the level of ICT competency significantly predicted AI literacy ($\beta$=0.535, $p < .001$). Gender, year of study, and AI tool usage were insignificant predictors ($p > .05$), suggesting no meaningful differences in AI literacy based on those variables alone. Afterward, Model II added the LLL tendency (WielkLLS) to the demographic predictors, and it was revealed that an additional factor explained a further 10% variance in AI literacy [$R_{change}$=0.10, $F_{change}$ (1, 312) =45.227, $p < .001$]. The model's explanatory power increased to $R^2$=0.310, with an adjusted $R^2$ of 0.299. Both ICT competency ($\beta$ =0.463, $p < .001$) and WielkLLS ($\beta$ =0.322, $p < .001$) were significant predictors.

**Conclusion, Discussion, and Recommendations**

The findings revealed that PSTs' LLL tendencies were significantly associated with their AI literacy levels. The strong positive correlations observed between the WielkLLS and the overall AILS score underscored the integral role of LLL in developing AI-related competencies. These results align with previous research emphasizing that

LLL supports individuals in adapting to technological advancements and integrating emerging tools such as AI into their learning and professional practices (Asad & Aijaz, 2025; Laupichler et al., 2022; Pu et al., 2024). Specifically, the findings suggested that PSTs who exhibited a strong disposition toward LLL were more likely to be aware of, effectively use, critically evaluate, and ethically engage with AI technologies. This highlights the importance of embedding LLL principles within teacher education programs to better prepare future educators for the evolving demands of AI-integrated educational environments (Bozkurt et al., 2023; Schmidt-Hertha, 2025; UNESCO, 2025).

There are several key implications for practitioners, policymakers, and researchers. Teacher education programs should integrate LLL activities like peer coaching, self-directed project work, and professional learning communities throughout their curricula. This integration would enhance PSTs' commitment to continuous professional growth. Such models can promote LLL and support the development of competencies related to AI literacy. Since ICT competency significantly predicted AI literacy, several resources should be allocated to strengthen digital infrastructures and deliver comprehensive ICT professional development as a precursor to effective AI integration. From a policy perspective, teacher education curricula should include structured opportunities to develop AI literacy and LLL competencies through project-based learning, AI-focused workshops, and reflective digital portfolios. Educational policymakers should support the integration of AI literacy as a core component of teacher standards and provide sustained professional development pathways to ensure future educators remain adaptive in a rapidly changing technological landscape. By institutionalizing these strategies, initial teacher preparation programs can contribute to building a more agile, ethical, and digitally competent teaching workforce.

## INTRODUCTION

The digitalization in education has accelerated with the latest developments in technology. The incorporation of artificial intelligence (AI) across numerous fields, including education has accompanied this transformation with the widespread use of big data, online storage, and machine learning (Kumar & Thakur, 2012; Zhai et al., 2021). AI is often used to personalize learning, automate administrative and assessment tasks, and support intelligent tutoring systems (Cukurova & Miao, 2024; Luckin et al., 2016). This technological innovation is a part of the Fourth Industrial Revolution. In the field of education, it is identified as the "Fourth Education Revolution" and is characterized with the changing roles and responsibilities of teachers and students. (Zhai et al., 2021; Zhai, 2024). In this new learning ecosystem, preservice teachers (PSTs) must acquire the necessary AI-related knowledge and skills, and they should enhance their AI literacy in order to effectively perform in future teaching environments (Cukurova & Miao, 2024; Pokrivcakova, 2023; Zhang et al., 2023).

AI and the AI literacy are critical topics on the agendas of numerous nations. Dedicated governmental units have been established to address the issue. In parallel, Türkiye has prioritized digitalization and AI within its strategic framework. The establishment of the Digital Transformation Office under the presidency demonstrates this commitment, positioning itself as a leader in integrating AI into various state functions (Türkiye Cumhuriyeti Cumhurbaşkanlığı Dijital Dönüşüm Ofisi, 2025). AI technologies have been particularly emphasized in the education sector, leading to enhancements in the content offered through the

Education Information Network (EBA). Additionally, an innovative and flexible AI-supported individual learning platform, MEBI, has been introduced for secondary school students, allowing for completely personalized learning experiences (Ministry of National Education, 2025). In March 2025, the Artificial Intelligence and Big Data Applications Department was established by the Ministry of National Education within the General Directorate of Innovation and Education Technologies. This center will conduct research and development studies to ensure that teachers, students, and parents can safely use AI-supported systems.

The rise and widespread availability of generative AI tools and numerous AI-supported applications highlight the necessity for effectively utilizing these technologies. A strong understanding of AI is regarded as crucial in the age of generative AI (Bozkurt, 2024; Bozkurt et al., 2023; Laupichler et al., 2022; Low et al., 2025; Ng et al., 2021). Similarly, for PSTs AI literacy is crucial to integrate AI into future classrooms. They can comprehend, engage with, and critically assess AI technologies and their implications when they are AI literate (Laupichler et al., 2022; Shiri, 2024).

One potential way to promote AI literacy of PSTs could be by examining their orientation toward lifelong learning (LLL). PSTs' attitudes and willingness to LLL and professional development may significantly influence their AI literacy and capacity, and therefore, they may more effectively adapt to emerging AI-driven educational practices. In the current age, "the learning ecosystem is interconnected, employing both online and offline resources to enable learning to take place anywhere, anytime, via individualized pathways" (UNESCO, 2025, para.1). By actively engaging in LLL, PSTs would be better at keeping pace with rapid AI innovations and evolving pedagogical demands. Thus, this study explores the relationship between PSTs' LLL tendency and AI literacy. Though the significance of LLL for educators and PSTs is highly studied and well-established (e.g., Hagger et al., 2008; Sunthonkanokpong & Murphy, 2019; Sahin et al., 2010), its interplay with AI literacy remains underexplored. In addition, AI literacy in LLL research is an emerging and new subject and requires further analysis (Laupichler et al., 2022). Thus, this study explores the association between PSTs' LLL tendency and AI literacy. Although the importance of LLL for teachers and PSTs is widely recognized (e.g., Hagger et al., 2008; Sahin et al., 2010; Sunthonkanokpong & Murphy, 2019), little is known about how it interacts with AI literacy. Furthermore, LLL research on AI literacy is still in its early stages and needs more investigation (Laupichler et al., 2022). Therefore, this study provides evidence for the hypothesis that PSTs who exhibit greater LLL tendencies are more likely to become AI literate, and the study aims to put forth how cultivating LLL may support future educators’ development of AI literacy by examining this relationship.

## CONCEPTUAL FRAMEWORK

### Lifelong Learning

LLL is a broad concept that changes and evolves over time. It was first used in the late 1960s (Vislie, 2008). In its traditional usage, the term predominantly referred to the processes and structures designed to facilitate learning in adulthood and across the span of an individual’s professional life. Jarvis (2004) emphasized the complexity of the concept and highlighted that LLL encompasses both individual, lifelong personal learning and institutionalized, formal education. In this regard LLL occurs not only within educational systems but also across non-educational sectors, such as workplaces and communities.

There have been various policy documents published on LLL. For example, in its report, the Organization for Economic Cooperation and Development (OECD, 2021) emphasized LLL and positioned it as a foundational pillar for future societal development. Accordingly, LLL plays a significant role both in knowledge economy, employment and democratic values with social cohesion (Cummins & Kunkel, 2015; OECD, 2021). OECD underscores the potential of LLL as a strategic tool for addressing the challenges of globalization, technological change, and demographic shifts. Delors Report introduced a comprehensive framework for lifelong education, rising on four pillars of learning which are “learning to know, learning to do, learning to live together, and learning to be” (Delors, 1996). These pillars, rather than focusing only on the acquisition of knowledge or skills, emphasize the intellectual, social, emotional and agentic development of the whole person across the lifespan.

The 2030 Agenda for Sustainable Development, adopted by United Nations (UN) member states, includes 17 goals aiming to foster a better future for all (UN, 2015). The sustainable development goal four (SDG4) specifically highlights the need for quality education and LLL opportunities for everyone. Additionally, LLL is highlighted as one of the key tools for achieving many other SDG targets, such as LLL could help in eliminating poverty and reducing inequality by helping people gain important skills and knowledge to boost their chances of finding work and earning better income. According to the seventh and the latest report of International Conferences on Adult Education called CONFINTEA (UNESCO Institute for Lifelong Learning, 2022), representatives from more than 140 countries underscored their dedication to the SDGs by acknowledging the pivotal role of adult education as an integral aspect of LLL and collectively pledged to actualize LLL.

In time LLL policies and therefore its scope entails more holistic features that encompass formal, non-formal, and informal learning, each contributing to continuous personal and professional development across the lifespan (Laal, 2011). This perspective highlights the multifaceted nature of LLL which occurs not only in traditional educational settings but also through everyday experiences and workplace engagement. According to another recent international report, Making lifelong learning a reality: a handbook, (UNESCO Institute for Lifelong Learning [UIL], 2022), LLL is a comprehensive concept that connects learning with everyday life across all ages, settings, and methods. It emphasizes that learning should not be seen as limited to childhood or early adulthood but as a continuous process throughout a person's life.

Therefore, the essential role of LLL in contemporary society cannot be overstated, particularly in navigating the complexities of a rapidly changing world in the age of AI. LLL serves not only to enhance PSTs' capabilities but also to foster active citizenship. As AI increasingly integrates into education, equipping future educators with the LLL mindset seems essential for improving growth, professional excellence, and overall well-being.

**Artificial Intelligence Literacy**

Since the term of AI was first used by McCarthy, Minsky, Rochester and Shannon in a study in 1955 (McCarthy et al., 1955), the definition of the term has been extended and diversified. For example, the Joint Research Centre of the European Commission addressed both core domains and broader themes of AI and proposed an operational definition (Samoili et al., 2021). According to OECD's definition: "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment" (OECD, 2024, para. 14).

Generative AI represents a cutting-edge segment of AI technology, showcasing systems that mirror human language abilities. These systems are usually trained using sophisticated techniques such as deep learning and neural networks, which allow them to analyze and process vast amounts of data (Bozkurt & Sharma, 2023). As a result, they can understand context, generate coherent text, and transform information into creative ways (Bozkurt & Sharma, 2023; Laupichler et al., 2022; Low et al., 2025).

AI literacy is about competencies and abilities that enable individuals to understand, interact with, and critically evaluate AI technologies and their implications (Laupichler et al., 2022; Samoili et al., 2021; Shiri, 2024; Wang et al., 2023). AI literacy is one of the technological literacies, along with media literacy (Potter, 2018), data literacy (Gummer & Mandinach, 2015), computational literacy (diSessa, 2018), and scientific literacy (Laugksch, 2000); and it is closely related to digital literacy and AI education (Ng et al., 2021; Shiri, 2024). Many contemporary literacies are interrelated and do not exist as distinct categories, but they are useful for comprehending conceptualization (Stordy, 2015) emphasizes that many contemporary literacies are interconnected and do not exist as exclusive categories, but they are valuable for understanding conceptualization. Therefore, AI literacy includes important elements of a larger conceptual framework focused on AI competency. For example, Ng et al. (2021) outlined several essential elements of AI literacy that are based on Bloom's taxonomy. Educators should focus on them to enhance learners' AI competencies. These components include knowledge and understanding, application and use, evaluation and creation, and ethical considerations. Cetindamar et al. (2022) identified four sets of skills linked with AI literacy for employees, namely technology-related, work-related, human-machine-related, and learning-related capabilities. And Wang et al. (2023, 1324) conceptualized AI literacy through four core dimensions, as "awareness, usage, evaluation, and ethics". Overall, AI literacy is conceptualized as a multifaceted and evolving concept that encompasses understanding AI principles, being able to use and interact with AI technologies, critically evaluating their capabilities and limitations, and considering their ethical and societal implications.

## Preservice Teachers' Lifelong Learning and Artificial Intelligence Literacy

Developing a strong understanding of AI has become crucial for PSTs in the age of AI (Bozkurt, 2024; Bozkurt et al., 2023; Laupichler et al., 2022). They should be better equipped to keep pace with rapid technological innovations and evolving learning ecosystem demands. It is important to understand the current state of AI and its potential advancements in future. This foundational understanding can be integrated into undergraduate teacher training programs. Therefore, future educators should be supported to navigate an increasingly digital learning environment better and provided and upskilled via ongoing professional development opportunities to utilize AI in their teaching practices (Schmidt-Hertha, 2025). Investigating the relationship between PSTs' LLL tendency and AI literacy and revealing the predictive effects on AI literacy could be regarded as one of the important steps that can enhance the initial teacher training programs.

In the context of LLL, the rise of digital technologies and AI has fostered highly interconnected learning ecosystems, where the integration of online and offline platforms enables continuous, personalized learning across diverse settings and timeframes (UNESCO, 2025). In coherence with this, the studies conducted in the literature primarily focus on how AI and AI literacy influence LLL. For instance, Pu et al. (2024) explored the influence of AI-related learning and digital literacy on LLL outcomes in China. They underscored the role of AI technologies in fostering effective LLL. In another study, the key factors influencing the adoption and effectiveness of AI tools—like ChatGPT—in supporting LLL in educational and workplace settings were analyzed (Ahn, 2024). The study results indicated that if AI tools are practical, individuals experience greater benefits, positively influencing academic and job performance. Similarly, Asad and Aijaz (2025) found that generative AI positively influences continuous learning and skill enhancement among students of higher education institutions in Pakistan. However, little is known about the PSTs' LLL tendency's role in AI literacy so far. Therefore, this study addressed a critical gap by investigating the predictive role of LLL tendencies on AI literacy among PSTs. These novel insights could reveal how initial teacher education programs can be designed to promote continuous professional development and effectively integrate AI technologies into teaching practices.

## METHOD

### Research Model and Hypotheses

Employed as a quantitative research design, this study aimed to investigate the predictive role of LLL tendencies on AI literacy among PSTs. Accordingly, the subsequent hypotheses were formulated to test the survey data statistically through correlation and hierarchical multiple linear regression analyses.

Hypothesis 1: PSTs with higher LLL tendencies will report significantly higher levels of AI literacy, including the subdimensions of AI literacy (awareness, usage, evaluation, and ethical understanding of AI tools).

PSTs with strong LLL tendencies would be more likely to seek new information, experiment with AI tools, and reflect on their ethical and practical implications. In this context, it is essential to investigate whether PSTs' orientations toward LLL are associated with their levels of AI literacy.

Hypothesis 2: Gender, year of study, ICT competency level, frequency of AI tool usage, and LLL tendencies will significantly predict AI literacy levels among PSTs.

Hypothesis 2 was that demographic characteristics (gender, year of study, ICT competency level, and frequency of AI tool usage) would predict the AI literacy of PSTs. Previous studies proved that males were more interested in technology and AI (Fietta et al., 2022; Schepman & Rodway, 2022). Thus, studying gender as a predictor of AI literacy seems important. The demographic feature of the year of study could provide insights into the impact of the education faculties. As PSTs progress each year, they take numerous courses that may include technology and AI. Therefore, the year of study could predict AI literacy levels. Schepman and Rodway (2022) explored the role of age, education, and computer expertise. They indicated that these variables had a significant impact on attitudes toward AI. Similarly, several studies showed that age and a higher level of education significantly influenced attitudes and willingness to use new technologies (González-Anleo et al., 2024; Kacperski et al., 2025; Kuo et al., 2009; Méndez-Suárez et al., 2023).

The adoption and usage of specific technologies are known to be influenced by contextual factors, attributes, and habits particular to those technologies (Celik, 2023; Hong et al., 2014; Venkatesh et al., 2011; Venkatesh, 2022; Yilmaz & Yilmaz, 2023). Therefore, analyzing self-reported ICT competency levels and AI tool usage could provide predictions on the AI literacy of PSTs.

Hypothesis 3: LLL tendency is a significant predictor of AI literacy even after controlling the demographic factors.

Hypothesis 3 was that LLL is a comprehensive, life-spanning, and self-directive process (Cummins & Kunkel, 2015; UNESCO, 2025); thus, it serves as a critical driver for personal growth and professional excellence for PSTs, too. This continuous pursuit of knowledge and skill development would enable them to respond effectively and adapt to new technologies such as AI. Therefore, analyzing the predictive role of LLL tendency on AI literacy could play a critical role in preparing PSTs to engage with AI technologies in educational settings effectively.

### *Sample*

The sample of the current study was composed of 318 PSTs from various departments and universities in Türkiye. The convenience sampling strategy was adopted to select the participants of the study. In the convenience sampling strategy, the researcher reaches the most appropriate sample group in the most economical, time-saving, and accessible way (Creswell, 2014). Table 1 presents the demographic characteristics of the participants:

**Table 1**. Demographic Characteristics of the Sample

| Demographic Variables | Groups | *n* | % |
|---|---|---|---|
| Gender | Female | 209 | 65.7 |
| | Male | 109 | 34.3 |
| Year of study | 1st | 33 | 10.4 |
| | 2nd | 153 | 48.1 |
| | 3rd | 101 | 31.8 |
| | 4th | 31 | 9.7 |
| ICT competency | Poor | 10 | 3.1 |
| | Moderate | 115 | 36.2 |
| | Good | 125 | 39.3 |
| | Very good | 68 | 21.4 |
| AI tool usage | Never | 29 | 9.1 |
| | Sometimes | 85 | 26.7 |
| | Always | 204 | 64.2 |
| Total | | 318 | 100 |

As Table 1 shows, the sample comprised 65.7% females ($n$ = 209) and 34.3% males ($n$ = 109). Regarding the year of study, 10.4% were first-year students (n = 33), 48.1% were in their second year ($n$ = 153), 31.8% were third-year students ($n$ = 101), and 9.7% were in their fourth year ($n$ = 31). In terms of ICT competency level, 3.1% of participants ($n$ = 10) reported having poor skills, 36.2% ($n$ = 115) had moderate skills, 39.3% ($n$ = 125) indicated good skills, and 21.4% ($n$ = 68) rated their skills as very good. Concerning the frequency of AI tool usage, 9.1% ($n$ = 29) indicated they did not use AI tools, 26.7% ($n$ = 85) reported using them sometimes, and 64.2% ($n$ = 204) reported always using AI tools.

A post hoc power analysis was performed using G*Power 3.1.9.7. The analysis confirmed that with the sample size (N = 318), alpha level ($\alpha$ = 0.05), and observed effect size, the achieved power exceeded 0.99. This outcome showed that the study was sufficiently powered to detect the effect.

***Instruments for data collection***

The questionnaire used in this research consisted of three parts, which were demographic information form, the "Artificial Intelligence Literacy Scale (AILS)" developed by Wang et al. (2023), and the "Lifelong Learning Scale (WielkLLS)" produced by Wielkiewicz and Meuwissen (2014).

*The demographic information form*

The researcher developed the demographic information form that included questions about pre-service teachers' gender, year of study, level of ICT competency (rated as poor, moderate, good, and very good), and frequency of AI tool usage (rated as never, sometimes, and always).

*AI literacy scale (AILS)*

AI Literacy Scale (AILS) scale was developed by Wang and colleagues (2023) to obtain accurate data regarding the AI literacy of ordinary users. The items were formatted in the form of a seven-point Likert scale ranging from 1=strongly disagree to 7= strongly agree. The scale was adapted to the Turkish language and culture by Celebi and colleagues (2023). The factor structure of the original scale was confirmed in the adapted version ($X^2/df$=1.82, $RMSEA$=0.04, $RMR$=0.03, $NFI$=0.95, $CFI$=0.98, $GFI$=0.96 and $AGFI$=0.94). As in the original version, the adapted scale has 12 items and four constructs: awareness, usage, evaluation, and ethics, and consists of three items for each factor. The internal consistency reliability coefficients were α=0.72 for awareness, α=0.74 for usage, α=0.76 for evaluation, α=0.72 for ethics, and α=0.85 for the whole scale (Celebi et al., 2023). In this study, Cronbach's alpha values for awareness, usage, evaluation, ethics, and whole scale were 0.65, 0.71, 0.70, 0.68 and 0.716, respectively. Although the coefficients for awareness (α =0.65) and ethics (α = 0.68) were slightly below the usual threshold of 0.70, values between 0.60 and 0.70 are considered acceptable when the subscale has limited number of items (Taber, 2018; Ursachi et al., 2015). Three item examples of AILS include "I can distinguish between smart devices and non-smart devices", "I can use AI applications or products to improve my work efficiency", and "I always comply with ethical principles when using AI applications or products".

*Lifelong learning scale (WielkLLS)*

The LLL scale (WielkLLS) was developed by Wielkiewicz and Meuwissen (2014) to obtain the tendency of college students and others to practice LLL associated with learning, curiosity, and critical thinking. The items were formatted as a five-point Likert scale ranging from 1=never to 5=always. The scale was adapted to the Turkish language and culture by Boztepe and Demirtas (2016). According to the confirmatory factor analysis results, adequate fit index values for the 16-itemed and unidimensional scale are $X^2$= 277.09, *DF*= 64, *RMSEA*=0.091, *NFI*=0.92, *NNFI*=0.93, *CFI*=0.94, *IFI*=0.94, *SRMR*=0.061. The internal consistency reliability coefficient of the scale was α=0.78, and the Cronbach's alpha value was found to be 0.85 for the whole scale of the Turkish adaptation (Boztepe & Demirtas, 2016). In this study, Cronbach's alpha value the scale was 0.877. Three example items are "I enjoy intellectual challenges", "I am a self-motivated learner", and "I am curious about many things".

***Data collection***

Survey, as a primary data collection procedure, was adopted in the study. Accordingly, before the data collection process, the Board of Ethics of the researcher's affiliated institution approved the study with an approval number of 2025/84 dated April 4, 2025. The survey questions were structured on an online platform, and the link was shared with PSTs. At the beginning of the survey, all participants were provided with detailed information about the purpose of the research, the voluntary nature of their participation, and the measures to ensure their anonymity and data confidentiality. Informed consent was then obtained from all participants before they could access the survey. Of more than 600 surveys delivered, 318 valid responses were collected from various universities across Türkiye.

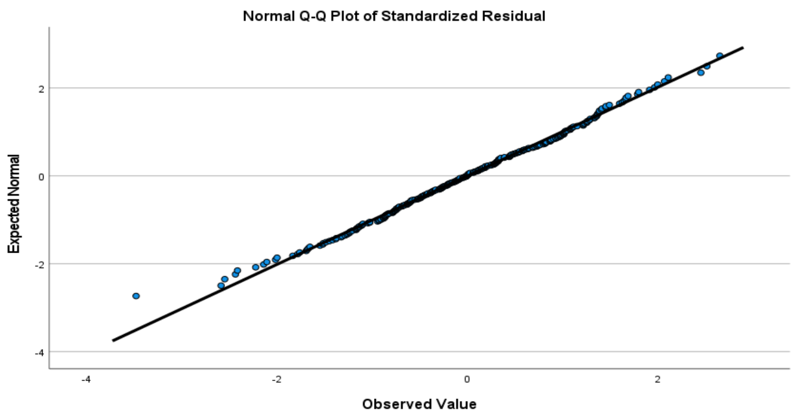
***Data Analysis***

After the data collection, all the data was screened and checked for data clarity. Data analyses were performed with SPSS v27. The dataset did not contain any missing values or outliers. The skewness and kurtosis values were assessed to determine normality. As a result, the findings were determined to range from -1 to +1, indicating that the data followed a normal distribution (Huck, 2012). For the hierarchical regression analysis, year of study, ICT competency, and AI tool usage were treated as ordinal variables. This approach was adopted because these variables reflect progressive levels, and the intervals between levels were assumed to be approximately equal (Norman, 2010).

First, the necessary sample size was determined to ensure that it was sufficient. Using the criterion ($n \geq 50 + 8m$) of Tabachnick and Fidell (2014), it was found that the sample of 318 participants satisfied the suggested sampling requirement ($318 \geq 50 + 8x5 = 90$) for the regression analysis with five independent variables investigated in this research.

Following the validation of the data’s suitability, the assumptions required for hierarchical multiple regression analysis were examined. Linearity was confirmed through scatterplots, homoscedasticity through residual spread, and normality through a Q-Q plot. The scatterplot indicated that the data met the assumption of linearity, because the points were randomly distributed without systematic curvature. Visual inspection of residuals revealed a constant spread, indicating that homoscedasticity assumption was satisfied (Field, 2013). Additionally, the assumption of normally distributed residuals was assessed through a visual inspection of a Normal Q-Q plot (see Figure 1).

**Figure 1** Normal Q-Q Plot of Standardized Residuals




As depicted in Figure 1, the points on the Q-Q plot cluster tightly around the diagonal reference line, confirming the assumption that the residuals were normally distributed. The Durbin-Watson statistic was employed to evaluate autocorrelation in multiple regression. As reported by Durbin and Watson (1950), the test statistic values should be 1 to 3. In this analysis, the Durbin-Watson coefficient was 1.989, indicating that the regression model did not display autocorrelation. The relationships among the variance inflation factor (*VIF*), tolerance value, and predictive variables were examined to assess the multicollinearity assumption. Accordingly, the correlations among predictor variables ought to be less than 0.900 (Field, 2013; Pallant, 2020). Furthermore, as Tabachnick and Fidell (2014) indicates, the tolerance value should be greater than 0.200 and the *VIF* value should be less than 5. The tolerance values varied between 0.855 and 0.962 for both models and they were all >0.200. These results confirm that the multicollinearity assumption was satisfied. Lastly, Cook’s *D* was assessed to check for the presence of multivariate outliers, which is the final assumption of multiple regression. Cook’s *D* values greater than 1 should be considered as potential outliers (Field, 2013). In this analysis, it was found that no Cook’s *D* values exceeded 1 for either model.

## FINDINGS

The data analysis started with providing descriptive analysis. Table 2 displays the descriptive statistics for the main variables examined in this study. Accordingly, for the AILS, the mean score was 63.59 (*SD* = 9.01), with a skewness of -0.131 and a kurtosis of -0.239. The WielkLLS had a mean of 48.86 (*SD* = 8.34), with a skewness of -0.149 and a kurtosis of -0.072. Overall, the skewness and kurtosis values suggested that the data distributions did not substantially deviate from normality.

**Table 2** Descriptive Statistics of Variables

| Variables | *N* | *M (SD)* | Skewness | *SE* | Kurtosis | *SE* |
|---|---|---|---|---|---|---|
| AILS | 318 | 63.59(9.01) | -0.131 | 0.137 | -0.239 | 0.273 |
| Awareness | 318 | 16.04(2.97) | -0.129 | 0.137 | -0.823 | 0.273 |
| Usage | 318 | 15.83(3.21) | -0.358 | 0.137 | -0.522 | 0.273 |
| Evaluation | 318 | 16.40(2.94) | -0.779 | 0.137 | 0.625 | 0.273 |
| Ethics | 318 | 15.32(3.35) | -0.389 | 0.137 | -0.427 | 0.273 |
| WielkLLS | 318 | 48.86(8.34) | -0.149 | 0.137 | -0.072 | 0.273 |

Table 2 indicates that all scales used in the study showed a normal distribution. Following this, correlation analysis was conducted, with results shown in Table 3.

**Table 3** Correlations Between WielkLLS and AILS and Its Subdimensions

| | AILS | WielkLLS | Awareness | Usage | Evaluation | Ethics |
|---|---|---|---|---|---|---|
| WielkLLS | 0.398*** | - | | | | |
| AILS' subdimensions | | | | | | |
| Awareness | 0.729*** | 0.272*** | - | | | |
| Usage | 0.789*** | 0.291*** | 0.503*** | - | | |
| Evaluation | 0.747*** | 0.324*** | 0.395*** | 0.529*** | - | |
| Ethics | 0.632*** | 0.264*** | 0.245*** | 0.253*** | 0.272*** | - |

*Note. ***p <.001*

Table 3 presents the correlation coefficients between the WielkLLS and the AILS, including its subdimensions (awareness, usage, evaluation, and ethics). The results showed that WielkLLS was positively and significantly correlated with the overall AILS score ($r = 0.398$, $p < .001$). Furthermore, significant positive correlations were found between WielkLLS and each of the AILS subdimensions ($r_{awareness}=0.272$, $r_{usage}=0.291$, $r_{evaluation}=0.324$, $r_{ethics}=0.264$, $p < .001$). Additionally, strong positive correlations were observed among the AILS subdimensions themselves. These findings suggest that PSTs who exhibit higher levels of LLL tendencies also tend to demonstrate higher AI literacy. In particular, greater LLL is moderately associated with higher awareness, usage, evaluation, and ethical understanding of AI tools. The strong correlations among AILS subdimensions imply that PSTs who are more aware of AI also tend to use it more actively, evaluate it more critically, and consider ethical issues more carefully.

In conclusion, a hierarchical multiple linear regression analysis was conducted to investigate the predictive effects of gender, year of study, ICT competency level, AI tool usage, and WielkLLS on AI literacy. The results are shown in Table 4.

**Table 4** Hierarchical Multiple Linear Regression Analysis Results in the Predictive Role of Various Variables on AI Literacy

| Model/ Variables | *B* | *SE* | β | *t* | *p* | 95% CI for β | |
|---|---|---|---|---|---|---|---|
| | | | | | | *LL* | *UL* |
| **Model I** | | | | | | | |
| Constant | 50.064 | 2.605 | | 19.215 | <0.001 | -2.120 | -0.872 |
| Demographic | | | | | | | |
| Gender | -0.082 | 0.983 | -0.009 | -0.084 | 0.933 | -0.235 | 0.247 |
| Year of study | 0.473 | 0.579 | 0.052 | 0.817 | 0.414 | -0.096 | 0.199 |
| ICT competency | 4.824 | 0.595 | 0.535 | 8.114 | <0.001 | 0.408 | 0.662 |
| AI tool usage | -0.590 | 0.533 | -0.065 | -1.108 | 0.269 | -0.166 | 0.048 |
| $R^2$ | 0.210 | | | | | | |
| Adjusted $R^2$ | 0.200 | | | | | | |
| $\Delta R^2$ | 0.210 | | | | | | |
| *F* for Change in $R^2$ | 20.846*** | | | | | | |
| **Model II** | | | | | | | |
| Constant | 34.847 | 3.327 | | 10.475 | <0.001 | -1.845 | -0.794 |
| Demographic | | | | | | | |
| Gender | 0.104 | 0.921 | 0.012 | 0.113 | 0.910 | -0.193 | 0.244 |
| Year of study | 0.331 | 0.542 | 0.037 | 0.611 | 0.542 | -0.080 | 0.155 |
| ICT competency | 4.174 | 0.565 | 0.463 | 7.389 | <0.001 | 0.342 | 0.590 |
| AI tool usage | -0.524 | 0.499 | -0.058 | -1.051 | 0.294 | -0.157 | 0.054 |
| WielkLLS | 0.348 | 0.052 | 0.322 | 6.725 | <0.001 | 0.207 | 0.440 |
| $R^2$ | 0.310 | | | | | | |
| Adjusted $R^2$ | 0.299 | | | | | | |
| $\Delta R^2$ | 0.100 | | | | | | |
| *F* for Change in $R^2$ | 45.227*** | | | | | | |

*Note.* Gender: 1 for females, 2 for males. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. ***$p < .001$

Table 4 presents the results of a hierarchical regression analysis examining the predictors of AI literacy. Two models were tested. Model I included only gender, year of study, ICT competency, and AI tool usage. The first model explained 21% of the variance in AI literacy [$F$ (4, 313) =20.846, $p < .001$], indicating that the level of ICT competency significantly predicted AI literacy (β=0,535, $p < .001$). According to Cohen's (1988) guideline, this represents a medium-to-large effect size ($f^2 = 0.27$). Gender, year of study, and AI tool usage were insignificant predictors ($p > .05$), suggesting no meaningful differences in AI literacy based on those variables alone. Afterward, Model II added the LLL tendency (WielkLLS) to the predictors, and it was revealed that an additional factor explained a further 10% variance in

AI literacy [$R_{change}$=0.100, $F_{change}$ (1, 312) =45.227, $p < .001$], which is a moderate effect size ($f^2 = 0.15$). The model's explanatory power increased to $R^2$=0.310, with an adjusted $R^2$ of 0.299. In this final model, both ICT competency (β =0.463, $p < .001$) and WielkLLS (β =0.322, $p < .001$) were significant positive predictors, while AI tool usage and demographics remained nonsignificant.

## DISCUSSION

The findings revealed that PSTs' LLL tendencies, as measured by the WielkLLS, were significantly associated with their AI literacy levels. The strong positive correlations observed between the WielkLLS and the overall AILS score underscored the integral role of LLL in developing AI-related competencies. These results align with previous research emphasizing that LLL supports individuals in adapting to technological advancements and integrating emerging tools such as AI into their learning and professional practices (Asad & Aijaz, 2025; Laupichler et al., 2022; Pu et al., 2024). Specifically, the findings suggested that PSTs who exhibited a strong disposition toward LLL were more likely to be aware of, effectively use, critically evaluate, and ethically engage with AI technologies. This highlights the importance of embedding LLL principles within teacher education programs to better prepare future educators for the evolving demands of AI-integrated educational environments (Bozkurt et al., 2023; Schmidt-Hertha, 2025; UNESCO, 2025).

Model I of the hierarchical regression showed that demographic variables explained 21% of the variance in AI literacy with ICT competency emerging as a significant predictor (β = 0.535, $p < .001$) meaning ICT competency and LLL tendency are strong and significant predictors of AI literacy among PSTs. In contrast, gender, year of study, and AI tool usage were not significant predictors, indicating that these factors alone do not account for meaningful differences in AI literacy levels.

While prior AI education efforts were primarily centered on university-level learners due to the advanced programming competencies required, more recent developments in age-appropriate tools and applications have made AI literacy increasingly accessible to a broader demographic, including younger learners (Ng et al., 2021; Yim, 2024). Aligned with this, the current study found no significant prediction of the year of study on AI literacy, meaning exposure to AI is not dependent on student's academic progression. Integrating AI into everyday technologies and the availability of user-friendly learning tools may contribute to a more uniform distribution of AI literacy across PSTs, regardless of how far along they are in their studies (Williams et al., 2024).

Literature frequently highlights that gender influences technology acceptance and use (Fietta et al., 2022; Ong & Lai, 2006; Schepman & Rodway, 2022; World Economic Forum, 2024). Various studies have reported gender-based differences in technology acceptance and perception of AI, with female students being more influenced by factors such as computer self-efficacy, awareness of AI, ease of use, and positive expectations towards technology (Cachero et al., 2025; Ong & Lai, 2006; World Economic Forum, 2024; Yim, 2024). Moreover, previous research indicates that female students are more anxious and have little interest in using technology (Dai et al., 2020; Sindermann et al., 2020; World Economic Forum, 2024). However, the findings of this study contradict this assumption. Kaya et al. (2024) did not find any statistically significant gender differences in understanding AI concepts or attitudes toward AI, like the results of the current study. The difference between the findings of the previous studies and this study could reflect the current trend in rich technology use and familiarity across genders. The increased integration of AI technologies into everyday life and education may contribute to more equitable processes. In addition to this common trend, the characteristics of the participant group in the current study could explain the deficiency of a statistically significant gender prediction on AI literacy. The participant PSTs attend faculties and take a special education program and, therefore, possess a certain level of academic readiness. This shared educational background may minimize differences among general populations and lead to more uniform levels of AI literacy across genders.

The current study exhibited that the frequency of AI tool usage was not a significant predictor. This finding could mean that AI tool usage alone does not account for meaningful differences in the AI literacy levels of PSTs. This result contradicts previous studies that emphasized that higher engagement with technologies enables people to understand and utilize that technology (Celik, 2023; Kale et al., 2018; Ung et al., 2022) and digital inequalities significantly influence digital literacies (Celik, 2023; Wang & Wu, 2021).

ICT competency is a type of skill that falls under digital competencies (UNESCO, 2018; Fayda-Kinik, 2023). The current study exhibited that ICT competency is a significant predictor of AI literacy for PSTs. This finding emphasizes the role of general digital competency in shaping individuals' ability to engage with recent technologies (Hava & Babayigit, 2025; Pu et al., 2024; Shiri, 2024). Strong ICT abilities can be a basis for growing AI integration in education, as demonstrated by Hava and Babayigit (2025). According to their findings, digital competencies substantially predicted teachers' AI-related technical, pedagogical, and content knowledge (AI-TPACK). Accordingly, people who are eager and skillful in using ICTs are better at evaluating and understanding AI-powered systems. Celik (2023) found that teachers with higher technological knowledge of AI could better assess the ethical implications and decisions of AI-related tools such as chatbots, intelligent tutoring systems, dashboards, and automated scoring software.

After controlling demographic variables and ICT competency, LLL tendency even remained a significant predictor of AI literacy ($\beta = 0.322$, $p < .001$) in Model II, indicating a moderate and unique contribution to PSTs' AI literacy levels. This final model, therefore, suggests that PSTs who exhibit stronger tendencies toward LLL are more likely to have higher levels of AI literacy, and demographic characteristics such as gender, year of study, and self-reported AI tool usage did not significantly contribute to the model. This finding coincides with previous studies that provide an increasing link between LLL and AI literacy. For instance, Humble (2023), in his scoping review, highlighted the nurturing readiness theme in the face of rapid technological advancements by noting that LLL is essential to preparing individuals, particularly educators, for an AI-integrated future. Similar to this, Ng (2021) stressed the importance of developing adult learning programs to integrate AI literacy into education, especially for teachers who do not have any prior expertise. Laupichler et al. (2022) also supported this claim and noted that various studies have conceptualized AI literacy as a multifaceted and evolving construct, and AI literacy links with adult education, higher education, and LLL. Their review has shown that AI literacy involves technical knowledge and reflective, evaluative, and adaptive competencies. These competencies are named as the core elements of LLL. This finding also connects well with the current research.

In addition to these, earlier research revealed that AI literacy requires continuous professional learning. Teachers need to keep up with the latest developments to provide contemporary and effective teaching and overcome technological and structural barriers (Gong et al., 2020; Vazhayil et al., 2019). Both preservice and in-service teachers must keep pace with technological advancements and the demands of new educational ecosystems. In the context of the Fourth Education Revolution (Zhai, 2024), educators with strong AI literacy can enhance instruction and support students through AI-integrated education (Cavalcanti et al., 2021; Xu, 2021). These findings highlight AI literacy's dynamic nature and its close relationship with LLL and reinforce the current study's result.

## Implications

The current study provides several key implications for practitioners, policymakers, and researchers. Teacher education programs should integrate LLL activities like peer coaching, self-directed project work, and professional learning communities throughout their curricula. This integration would enhance PSTs' commitment to continuous professional growth. Such models can promote LLL and support the development of competencies related to AI literacy.

Since ICT competency significantly predicted AI literacy, several resources should be allocated to strengthen digital infrastructures and deliver comprehensive ICT professional development as a precursor to effective AI integration. From a policy perspective, teacher education curricula should include structured opportunities to develop AI literacy and LLL competencies through project-based learning, AI-focused workshops, and reflective digital portfolios.

Educational policymakers should support the integration of AI literacy as a core component of teacher standards and provide sustained professional development pathways to ensure future educators remain adaptive in a rapidly changing technological landscape. By institutionalizing these strategies, initial teacher preparation programs can contribute to building a more agile, ethical, and digitally competent teaching workforce.

## Limitations and Further Considerations

Several limitations of this study should be acknowledged. This research was based on quantitative data and methods. Although validated scales were used in the study, the findings were obtained based on self-reported data. Future studies on this subject may diversify the data and methods. Although the study's sample size was sufficient for validity and reliability, a larger sample size would increase the generalizability. Although economical and time-efficient, convenience sampling, as a type of non-probability sampling method, is prone to selection bias. In the current study, this method resulted in a sample that is nonrepresentative of the gender distribution. The predominance of female participants is a crucial point of consideration, as research indicates that gender can play a role in technology acceptance and use (Cachero et al., 2025; Sindermann et al., 2020; World Economic Forum, 2024). As a result, the perspectives and experiences of male PSTs may not be fully reflected in this study. Researchers should target more balanced gender representation in future studies.

Additionally, the current cross-sectional study drew data from only one context, which was PSTs. Future research could explore in-service teachers so that the positions of more experienced teachers in the profession can be revealed. Similar studies could have significant practical implications in fields where knowledge is rapidly evolving, such as health. Therefore, conducting similar research in these dynamic areas is also recommended.

A further significant limitation of this study is its geographic restriction to PSTs in Türkiye. The findings are valuable within the Turkish context; however, they may not be generalizable to other countries due to substantial differences in educational systems, technological infrastructure, and socio-cultural factors that heavily influence teacher training and technology adoption.

## CONCLUSION

AI-related tools are becoming widespread in the K-12 and higher education context. However, PSTs' knowledge and skills in integrating AI in learning are little known. The LLL tendency of PSTs emphasizes their intellectual, social, emotional, and agentic development for addressing the challenges of a rapidly changing world in the age of AI. This study provided empirical evidence that PSTs with stronger LLL tendencies are significantly more likely to demonstrate higher levels of AI literacy. The findings indicated that LLL is positively associated with all dimensions of AI literacy—awareness, usage, evaluation, and ethics—highlighting the multifaceted benefits of fostering a LLL mindset among future educators. The hierarchical regression analysis further underscored the importance of ICT competency and LLL tendencies as significant predictors of AI literacy. These results suggested that developing PSTs' commitment to continuous learning and enhancing their ICT skills can play a critical role in preparing them to engage with AI technologies in educational settings effectively.

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