



Pre-service teachers' AI literacy: An exploratory study of predecessor literacies and personal characteristics predictors

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ABSTRACT

Literacy is embedded in social practices that adopt socially constructed technologies. In the 20th century, the invention of the computer facilitated information literacy and computational thinking. Media literacy emerged alongside the development of media. In the 21st century, the accessibility of artificial intelligence (AI)-powered chatbots using conversational language has expanded significantly, creating a need for their integration in education. AI literacy is being studied within frameworks similar to those of its predecessors, requiring conceptualization and differentiation from related literacy concepts. As of 2025, teacher education regarding AI literacy has been identified as an under-researched area. This article examines AI literacy through the lens of pre-service teachers' literacy competencies that will shape the literacy practices of future generations. During their own schooling, the current generation of prospective teachers encountered information, digital, and media literacy, as well as computational thinking; these are analyzed here as predictors of AI literacy, measured using the scale for the assessment of non-experts' artificial intelligence literacy (SNAIL) instrument. Personality traits and mindset are also investigated as predictors of the prospective teachers' professional competence. The study was conducted in 2024/25 with a sample of pre-service teachers. The research questions are: What is the structure of AI literacy in the sample? To what extent can AI literacy be predicted by components of information literacy? How much of AI literacy can be explained by various established technology-related literacies? To what extent do personality and mindset contribute to predicting AI literacy? The findings confirmed a two-factor solution for SNAIL, comprising technical understanding and critical application. Student perception of information literacy skills proved accurate in predicting the critical application of AI. In addition to information literacy, predictors included the media production subscale of media literacy and mindset. Technical understanding of AI was predicted by the media production subscale, the computational thinking subscales algorithmic thinking and cooperativity, and the personality trait of agreeableness. Establishing AI literacy as an essential teacher competency requires thorough research into AI's educational impacts and strict alignment with pedagogical goals. Navigating the ethical and moral dimensions of AI usage provides the necessary foundation for this literacy. Consequently, training programs can intentionally foster AI competence by merging specialized

literacy modules with algorithmic thinking, media production, and growth-mindset interventions.

Keywords: pre-service teachers, artificial intelligence literacy, information literacy, media literacy, computational thinking, personality traits, growth mindset

INTRODUCTION

In the 21st century, we discuss multiliteracy. The implications and understanding of literacy reflect diverse societal structures and social groups, with varying literacy functions and practices which manifest in education, literacy assessment, civic functioning, and professional requirements. Literacy is embedded in social practices that involve the use of socially constructed technologies in various ways. The conceptualization of literacy entails a complex interplay of factors and social conditions. Literacy is discussed as a factor that enables social change and influences social organization, memory and mnemonic systems, and the transmission of knowledge (Goody, 1977; Havelock, 1986; Ong, 1982). Ong (1982) defines literacy as a technology that transforms human cognition and culture, viewing the transition from oral to written culture as a cognitive and cultural shift. Street (1984) challenges technological determinism, the notion that technological characteristics inherently determine literacy and influence cognitive processes. He examines what is involved in the transition from an oral culture, dominated by memory, to a written culture, dominated by written records. Street (1984) cites Finnegan (1981), who emphasizes that literacy must be viewed within the context of various factors, social structures, ideologies, and political and economic conditions. Within the “ideological model,” Street (1984) conceptualizes literacy as a cultural practice linked to its social context, thereby contrasting it with the “autonomous model” of literacy. In shifting from an understanding of literacy as a cognitive entity to a sociocultural conception, he identifies four dominant approaches to literacy: literacy and the learning process, the cognitive approach to literacy, the sociocultural conception of literacy, and literacy as text (Street, 2006).

In the field of education, Vygotsky's (1978, 1986) ideas regarding language as a psychological tool and the zone of proximal development are significant, as they are critical to the development of a child's intellectual functions within the context of social interactions and culture. Buckingham (2006) defines literacy more broadly than the original concept, which was rooted in the written medium. While literacy was historically linked to print technology, sociocultural practices in the digital age encompass diverse interactive activities that shape literacy according to context, audience, and medium (Buckingham, 2006). The advent of computer technology enabled the development of information literacy (Zurkowski, 1974) and computational thinking (Wing, 2006); Jacob and Warschauer (2018) address the latter two concepts within the framework of computational thinking literacy. The emergence of mass media, television, and film spurred the development of media literacy (Hobbs & Jensen, 2009).

Discussions on literacy in the post-computer and post-Internet era encompass resource accessibility and the competence to use them, as well as the consideration of broader contextual factors; this elevates the understanding of literacy beyond a purely technological perspective (Collis, 1996). Bruce (2000) addresses information literacy through the lens of transformed knowledge and learning practices, foregrounding critical theory as an empowering, emancipatory, and participatory framework for integrating it into higher education curricula. Merchant and Hepworth (2002) examine the information literacy of teachers and students, exploring the value of information (Bruce, 1997, in Merchant & Hepworth, 2002), critical evaluation (Pennell, 1999, in Merchant & Hepworth, 2002), and problem-solving (Hancock, 1993, in Merchant & Hepworth, 2002), while also discussing the importance of information access with a particular focus on electronic resources (Merchant & Hepworth, 2002). Initially introduced as a skill for the general population (Wing, 2006), computational thinking has since evolved into a broader framework of computational thinking literacy (Jacob & Warschauer, 2018). Celik (2023) and Biagini (2025) position computational thinking at the core of AI literacy.

The conceptualization of media literacy, much like that of information literacy, incorporates a critical dimension that recognizes the complex factors contextualizing information and media use while prioritizing ethical considerations (Hobbs & Jensen, 2009). With the expansion of online media practices, media literacy is increasingly being studied in relation to the production of and access to online content. Its latest iteration, artificial intelligence (AI) literacy, is examined within the same frameworks as its predecessors (Ng et al., 2021);

research also explores how AI technology is transforming the fields of information literacy (Matthews & Bartley, 2025; Wetzel & Kani, 2024) and media literacy (Ndungu, 2024). Hackl et al. (2026) analyze the dimensions of AI literacy, drawing attention to conceptual ambiguity and the need to distinguish this form of literacy from related literacy concepts.

Artificial Intelligence Literacy of Pre-Service Teachers

Technology literacy is considered a key competency for teachers (Chalkiadaki, 2018; Greenhill, 2010; Ng, 2021). Alongside calls for technology literacy among the general population, the integration of information and media literacy (Hobbs & Jensen, 2009) and computational thinking (Wing, 2006) into curricula, AI literacy has recently emerged as a focal point of discussions of curricula and teacher preparation (Touretzky et al., 2019).

Ng et al. (2021) report a few studies concerned with teacher AI literacy. Discussions focus on the moral responsibility and authority of teachers regarding AI use, while also questioning the significance of the human element in education (Jorolan et al., 2025; Leite, 2025). The implications of AI integration for human agency have been discussed (Istenič Starčič, 2019), as AI, more so than previous technologies, raises concerns regarding its incorporation into pedagogical processes concerning professional ethics and moral agency (Istenič et al., 2021a, 2021b). Bewersdorff et al. (2025) note that teacher education regarding AI literacy remains under-researched. Hackl et al. (2026) highlight gaps in research concerning AI literacy frameworks, pedagogical guidelines, and their integration into higher education.

We focus on the field of education, particularly initial teacher education, as these teachers will shape the literacy practices of future generations throughout their professional careers. Conceptual understanding is essential for lesson and curriculum planning (Hackl et al., 2026); therefore, our study focuses on AI literacy among pre-service teachers. We aim to examine AI literacy by building upon earlier forms of literacy (Ng et al., 2023) that have evolved alongside the information and digital society. The study involves a self-assessment of AI literacy among pre-service teachers and identifies predictive factors for this literacy, utilizing scales to analyze their perceptions of their own information and digital literacy as well as computational thinking. Pre-service teachers had already encountered these forms of literacy within the curricula during their own schooling. In the rapid expansion of AI usage, we address the question of their literacy in this domain and the predictive role of prior technical literacies.

Personal Characteristics and AI Literacy

Research examines personality in relation to the process of acquiring professional competencies, as well as professional effectiveness and performance (Schneider, 2020). Schneider et al. (2020) find that personality traits are significant predictors of the assessment literacy of prospective teachers. Personality traits have been studied as predictors of information competence and information-seeking behavior (Ahmed & Rashed, 2020), as well as information literacy in relation to computer skills and self-efficacy (Aharony & Gur, 2019). The five-factor model of personality traits (McCrae & Costa, 1987), which posits the existence of five broad personality traits (extraversion, conscientiousness, agreeableness, neuroticism, and openness), has been used in studies examining the relationship between personality and the use of various technologies, such as social media (Huang, 2019; Liu & Campbell, 2017) or course management systems (Barnett et al., 2015). The direction and strength of these associations vary depending on the type of usage and the type of technology. More recently, the role of personality traits in the context of AI usage has also been investigated, though empirical findings remain limited and inconsistent. Conscientiousness emerged as a significant predictor in two studies examining the educational use of generative AI among higher education students (Arpaci et al., 2025; Azeem & Abbas, 2025), although the direction of the correlations varied across the studies. Neuroticism was negatively associated with the use of generative AI for educational purposes (Arpaci et al., 2025) and positively associated with the compulsive use of generative AI (Hu et al., 2025). Extraversion and openness showed positive correlations with the use of generative AI (Arpaci et al., 2025), but this was not observed in three other studies (Azeem & Abbas, 2025; Deng et al., 2026; Hu et al., 2025). Agreeableness did not show significant associations with the use of AI. Another factor that may be significant for AI literacy is mindset. Mindset (Dweck, 2000, 2006) influences an individual's motivation and achievements. Teachers' mindset influences their pedagogical thinking (Ronkainen et al., 2019) and is reflected in students' experiences and achievements

(Yeager et al., 2022). According to Dweck (2006), some people believe their intelligence is relatively unchangeable; this belief is termed a fixed mindset regarding intelligence. Conversely, individuals with a mindset oriented toward the development of intelligence (a so-called growth mindset) perceive human mental abilities as something that can be developed and believe that progress is possible through effort, persistence, the testing of various strategies, and guidance from others. Growth mindset interventions are introduced as deliberate educational activities for scaffolding and affordance of students to acting on their growth mindsets (Yeager et al., 2022). It can be hypothesized that individuals with a growth mindset view AI as a tool to enhance their own capabilities. Dang and Liu (2022) found that people with a growth mindset regarding intelligence demonstrate a more positive attitude and a greater willingness to interact with AI-based robots.

Drawing on related studies that highlight the importance of personality-related predictors, our research examines personal factors: personality traits (Rammstedt & John, 2007) and mindset (Dweck, 2006).

AI Literacy in the Landscape of Multiple Literacies

The 20th century, characterized by the transition from an industrial to an information society, was marked by the spread of information and communication technology. Collis (1996) highlights the impact of computer technology on education through two key shifts: the proliferation of personal computer technology and the development of the Internet. The world wide web (Berners-Lee et al., 1994), which enabled access to and sharing of documents on the Internet, contributed to a multitude of information sources and formats, thereby shaping the perception and representation of all areas of social life. The advent of computer technology brought about a shift from print technologies to digital formats, enabling the storage, processing, and retrieval of vast amounts of data. Zurkowski (1974) introduced the term “information literacy” to encompass the skills employees needed to use information tools and resources in the workplace. With the spread of computer technology, information literacy evolved into a comprehensive concept that includes information processing – searching for, evaluating, using, and citing information, grounded in critical thinking and ethics (Foasberg, 2015). The information literacy standards for higher education developed by the Association of College and Research Libraries (ACRL) in 2015 comprise six components:

- (1) authority is constructed and contextual,
- (2) information creation as a process,
- (3) information has value,
- (4) research as inquiry,
- (5) scholarship as conversation, and
- (6) searching as strategic exploration (Aharony & Gazit, 2018; Hsieh et al., 2016).

Doyle et al. (2019) outline the following: authority is constructed and contextual; information has value; research as inquiry; searching as strategic exploration – tools; scholarship as conversation; searching as strategic exploration – mindset; information creation as a process.

Media literacy extends the contents from predominantly information storage, such as libraries and search engines, to mass media, television, social media, and advertising platforms and focuses on critical evaluation of media content. Buckingham (2006, 2007) notes that media do not merely reflect the world but represent it; therefore, media education should address issues of authority, reliability, and bias, specifically, questions regarding whose voices are heard and whose perspectives are presented (2015, p. 25).

Hobbs and Jensen (2009) discuss the historical development of media literacy education as a response to the emergence of mass media, popular culture, commercial media, and technology integration in education. The authors discuss the theoretical framework of media analysis and the necessity of critical analysis, thereby foregrounding ethical considerations: “With the rise of digital media, there are a range of important new media literacy skills, where we must consider issues of personal and social identity, the complex interplay between what’s private and what’s public, and legal and ethical issues” (Hobbs & Jensen, 2009, p. 9).

The expansion of the World Wide Web, which enabled the development of networks and online practices, has led to increased attention being paid to digital media literacy and the examination of concepts such as representation, language, production, and audience (Buckingham, 2007). Given the growing importance of

media access and media production, Hallaq (2016) developed an instrument for measuring digital media literacy (digital online media literacy assessment [DOMLA]) that encompasses the following dimensions: ethical awareness, media access, media awareness, media evaluation, and media production. Media literacy has also been studied in conjunction with AI literacy (Seker et al., 2025).

With the invention of the computer, computational thinking, referring to solving problems using concepts related to computer science, evolved from the subject-specific competence of computer programmers to competence for the general population (Wing, 2006). According to Wing (2006), computational thinking encompasses 11 cognitive processes, including abstraction, algorithm design, decomposition, pattern recognition, and data representation, culminating in problem-solving. It is applied to diverse disciplines and does not necessarily involve a machine (Hsu et al., 2018). Validation of computational thinking assessment instruments indicates a link to the evaluation of problem-solving skills (Shute et al., 2017). In education, computational thinking should be addressed alongside information literacy, digital literacy, and media literacy (Gretter & Yadal, 2016); consequently, these various forms of literacy are inherently predicated upon analysis and critical thinking (Gretter & Yadal, 2016). Due to the increasing prevalence of online tools and platforms controlled and managed by algorithms (Archambault, 2023), there is a need to expand information literacy to include algorithmic literacy. Users' knowledge of algorithmic processes and parameters for achieving specific goals, as well as the issue of algorithmic bias, must be considered within the framework of the following dimensions of information literacy: "authority is constructed, and contextual", "information has value", and "searching as strategic exploration" (Archambault, 2023).

To assess computational thinking, the computational thinking scale (CTS) (Korkmaz et al., 2017) was developed, encompassing critical thinking, algorithmic thinking, cooperativity, creativity, and problem-solving. The scale was validated for German-speaking countries (Guggemos et al., 2019). Computational thinking is regarded as a form of literacy (Jacob & Warschauer, 2018). CTS has been studied in relation to students' AI literacy (Seker et al., 2025).

AI technology is designed to mimic human processes in performing cognitive tasks, such as learning and problem-solving (Leite, 2025; Ng et al., 2021). The development of AI is grounded in an understanding of human learning and, in turn, contributes to the understanding thereof (Istenič Starčič, 2019). With the widespread use of AI across all areas of human life, a need for AI literacy has emerged among the general population (Long & Magerko, 2020; Ng et al., 2021). Using AI does not require specialized knowledge of complex programming languages; instead, the operation of digital applications is based on conversational language. A user provides an instruction (a so-called "prompt") to an AI agent and, through interaction with it, obtains information, data, answers, and solutions. Anyone can use AI, yet doing so requires specific skills and knowledge. Bećirović et al. (2025) examined the relationship between technological understanding of AI and its critical evaluation, usage, generated results, and academic achievements. Their findings indicate that technological understanding is linked to the field of study but is not significantly associated with the quality of the results produced by AI (Bećirović et al., 2025).

Long and Magerko (2020) address the understanding of AI, incorporating interdisciplinary perspectives that have evolved since its inception in the 1950s. Based on a review of thirty existing peer-reviewed articles, Ng et al. (2021) identified four aspects of AI literacy: knowledge and understanding, use and application, evaluation and creation, and ethical issues. AI literacy entails an expectation that the general public possesses an understanding of algorithms and technical concepts (Long & Magerko, 2020), aspects that also constitute integral parts of computational thinking (Archambault, 2023; Celik, 2023). Long and Magerko (2020, p. 598) defined AI literacy as *"... a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace."*

With the growing prevalence of AI, a need has emerged for AI literacy grounded in concepts from earlier forms of literacy (Long & Magerko, 2020; Ng et al., 2021). AI literacy is discussed in relation to computational thinking (Biagini, 2025; Celik, 2023), information literacy (Hovious, 2024; Matthews & Bartley, 2025; Ndungu, 2024; Wetzel & Kani, 2024), and media literacy (Ndungu, 2024). Information literacy is evolving through the use of AI-generated content in the information-seeking process, raising questions regarding credibility and authority (Hovious, 2024; Matthews & Bartley, 2025). Hovious (2024) defines information seeking as issuing a prompt to an AI system, a process involving continuous source verification, while the authority of the

information source remains unknown. Interpreting knowledge-handling practices leads to the concept of *"information creation as a process"* and a shift in the perception of *"... the authority from "constructed and contextual" (ACRL, 2015, p. 4) to authority as unknown"* (Hovious, 2024, p. 2).

Review studies examine instruments for measuring AI literacy, identifying variables related to digital, information and data literacy (Bewersdorff et al., 2025). These studies investigate the dimensional structure of instruments in question (Bewersdorff et al., 2025; Biagini, 2023; Lintner, 2024; Ng et al., 2023). Lintner (2024) summarizes seventeen AI literacy scales and identifies a similar dimensional structure comprising technical understanding of AI, societal impact of AI (as a critical component), and AI ethics. Biagini (2024) presents an overview of nine AI literacy instruments and highlights three scales: the scale for the assessment of non-experts' artificial intelligence literacy (SNAIL) scale (Laupichler et al., 2023b) for assessing AI literacy among non-experts, which was used with higher education students; the AILQ (Ng et al., 2023) for secondary school students; and the LTE (Biagini et al., 2023), which is the most comprehensive, incorporating affective, behavioral, and ethical dimensions alongside cognitive and technical skills. Ng. et al. (2023) likewise define similar dimensions of learning: the affective, behavioral, cognitive, and ethical.

Reviews of AI literacy self-assessment scales designed for various populations (Biagini, 2024; Lintner, 2024) highlight more recent instruments introduced in 2023 or 2024, with two exceptions cited by Lintner (2024): an instrument for medical students by Karaca et al. (2021) and one for lower secondary school students by Kim and Lee (2022). Ng et al. (2023) report on the first instrument designed and validated for upper secondary school students by Sing et al. (2022).

Review studies (Bewersdorff et al., 2025; Biagini, 2024, 2025; Koch, 2025; Lintner, 2024) employ the SNAIL instrument for the (self-)assessment of AI literacy among students, who are not experts in the field; this instrument covers technical understanding, critical judgment, and practical understanding. It is noted that the SNAIL instrument possesses good structural validity and internal consistency; furthermore, the SNAIL scale is the only one among the identified scales for which the authors have provided open data (Lintner, 2024).

Biagini (2024) highlighted the need to incorporate psychological aspects into AI literacy scales. In a review study on AI literacy conducted by Feng and Carolus (2026), the established trend of considering psychological dimensions is steering instrument development toward approaches based on psychological insights. Laupichler et al. (2024) examined the relationship between AI literacy (the SNAIL three-factor solution) and attitudes toward AI among medical students, finding a positive correlation between high levels of AI literacy and positive attitudes toward AI. Bewersdorff et al. (2025) report that AI literacy is associated with cognitive (e.g., mindset), affective, and behavioral variables. El-Sayed et al. (2025) reported a link between AI literacy and an innovation mindset. A connection has been demonstrated between attitudes toward AI (the ATTARI-12 scale) and personality traits, utilizing the 44-item big five scale (Stein et al., 2021) and the 10-item big five scale (Mubashir, 2025). When examining attitudes toward AI, Mubashir (2025) suggests measuring psychological predictors. In our study, we selected two types of personality characteristics that could predict AI literacy. The first, personality traits, are relatively stable and difficult to change, whereas the second, mindset, can be altered through targeted interventions.

In this article, we aim to address several research questions regarding the nature and determinants of AI literacy among pre-service teachers. We hypothesize that the dimensions of self-assessed AI literacy, technical understanding and critical application, are influenced by components of information literacy, computational thinking, and media literacy (specifically the dimensions of media access and media production), as well as personal variables (personality and mindset).

Specifically, we examine:

- What is the structure of AI literacy in our sample?
- To what extent can AI literacy be predicted by components of information literacy?
- How much of AI literacy can be explained by various established technology-related literacies?
- To what extent do personality and mindset contribute to predicting AI literacy?

METHODS

Research Design

This exploratory correlational study examines Slovene pre-service teachers' AI literacy structure utilizing the SNAIL instrument (Laupichler et al., 2023b) for non-experts. Correlational analysis was utilized to identify the relationship between AI literacy and the predecessor literacies utilizing instruments: Student perception of information literacy skills (PILS) (Doyle et al., 2019), CTS (Guggemos et al., 2019; Korkmaz et al., 2017), DOMLA (Hallaq, 2016), the ten-item personality inventory (TIPI) (Gosling et al., 2003), and implicit theories of intelligence (self-theory scale; De Castella & Byrne, 2015).

Sample and Data Collection

For the research, the Commission of the University of Primorska for Ethics in Human Subjects Research issued the ethical approval 4264-24-6/23. An online survey was conducted in 2024/25 according to the ethical approval; the invitation to participate in the online survey was provided by the course leader in the courses. For each invitation, the link was accessible for a limited time. Students were informed that the survey is voluntary and anonymous, and that the data will be collected based on the personal data minimization principle and processed in a condensed form, with no possibility to identify persons' responses. At the beginning of the survey, all participants read and approved written consent to participate, knowing that they can withdraw their consent.

In the survey, 323 Slovene students from one of three Slovene universities that educate teachers and educators, the University of Primorska, participated. Participants were students from teacher education courses and education science courses. The average age in our survey was 20.87 (standard deviation [SD] = 1.35). Related research did not report on the importance of gender or age-related factors, and the measurement extends beyond the university setting (Bewersdorff et al., 2025). Studies in AI literacy also use convenience samples (Bećirović et al., 2025; Laupichler et al., 2023a). Concerning the magnitude of the sample size, our sample includes more than 300 participants, which several scholars consider an adequate sample size for performing exploratory factor analysis (EFA) and obtaining reliable factor solutions (Field, 2013).

Instruments

In the study, 6 existing measures were applied. Among those, 4 instruments measured different types of technology-related literacies. 2 measures were adopted to investigate personality characteristics of the participants.

SNAIL (Laupichler et al., 2023b) is a relatively new but widely used instrument. It is based on the three-factor TUCAPA model of AI literacy (Laupichler et al., 2023b). The scale consists of 31 items rated on a 7-point scale for students to report self-assessed AI literacy. The original SNAIL consists of three subscales (Laupichler et al., 2024). A set of exploratory analyses (principal axis factoring with Varimax rotation) was conducted on our sample to obtain an interpretable factorial structure. Inspecting the scree plot, a three-factor solution was initially identified as adequate; however, all items showed high loadings on only two factors. In the two-factor structure solution, communalities after extraction remained above 0.30 for all items, and both obtained factors demonstrated high internal reliability. The results of the EFA of the SNAIL are further presented in more detail in the results section, together with a commentary on construct validity.

PILS (Doyle et al., 2019) measures students' self-assessed information literacy on a 7-point scale from novice (1) to expert (7). The original scale had 42 items, but only 36 were deemed suitable, according to Doyle et al. (2019). In this study, EFA was conducted to evaluate construct validity. Using all 42 items yielded no interpretable solution; using 36 items produced a 4-factor solution (following Kaiser's criterion) that did not match the original scale. To align with the original structure, 7 factors were forced to be extracted using principal axis factoring with Oblimin rotation. Even though the 7-factor solution is not aligned with Kaiser's criterion, communalities after extraction are all higher than 0.30 (see [Appendix A](#)), and the solution closely resembles the original scale by Doyle et al. (2019). Therefore, PILS initially produced a four-factor solution, but seven factors were later forced to obtain a structure closer to the original instrument.

- Three factors: *authority is constructed and contextual, information has value, and searching as strategic exploration – mindset*, matched the original.
- The other four factors: *information creation as a process, research as inquiry, scholarship as conversation, and searching as strategic exploration – tools, and tasks*, slightly deviated but retained content validity.
- Four cross-loaded items were removed, yielding a final PILS version with 32 items.

The full factorial structure of the validated PILS is provided in [Appendix A](#). All subscales as well as the total scale have been confirmed as reliable on our data.

CTS (Guggemos et al., 2019; Korkmaz et al., 2017) measures computational thinking with five subscales: *critical thinking, algorithmic thinking, cooperativity, creativity, and problem-solving*. The use of the total score is not advisable, as several subscales have shown negative inter-correlations (Guggemos et al., 2019). In our survey, we used a shortened version (15 items) of the scale, adopted by Guggemos et al. (2019). Principal axis factoring with Varimax rotation revealed a factorial structure (see [Appendix B](#)), identical to the original scale (Guggemos et al., 2019). A 5-point Likert's scale was used in our sample. All factors demonstrated adequate internal reliability.

DOMLA (Hallaq, 2016) is a self-assessed questionnaire for measuring digital literacy among university students. The instrument comprises 50 items distributed across five subscales: *ethical awareness, media access, media awareness, media evaluation, and media production*. EFA of our data (see [Appendix C](#)) did not show a similar factorial structure. For further analysis, we therefore used only items that were originally organized in the subscales *media access* and *media production*. Both factors showed adequate internal reliability. The two DOMLA subscales of *media access* and *media production* were retained for further analysis, because we wanted to include variables measuring active participation of users.

Implicit theories of intelligence (self-theory scale) (De Castella & Byrne, 2015) evaluate individuals' beliefs regarding their capacity to modify their own intelligence. It comprises eight statements, with half reflecting the belief that intelligence is a fixed trait and the other half reflecting the belief that intelligence is malleable. Responses are rated on a six-point Likert scale, ranging from 1 ("strongly disagree") to 6 ("strongly agree"), indicating the extent to which each statement applies to the respondent. Higher scores indicate a growth mindset (believing one's own intelligence is malleable), and lower scores indicate a fixed mindset (believing that one's intelligence is not malleable). Principal factor analysis, done on our sample, confirmed the adequacy of a one-factor solution.

TIPi by Gosling et al. (2003) was used to measure big-five personality dimensions. It is a 10-item instrument that has been validated before and is used when there is a need for time-efficient measurements of personality, especially in cases where personality is not the central research topic of the study (Gosling et al., 2003). We used the Slovenian translation of the scale (Erčulj, 2020). Each of the subscales (extraversion, neuroticism, openness, conscientiousness, agreeableness) has two items. Because the scale does not include at least three items per latent factor, the EFA does not provide relevant information on the construct validity of the scale (Laverdière et al., 2020).

Statistical Analysis

Statistical analysis was conducted using SPSS. First, we performed a series of EFA to examine the dimensional structure of each technology-related literacy measurement scale (SNAIL, PILS, CTS, and DOMLA). Assumptions for performing EFA (KMO, Bartlett's test, value of determinant, inspecting for very high correlations between items) were checked before conducting the analysis. Items with cross-loadings or low loadings were excluded. Principal component analysis was conducted to confirm the structure of the instrument measuring mindset. Next, we computed descriptive statistics (means, SDs, skewness, and kurtosis) for all factors and assessed normality through skewness, kurtosis, and graphical inspection. The reliability of the scales was evaluated using Cronbach's alpha, and in the case of two-item scales, the Spearman-Brown coefficient was calculated. Following this, bivariate correlations (Pearson's or Spearman's coefficients) were computed.

Subsequently, multiple regression analyses were performed. Prior to conducting regression analyses, key assumptions (linearity, independence of errors, homoscedasticity, and absence of multicollinearity) were verified. Finally, bootstrap analyses were employed, where necessary, to obtain bias-corrected confidence

Table 1. Results of the exploratory analysis and communalities after extraction for items of the instrument SNAIL (N = 323)

Items	Technical understanding	Critical application	h ²
TU1	.771	.096	.603
TU2	.788	.059	.625
TU3	.767	.116	.602
TU4	.657	.237	.487
TU5	.785	.108	.628
TU6	.688	.191	.510
TU7	.781	.133	.628
TU8	.742	.052	.554
TU9	.812	.050	.662
TU10	.804	.119	.660
TU11	.719	.240	.575
TU12	.762	.237	.637
TU13	.734	.198	.578
TU14	.660	.321	.539
CRITIC1	.311	.516	.363
CRITIC2	.349	.544	.418
CRITIC3	.363	.591	.481
CRITIC4	.169	.710	.533
CRITIC5	.008	.700	.490
CRITIC6	.210	.633	.444
CRITIC7	.032	.692	.479
CRITIV8	.077	.720	.524
CRITIV9	.183	.660	.469
CRITIC10	.125	.638	.422
PRACTIC1	-.027	.685	.470
PRACTIC2	.118	.632	.413
PRACTIC3	.259	.641	.478
PRACTIC4	.134	.686	.489
PRACTIC5	.345	.582	.458
PRACTIC6	.092	.650	.431
PRACTIC7	.044	.616	.381
Eigenvalues	8.57	7.46	
Percentage of explained variance (%)	27.65	24.06	

intervals (CIs). To assess the robustness of the regression coefficients, a bootstrapping procedure was conducted, where necessary. The procedure was based on 1,000 (if not noted otherwise) bootstrap samples drawn with replacement from the original sample. Bias-corrected and accelerated 95% CIs were calculated for the regression coefficients. A coefficient was considered statistically significant when its 95% CI did not include zero.

The sample sizes differ across analyses because of missing data. For the respective analyses, cases with missing values on any of the variables included in the analysis were excluded using listwise deletion. Thus, the N varies depending on the variables included in each analysis and is presented for each analysis separately. To assess the potential impact of the missing-data procedure on the results of the EFA, we additionally compared the results obtained using pairwise and listwise deletion. The results did not differ meaningfully, indicating that the choice of missing-data procedure did not affect the results of EFA.

RESULTS

Factor Analysis of the SNAIL Scale

Firstly, we examined the number of latent factors identified in a self-assessed measure of AI literacy, the SNAIL instrument (Laupichler et al., 2023b). A two-factor solution emerged. The first factor, technical understanding, was consistent with the original instrument. The second latent factor was labelled critical application, as it comprised items that originally constituted the factors *critical appraisal* and *practical application* (see Table 1).

Table 2. Descriptive statistics and reliability of factors

	Cronbach's alpha	M	SD	Skewness	Kurtosis
Authority is constructed and contextual	.88	3.39	1.16	-.039	-.486
Information has value	.92	3.58	1.21	-.047	-.539
Research as inquiry	.90	3.74	1.25	-.119	-.471
Searching as strategic exploration – tools	.85	3.87	1.28	-.116	-.546
Scholarship as conversation	.88	3.67	1.22	-.156	-.422
Searching as strategic exploration – mindset	.89	4.50	1.35	-.421	-.348
Information creation as a process	.88	4.23	1.33	-.341	-.468
PILS	.97	3.83	1.07	-.403	-.080
Technical understanding	.95	3.49	1.12	-.436	-.039
Critical application	.93	4.65	.85	-.216	.914
Creativity	.87	3.67	.83	-.983	1.160
Algorithmic thinking	.82	2.85	.93	-.202	-.447
Cooperativity	.83	3.49	.82	-.585	.413
Critical thinking	.74	3.64	.67	-.627	1.387
Problem-solving	.69	2.97	.69	.040	.558
Media access	.62	4.23	.79	-.564	.513
Media production	.67	3.98	.81	-.142	-.326
Mindset	.82	3.70	.69	.535	-.072
Extraversion	.40*	3.30	.80	.142	.141
Conscientiousness	.29*	3.30	.76	.173	.035
Neuroticism	.52*	3.27	.87	-.020	-.119
Agreeableness	.41*	3.93	.82	-.266	-.899
Openness	.14*	3.43	.80	.180	-.582

* Spearman-Brown coefficient

Table 3. Correlations (Spearman's rho or Pearson's r) between PILS and SNAIL

	1	2	3	4	5	6	7	8	9	10
1 PILS: Authority is constructed and contextual	1.000									
2 PILS: Information has value	.715**	1.000								
3 PILS: Research as inquiry	.676**	.726**	1.000							
4 PILS: Searching as strategic exploration – tools	.651**	.748**	.742**	1.000						
5 PILS: Scholarship as conversation	.728**	.746**	.843**	.799**	1.000					
6 PILS: Searching as strategic exploration – mindset	.520**	.604**	.668**	.703**	.682**	1.000				
7 PILS: Information creation as a process	.660**	.673**	.628**	.665**	.658**	.661**	1.000			
8 PILS: Total score	.842**	.875**	.877**	.874**	.909**	.786**	.831**	1.000		
9 SNAIL: Technical understanding	.120*	.162**	.099	.147*	.134*	-.049	.037	.125*	1.000	
10 SNAIL: Critical application	.298**	.304**	.350**	.376**	.350**	.384**	.351**	.411**	.333**	1.000

Note. **Correlation is significant at the 0.01 level (2-tailed); *Correlation is significant at the 0.05 level (2-tailed); Pearson's r coefficients are in *italics*

Descriptive Statistics and Reliability of Factors

Table 2 presents the descriptive statistics (M, SD, skewness, and kurtosis) for each of the (sub)scales. All subscales, except those from the personality questionnaire (TIPI), demonstrated adequate reliability (Cronbach's alpha > 0.6). The reliability of five TIPI two-item subscales, examined using split-half reliability measures, was poor (Spearman-Brown coefficients ranged from 0.14 to 0.51).

Predicting AI Literacy From Information Literacy

To determine which components of information literacy predict AI literacy among students, we performed a set of correlational analyses. **Table 3** presents the correlations between scores on the PILS and SNAIL. The PILS total score correlates positively and moderately with critical application of AI ($p = 0.41$). All PILS subscales correlate weakly but significantly and positively with critical application of AI. The highest correlations are observed between AI critical application and the PILS factors search as strategic exploration – mindset ($p = 0.38$) and search as strategic exploration – tools ($p = 0.37$). technical understanding of AI shows weak ($p < 0.3$) or non-existent correlations with the PILS scale and its subscales.

Linear regression using the forced entry method was employed to examine which PILS subscales significantly predict each of the SNAIL factors (see **Table 4**). The PILS scales explained 8.7% of the variance in

Table 4. Linear model of predictors of technical understanding predicted by PILS subscales

	<i>b</i>	SE B	β	p
Constant	3.19 (2.60, 3.74)	.30		< .001
Authority is constructed and contextual	0.01 (-0.17, 0.21)	0.10	0.01	.882
Information has value	0.20 (-0.02, 0.44)	0.11	0.21	.059
Research as inquiry	0.01 (-0.22, 0.21)	0.11	0.01	.941
Searching as strategic exploration – tools	0.16 (-0.03, 0.36)	0.10	0.18	.096
Scholarship as conversation	0.12 (-0.10, 0.33)	0.08	0.11	.274
Searching as strategic exploration – mindset	-0.26 (-0.42, -0.10)	0.08	-0.30	< .001
Information creation as a process	-0.10 (-0.25, 0.05)	0.08	-0.12	.184

Note. CIs and SEs are based on 1,000 bootstrap samples; N = 275; $R^2 = .087$

Table 5. Linear model of predictors of critical application predicted by PILS subscales

	<i>b</i>	SE B	β	p
Constant	3.22 (2.79, 3.65)	0.20		<.001
Authority is constructed and contextual	0.03 (-0.11, 0.16)	0.07	0.04	.640
Information has value	-0.01 (-0.14, 0.13)	0.07	-0.01	.923
Research as inquiry	0.08 (-0.07, 0.22)	0.07	0.12	.242
Searching as strategic exploration – tools	0.14 (0.01, 0.26)	0.06	0.20	.033
Scholarship as conversation	-0.09 (-0.24, 0.05)	0.07	-0.12	.237
Searching as strategic exploration – mindset	0.12 (0.02, 0.23)	0.05	0.18	.019
Information creation as a process	0.07 (-0.04, 0.19)	0.05	0.11	.187

Note. CIs and SEs are based on 1,000 bootstrap samples; N = 277; $R^2 = .210$

scores on the technical understanding scale. Several issues with the linear model were identified, including scatterplots not showing a clear linear relationship, non-normal residual distribution, and potential heteroscedasticity. Therefore, a bootstrap regression was conducted to obtain more reliable CIs and standard errors (SEs).

As shown in [Table 4](#), only the factor searching as strategic exploration – mindset significantly predicts technical understanding of AI. It should be noted, however, that the bootstrapped regression solution identified this subscale as a negative predictor ($\beta = -0.30$, $p < .001$), which was unexpected. As previously mentioned, this linear model may not be highly accurate due to assumption violations and low R^2 .

To assess the predictors of critical application of AI, the same procedure as described in the previous paragraph was applied (see [Table 5](#)).

The assumptions for linear regression were met, except for the normality of the residual distribution. Therefore, the bootstrap procedure was again conducted. Two PILS subscales significantly and positively predicted critical application: the most important predictor was searching as strategic exploration – tools ($\beta = 0.20$), followed by searching as strategic exploration – mindset ($\beta = 0.18$). The PILS subscales together explained 21.0% of the variance in critical application scores, indicating a moderate effect size. We can conclude that predicting critical application of AI based on the PILS subscales is more accurate and efficient than predicting technical understanding of AI.

Table 6. Results of the regression analysis predicting technical understanding (block 5)

	b	SE B	β	p	95% CI	
					Lower	Upper
(Constant)	1.273	.869 ^c		.156 ^c	-.406 ^c	3.125 ^c
PILS total	.026	.074 ^c	0.02	.736 ^c	-.128 ^c	.181 ^c
Media access	.037	.101 ^c	0.02	.717 ^c	-.164 ^c	.280 ^c
Media production	.425	.089 ^c	0.31	.001 ^c	.252 ^c	.599 ^c
Creativity	-.045	.101 ^c	-0.03	.657 ^c	-.241 ^c	.135 ^c
Algorithmic thinking	.421	.085 ^c	0.35	.001 ^c	.250 ^c	.598 ^c
Cooperativity	.177	.088 ^c	0.13	.043 ^c	.009 ^c	.333 ^c
Critical thinking	-.145	.131 ^c	-0.09	.276 ^c	-.392 ^c	.116 ^c
Problem-solving	.174	.111 ^c	0.11	.111 ^c	-.034 ^c	.411 ^c
Extraversion	-.065	.085 ^c	-0.05	.454 ^c	-.229 ^c	.091 ^c
Conscientiousness	.148	.090 ^c	0.10	.107 ^c	-.012 ^c	.280 ^c
Neuroticism	-.108	.080 ^c	-0.09	.174 ^c	-.260 ^c	.064 ^c
Agreeableness	-.274	.075 ^c	-0.20	.001 ^c	-.437 ^c	-.098 ^c
Openness	-.027	.089 ^c	-0.02	.769 ^c	-.189 ^c	.121 ^c
Mindset	-.035	.109 ^c	-0.02	.760 ^c	-.229 ^c	.165 ^c

Note. $DR^2 = 0.000$; ^a Unless otherwise noted, bootstrap results are based on 1,000 bootstrap samples; ^b Based on 749 samples; ^c Based on 748 samples; N = 232

The Role of Digital Literacies and Personal Factors for Predicting AI Literacy

To examine the contribution of personal factors and various forms of digital literacy to the prediction of AI literacy, we conducted two sets of hierarchical multiple linear regressions. The anticipated predictors in our model included information literacy (1 variable), media literacy (2 variables), computational thinking (5 variables), personality traits (5 variables), and mindset (1 variable). The outcome variables were two dimensions of AI literacy: technical understanding and critical application. Correlations among all 17 variables are presented in [Appendix D](#).

In the first hierarchical regression analysis, we examined predictors of technical understanding, followed by a second regression model predicting critical application. In both analyses, predictors were entered sequentially in five blocks using the enter method, in the following order:

- (1) information literacy,
- (2) media literacy,
- (3) computational thinking,
- (4) personality traits, and
- (5) mindset.

Because some assumptions were violated, the bootstrap method was applied. Entering only information literacy into the regression model did not significantly predict technical understanding ($\Delta R^2 = 0.012$, $F[1, 230] = 2.75$, $p = 0.09$). Adding media literacy resulted in a significant improvement of the model ($F[2, 228] = 17.21$, $p < .001$), accounting for an additional 13% of the variance. In the next step, computational thinking contributed a further 16.2% of the explained variance ($F[5, 223] = 10.35$, $p < .001$). Personality traits significantly added to the prediction ($\Delta R^2 = 0.048$, $F[5, 218] = 3.21$, $p = 0.008$), while the inclusion of mindset did not further significantly improve the model ($\Delta R^2 = 0.000$, $F[1, 217] = 0.11$, $p = 0.736$). Altogether, the predictor variables explained 35.2% of the variance in technical understanding of AI.

Examining the predictive strength of individual predictors (see [Table 6](#)), the strongest predictors of technical understanding were higher media production literacy ($\beta = 0.31$), stronger algorithmic thinking skills ($\beta = 0.35$), lower agreeableness ($\beta = -0.20$), and higher cooperativity ($\beta = 0.13$). The reported reliability of the TIPI subscales is low in this sample. Therefore, the finding concerning agreeableness should be considered tentative.

As shown in [Table 7](#), critical application was predicted by a different set of variables than technical understanding. Again, the bootstrap method was applied due to violations of some assumptions. Critical application was significantly predicted by information literacy in step 1 ($\Delta R^2 = .15$, $F(1, 232) = 42.06$, $p < .001$). Adding media literacy further improved the prediction in step 2 ($\Delta R^2 = .04$, $F(2, 230) = 6.93$, $p = .001$), and

Table 7. Results of the regression analysis predicting critical application

	b	SE B	β	p	95% CI	
					Lower	Upper
Block 5						
(Constant)	.637	.760 ^b		.402 ^b	-1.011 ^b	2.349 ^b
PILS total	.169	.061 ^b	.216	.007 ^b	.061 ^b	.282 ^b
Media access	.079	.088 ^b	.078	.369 ^b	-.103 ^b	.271 ^b
Media production	.151	.071 ^b	.148	.041 ^b	.005 ^b	.311 ^b
Creativity	.136	.075 ^b	.129	.058 ^b	-.013 ^b	.275 ^b
Algorithmic thinking	-.015	.054 ^b	-.017	.798 ^b	-.104 ^b	.083 ^b
Cooperativity	.123	.074 ^b	.123	.102 ^b	-.019 ^b	.251 ^b
Critical thinking	.020	.109 ^b	.016	.862 ^b	-.203 ^b	.247 ^b
Problem-solving	.055	.097 ^b	.045	.580 ^b	-.132 ^b	.219 ^b
Extraversion	.053	.061 ^b	.052	.403 ^b	-.056 ^b	.151 ^b
Conscientiousness	.057	.066 ^b	.053	.396 ^b	-.070 ^b	.174 ^b
Neuroticism	.044	.060 ^b	.047	.461 ^b	-.059 ^b	.150 ^b
Agreeableness	-.068	.062 ^b	-.069	.262 ^b	-.176 ^b	.045 ^b
Openness	.022	.071 ^b	.022	.755 ^b	-.121 ^b	.186 ^b
Mindset	.256	.079 ^b	.221	.001 ^b	.101 ^b	.382 ^b

Note. ^a Unless otherwise noted, bootstrap results are based on 1,000 bootstrap samples; ^b Based on 746 samples; ^c Based on 748 samples; N = 234

computational thinking variables contributed additional explanatory power in step 3 ($\Delta R^2 = .06$, $F(5, 225) = 3.39$, $p = .006$). In step 4, the inclusion of personality traits did not significantly improve the model ($\Delta R^2 = .01$, $F(5, 220) = 0.63$, $p = .679$), whereas adding mindset in step 5 did ($\Delta R^2 = .03$, $F(1, 219) = 10.66$, $p = .001$). Altogether, 30.2% of the variance in critical application scores was explained by the predictors. As shown in **Table 7**, in the final step, three predictors remained statistically significant: mindset ($\beta = 0.22$), information literacy ($\beta = 0.22$), and media production literacy ($\beta = 0.15$).

DISCUSSION

Review studies on AI literacy instruments address components that extend beyond mere technology knowledge and build upon prior forms of literacy, such as digital literacy (Bewersdorff et al., 2025; Biagini, 2025; Lintner, 2024; Ng et al., 2021), information literacy (Bewersdorff et al., 2025), and data literacy (Bewersdorff et al., 2025; Biagini, 2025), including computational thinking (Biagini, 2025).

In this study, we used the SNAIL tool (Laupichler et al., 2023b), designed for non-experts, to assess AI literacy. To address the first research question regarding the structure of AI literacy in our sample, we analyzed the indicators and structure of this literacy, including the latent factors defined within the self-assessment instrument.

The original SNAIL scale comprises three factors: technical understanding, critical judgment, and practical application; while a two-factor structure was also suggested as a possibility, the specific dimensions to be combined were not clearly defined (Laupichler et al., 2023b). Our study yielded a two-factor solution. The first factor, technical understanding, corresponded to the original instrument. We named the second latent factor critical use, as it combined items that originally constituted the factors critical judgment and practical use. Koch et al. (2024) also identified a similar two-factor structure in which technical understanding was one of the factors. Koch included all 47 items (Laupichler et al., 2023a) in the study, rather than just the final 31 items from the TUCAPA model (Laupichler et al., 2023b).

The aim of this study was also to examine predictors of AI literacy among students in teacher education programs. Considering prior forms of literacy, we examined the contribution of individual components of the PILS questionnaire (which measures information literacy). Addressing the second research question, regarding the extent to which information literacy components can predict AI literacy, we analyzed PILS information literacy subscales as predictors of AI literacy, specifically for two factors defined in the SNAIL scale: technical understanding and critical use. It was found that PILS components were more strongly associated with critical use than with technical understanding (at least not to the same degree). Since information literacy requires the critical evaluation of information, critical use is a central dimension of AI literacy (Laupichler et al., 2023b; Lintner, 2024) and entails verifying and critically assessing the information,

data, answers, and solutions obtained through interaction with an AI agent. The PILS subscales were also significant positive predictors of critical use: the most important predictor was “searching as strategic exploration – tools,” followed by “searching as strategic exploration – mindset.” This indicates that measuring an individual’s knowledge of the search process (e.g., the use of search tools and strategies) and their motivation to persist in the search can, to a certain extent, predict their use and critical evaluation of AI.

Conversely, only one PILS factor, searching as strategic exploration – mindset, significantly predicts technical understanding of AI. However, it was identified as a negative predictor, which raises a potential conceptual issue. Due to the low reliability of the TIPI subscales in this sample, the finding regarding agreeableness should be treated with caution. We concluded that predicting critical use of AI based on PILS subscales is more accurate and effective than predicting technical understanding of AI.

Addressing the third research question, regarding the extent to which AI literacy can be predicted based on various established technology-related literacies, we examined the relative predictive power of individual types of technological literacy for each of the factors.

In our study, which is based on the PILS subscales, information literacy did not predict technical understanding. Media literacy, specifically media production, and computational thinking (along with its algorithmic thinking subscale) accounted for variance in the regression model and emerged as significant predictors. These results indicate that both digital production skills and computational reasoning abilities, which Celik (2023) and Biagini (2025) place at the core of AI literacy, are crucial for understanding AI at a technical level. Bećirović et al. (2025) utilize the three-factor SNAIL instrument to discuss technical understanding of AI in relation to the field of study, identifying teachers with low technological affinity and limited knowledge regarding systems, concepts, models, and deep learning (Bećirović et al., 2025). Critical use of AI was significantly predicted by information literacy, media literacy (specifically the media production subscale), and computational thinking. Enhancing these predictor literacies could improve AI literacy. However, given the exploratory, correlational nature of our study, such claims warrant further investigation through experimental and longitudinal research designs.

In addressing the fourth research question, we examined the extent to which personality and mindset contribute to predicting AI literacy. Critical application of AI was positively associated with extraversion, conscientiousness and openness, a finding similar to that of Arpacı et al. (2025). However, while mindset proved to be a significant predictor for this component of AI literacy, these personality traits did not. As hypothesized, a growth mindset was associated with a higher level of critical application of AI. It can be assumed that students who believe human cognitive abilities can be developed use AI in a more constructive and critical manner, potentially viewing it as an aid to expanding their own cognitive capabilities.

technical understanding of AI was negatively associated with neuroticism and agreeableness. Agreeableness was also the only significant predictor among personality variables. Individuals lower in agreeableness are perceived as less cooperative, less gentle, and more competitive. Agreeableness has not previously been identified as a significant predictor of AI use; furthermore, we cannot currently provide an adequate theoretical explanation for these statistical results. Therefore, further research is needed to identify the potential factors contributing to both lower pleasantness and higher technical understanding of AI.

CONCLUSIONS

To prepare teachers is essential to address various factors influencing their readiness to equip future generations for life and work involving technology. Technological development is rapid, and the concept of literacy requires the inclusion of technology-related competencies. Key findings highlight the distinction between technical understanding and critical application within the realm of AI literacy, as well as the different predictors associated with these two dimensions.

Teacher education is facing the proliferation of AI and societal demands for generations of students who are AI-literate. Effective use of educational technology by teachers entails integrating AI technology into teaching methods and strategies. Currently, there are reports of a lack of AI literacy in higher education and teacher training programs (Bewersdorff et al., 2025). Examining the construct of AI literacy is a prerequisite for lesson and curriculum planning in initial teacher education. This study complements existing research on

AI literacy by utilizing the SNAIL instrument (Laupichler et al., 2023b), which defines a two-factor structure, technical understanding and critical application, incorporating critical assessment into AI usage. Given that the construct of AI literacy remains undefined across various groups, our results provide additional data regarding the number and content of AI literacy components among pre-service teachers.

As to its relationship with other forms of literacy, the results indicate that self-assessed AI literacy is strongly correlated with information literacy. In addition to information literacy, the media production subscale (from media literacy) and mindset emerged as statistically significant predictors. Technical understanding of AI was significantly predicted by the media production subscale, the computational thinking subscales of algorithmic thinking and cooperativeness, and the personality trait of (low) agreeableness. Consistent with related studies (Biagini, 2025; Celik, 2023), computational thinking lies at the core of AI literacy, specifically technical understanding. As advocated by Hackl et al. (2026), it is necessary to clarify the relationships between various forms of literacy, identify overlapping dimensions, and further define AI literacy, while conceptualizing its dimensions in clearly defined relation to prior literacy concepts. This study could inform teacher educators in instructional design and curriculum planning by recognizing AI literacy development as related to and differentiated from previous forms of literacy, recognizing overlapping dimensions. AI is rapidly changing not just the pace of access to data but also thinking and creativity, and for a teacher's pedagogical work in such a complex world needed are the novel methods and strategies for different dimensions of AI literacy (Hackl et al., 2026). It is important to note that growth mindset, which could be scaffolded and encouraged, was identified as a significant predictor of AI literacy and should be considered. To effectively build AI literacy within teacher education, institutions must first address the ethical complexities and moral judgments of integrating AI into the classroom. This requires a foundation of in-depth research into AI's effects and its alignment with pedagogical goals (Istenič et al., 2021a, 2021b). Once established as a vital teacher competency, AI literacy can be actively developed by embedding specialized AI modules, media production activities, and algorithmic thinking into growth-mindset training frameworks.

Limitations

Based on related studies, we incorporated specific instruments but encountered issues regarding the construct validity of some of them. A linear regression model was employed; however, this model may lack precision due to assumption violations and a low R^2 value, necessitating a cautious interpretation of the results. A correlational study does not imply causation; therefore, longitudinal or experimental research is required to establish a causal link.

Future Directions

The current generation of prospective teachers developed their technological literacy primarily during their primary and secondary education. Curricula at these levels encompassed information, digital, and media literacy, as well as computational thinking. With the rapid development and proliferation of AI, a need has emerged for AI literacy and an understanding of the structure of AI literacy among prospective teachers. AI literacy draws upon related literacy concepts and earlier forms of technological literacy; consequently, the relationship between these prior literacies and their predictive value for AI literacy is being examined. This supports future research aimed at distinguishing AI literacy from related literacy concepts. To bridge the gap in higher education curricula, concepts of AI literacy within curriculum and instructional design must address technological developments and implement pedagogical principles. Once greater consensus is reached regarding the components of AI literacy for (future) teachers, further research should explore how these components relate to student learning outcomes or to didactic and instructional strategies.

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of withdrawing at any time during the study. When applying instruments and procedures, special care was taken to follow the personal data minimization principle and ensure data anonymization. All participants were assured of anonymity and informed about why the research was conducted, how their data would be used, and that there were no risks associated.

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REFERENCES

- Aharony, N., & Gur, H. (2019). The relationships between personality, perceptual, cognitive and technological variables and students' level of information literacy. *Journal of Librarianship and Information Science*, 51(2), 527-544. <https://doi.org/10.1177/0961000617742450>
- Ahmed, S., & Rasheed, T. (2020). Relationship between personality traits and digital literacy skills: A study of university librarians. *Digital Library Perspectives*, 36(2), 191-206. <https://doi.org/10.1108/DLP-02-2020-0005>
- Archambault, S. G. (2023). Expanding on the frames: Making a case for algorithmic literacy. *Communications in Information Literacy*, 17(2), Article 11. <https://doi.org/10.15760/comminfolit.2023.17.2.11>
- Arpaci, I., Kuşci, I., & Gibreel, O. (2025). The role of personality traits in predicting educational use of generative AI in higher education. *Scientific Reports*, 15, Article 30440. <https://doi.org/10.1038/s41598-025-16339-0>
- Azeem, S., Abbas, M. (2025). Personality correlates of academic use of generative artificial intelligence and its outcomes: Does fairness matter? *Education and Information Technologies*, 30, 18131-18155. <https://doi.org/10.1007/s10639-025-13489-6>
- Barnett, T., Pearson, A. W., Pearson, R., & Kellermanns, F. W. (2015). Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, 24(4), 374-390. <https://doi.org/10.1057/ejis.2014.10>
- Bećirović, S., Polz, E., & Tinkel, I. (2025). Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance. *Smart Learning Environments*, 12, Article 29. <https://doi.org/10.1186/s40561-025-00384-3>
- Berners-Lee, T., Cailliau, R., Luotonen, A., Nielsen, H. F., & Secret, A. (1994). The world-wide web. *Communications of the ACM*, 37(8), 76-82. <https://doi.org/10.1145/179606.179671>
- Bewersdorff, A., Nerdel, C., & Zhai, X. (2025). How AI literacy correlates with affective, behavioral, cognitive and contextual variables: A systematic review. *Computers and Education: Artificial Intelligence*, 9, Article 100493. <https://doi.org/10.1016/j.caeai.2025.100493>
- Biagini, G. (2024). Assessing the assessments: Toward a multidimensional approach to AI literacy. *Media Education*, 15(1), 91-101. <https://doi.org/10.36253/me-15831>
- Biagini, G. (2025). Towards an AI-literate future: A systematic literature review exploring education, ethics, and applications. *International Journal of Artificial Intelligence in Education*, 35, 2616-2666. <https://doi.org/10.1007/s40593-025-00466-w>
- Biagini, G., Cuomo, S., & Ranieri, M. (2023). Developing and validating a multidimensional AI literacy questionnaire: Operationalizing AI literacy for higher education. In *Proceedings of the 1st International Workshop on High-performance Artificial Intelligence Systems in Education*.
- Bruce, C. (2000). Information literacy programs and research: An international review. *The Australian Library Journal*, 49(3), 209-218. <https://doi.org/10.1080/00049670.2000.10755921>
- Buckingham, D. (2006). Defining digital literacy – What do young people need to know about digital media? *Nordic Journal of Digital Literacy*, 1(4), 263-277. <https://doi.org/10.18261/ISSN1891-943X-2006-04-03>
- Buckingham, D. (2007). Digital media literacies: Rethinking media education in the age of the Internet. *Research in Comparative and International Education*, 2(1), 43-55. <https://doi.org/10.2304/rcie.2007.2.1.43>
- Celik, I. (2023). Exploring the determinants of artificial intelligence (AI) literacy: Digital divide, computational thinking, cognitive absorption. *Telematics and Informatics*, 83, Article 102026. <https://doi.org/10.1016/j.tele.2023.102026>

- Chalkiadaki, A. (2018). A systematic literature review of 21st century skills and competencies in primary education. *International Journal of Instruction*, 11(3), 1-16. <https://doi.org/10.12973/iji.2018.1131a>
- Collis, B. (1996). The Internet as an educational innovation: Lessons from experience with computer implementation. *Educational Technology*, 36(6), 21-30.
- Dang, J., & Liu, L. (2022). A growth mindset about human minds promotes positive responses to intelligent technology. *Cognition*, 220, Article 104985. <https://doi.org/10.1016/j.cognition.2021.104985>
- De Castella, K., & Byrne, D. (2015). My intelligence may be more malleable than yours: The revised implicit theories of intelligence (self-theory) scale is a better predictor of achievement, motivation, and student disengagement. *European Journal of Psychology of Education*, 30(3), 245-267. <https://doi.org/10.1007/s10212-015-0244-y>
- Deng, T., Wang, D., Ma, J., Wang, T., Li, B., Hussain, T., Yue, Y., & Wang, P. (2026). Associations between personality traits and ChatGPT usage: The dual mediating roles of social image and computer self-efficacy. *The Journal of Psychology*, 160(3), 312-331. <https://doi.org/10.1080/00223980.2025.2568758>
- Doyle, M., Foster, B., & Yukhymenko-Lescroart, M. A. (2019). Initial development of the perception of information literacy scale (PILS). *Communications in Information Literacy*, 13(2), 205-227. <https://doi.org/10.15760/comminfolit.2019.13.2.5>
- Dweck, C. S. (2000). *Self-theories: Their role in motivation, personality and development*. Psychology Press.
- Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House.
- El-Sayed, B. K. M., El-Sayed, A. A. I., Alsenany, S. A., & Asal, M. G. R. (2025). The role of artificial intelligence literacy and innovation mindset in shaping nursing students' career and talent self-efficacy. *Nurse Education in Practice*, 82, Article 104208. <https://doi.org/10.1016/j.nepr.2024.104208>
- Erčulj, V. (2020). Veljavnost in zanesljivost merjenja velikih pet dimenzij osebnosti s krajšo različico vprašalnika velikih pet dimenzij osebnosti [Validity and reliability of measuring the big five personality dimensions with a short version of the big five personality questionnaire]. In *Proceedings of the 39th International Conference on Organizational Science Development Organizations at Innovation and Digital Transformation Roundabout* (pp. 141-150). University Press.
- Feng, S., & Carolus, A. (2026). Artificial intelligence literacy at school: A systematic review with a focus on psychological foundations. *Computers and Education: Artificial Intelligence*, 10, Article 100551. <https://doi.org/10.1016/j.caeai.2026.100551>
- Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). SAGE.
- Foasberg, N. M. (2015). From standards to frameworks for IL: How the ACRL framework addresses critiques of the standards. *portal: Libraries and the Academy*, 15(4), 699-717. <https://doi.org/10.1353/pla.2015.0045>
- Goody, J. (1977). *The domestication of the savage mind*. Cambridge University Press.
- Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the big-five personality domains. *Journal of Research in Personality*, 37(6), 504-528. [https://doi.org/10.1016/S0092-6566\(03\)00046-1](https://doi.org/10.1016/S0092-6566(03)00046-1)
- Greenhill, V. (2010). 21st century knowledge and skills in educator preparation. *Partnership for 21st Century Skills*.
- Gretter, S., & Yadav, A. (2016). Computational thinking and media & information literacy: An integrated approach to teaching twenty-first century skills. *TechTrends*, 60(5), 510-516. <https://doi.org/10.1007/s11528-016-0098-4>
- Guggemos, J., Seufert, S., & Román-González, M. (2019). *Measuring computational thinking – Adapting a performance test and a self-assessment instrument for German-speaking countries*. International Association for Development of the Information Society. https://doi.org/10.33965/celda2019_201911L023
- Hackl, V., Müller, A. E., & Sailer, M. (2026). The AI literacy heptagon: A structured approach to AI literacy in higher education. *Computers and Education: Artificial Intelligence*, 10, Article 100540. <https://doi.org/10.1016/j.caeai.2026.100540>
- Hallaq, T. (2016). Evaluating online media literacy in higher education: Validity and reliability of the digital online media literacy assessment (DOMLA). *Journal of Media Literacy Education*, 8(1), 62-84. <https://doi.org/10.23860/jmle-8-1-5>
- Havelock, E. A. (1986). *The muse learns to write: Reflections on orality and literacy from antiquity to the present*. Yale University Press.
- Hobbs, R., & Jensen, A. (2009). The past, present, and future of media literacy education. *Journal of Media Literacy Education*, 1(1). <https://doi.org/10.23860/jmle-1-1-1>

- Hovious, A. (2024). Information creation as an AI prompt: Implications for the ACRL framework. *Kansas Library Association College and University Libraries Section Proceedings*, 14(1), Article 5. <https://doi.org/10.4148/2160-942X.1094>
- Hsieh, M. L., Dawson, P. H., & Yang, S. Q. (2021). The ACRL framework successes and challenges since 2016: A survey. *The Journal of Academic Librarianship*, 47(2), Article 102306. <https://doi.org/10.1016/j.acalib.2020.102306>
- Hsu, T.-C., Chang, S.-C., & Hung, Y.-T. (2018). How to learn and how to teach computational thinking: Suggestions based on a review of the literature. *Computers & Education*, 126, 296-310. <https://doi.org/10.1016/j.compedu.2018.07.004>
- Hu, Y., Tan, C.-S., Wang, S., Zhang, H., Qian, J., & Wang, Y. (2025). Who is hooked on AI? The role of the big five personality traits in compulsive ChatGPT use among Chinese students. *The Asia-Pacific Education Researcher*, 34, 1899-1907. <https://doi.org/10.1007/s40299-025-01001-0>
- Huang, C. (2019). Social network site use and big five personality traits: A meta-analysis. *Computers in Human Behavior*, 97, 280-290. <https://doi.org/10.1016/j.chb.2019.03.009>
- Istenič, A., Bratko, I., & Rosanda, V. (2021a). Pre-service teachers' concerns about social robots in the classroom: A model for development. *Education and Self-Development*, 16(2), 60-87. <https://doi.org/10.26907/esd.16.2.05>
- Istenič, A., Bratko, I., & Rosanda, V. (2021b). Are pre-service teachers disinclined to utilise embodied humanoid social robots in the classroom? *British Journal of Educational Technology*, 52(6), 2340-2358. <https://doi.org/10.1111/bjet.13144>
- Istenič Starčič, A. (2019). Human learning and learning analytics in the age of artificial intelligence. *British journal of educational technology*, 50(6). <https://doi.org/10.1111/bjet.12879>
- Jacob, S. R., & Warschauer, M. (2018). Computational thinking and literacy. *Journal of Computer Science Integration*, 1(1). <https://doi.org/10.26716/jcsi.2018.01.1.1>
- Jorolan, J., Cabillo, F., Batucan, R. R., Camansi, C. M., Etoquilla, A., Gapo, J., Hallarte, D. K., Milano, M. L., Gonzales, R., & Gonzales, G. (2025). Development and validation of moral ascendancy and dependency in AI integration scale (MAD-AI) for teachers. *Computers & Education*, 235, Article 105346. <https://doi.org/10.1016/j.compedu.2025.105346>
- Karaca, O., Çalışkan, S. A., & Demir, K. (2021). Medical artificial intelligence readiness scale for medical students (MAIRS-MS) – Development, validity and reliability study. *BMC Medical Education*, 21, Article 112. <https://doi.org/10.1186/s12909-021-02546-6>
- Kim, S.-W., & Lee, Y. (2022). The artificial intelligence literacy scale for middle school. *Journal of the Korea Society of Computer and Information*, 27, 225-238.
- Koch, M. J., Wienrich, C., Straka, S., Latoschik, M. E., & Carolus, A. (2024). Overview and confirmatory and exploratory factor analysis of ai literacy scale. *Computers and Education: Artificial Intelligence*, 7, Article 100310. <https://doi.org/10.1016/j.caeai.2024.100310>
- Korkmaz, Ö., Çakir, R., & Özden, M. Y. (2017). A validity and reliability study of the computational thinking scales (CTS). *Computers in Human Behavior*, 72, 558-569. <https://doi.org/10.1016/j.chb.2017.01.005>
- Laupichler, M. C., Aster, A., & Raupach, T. (2023a). Delphi study for the development and preliminary validation of an item set for the assessment of non-experts' AI literacy. *Computers and Education: Artificial Intelligence*, 4, Article 100126. <https://doi.org/10.1016/j.caeai.2023.100126>
- Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T. (2023b). Development of the "scale for the assessment of non-experts' AI literacy" – An exploratory factor analysis. *Computers in Human Behavior Reports*, 12, Article 100338. <https://doi.org/10.1016/j.chbr.2023.100338>
- Laupichler, M. C., Aster, A., Meyerheim, M., Raupach, T., & Mergen, M. (2024). Medical students' AI literacy and attitudes towards AI: A cross-sectional two-center study using pre-validated assessment instruments. *BMC Medical Education*, 24(1), Article 401. <https://doi.org/10.1186/s12909-024-05400-7>
- Laverdière, O., Gamache, D., Morin, A. J. S., & Diguier, L. (2020). French adaptation of the Mini-IPIP: A short measure of the big five. *European Review of Applied Psychology*, 70(3), Article 100512. <https://doi.org/10.1016/j.erap.2019.100512>
- Leite, H. (2025). Artificial intelligence in higher education: Research notes from a longitudinal study. *Technological Forecasting and Social Change*, 215, Article 124115. <https://doi.org/10.1016/j.techfore.2025.124115>

- Lintner, T. (2024). A systematic review of AI literacy scales. *npj Science of Learning*, 9(1), Article 50. <https://doi.org/10.1038/s41539-024-00264-4>
- Liu, D., & Campbell, W. K. (2017). The big five personality traits, big two metatraits and social media: A meta-analysis. *Journal of Research in Personality*, 70, 229-240. <https://doi.org/10.1016/j.jrp.2017.08.004>
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-16). <https://doi.org/10.1145/3313831.3376727>
- Matthews, A. S., & Bartley, B. (2025). Pay attention to the chatbot behind the curtain when AI 'is no place like home': A framework and toolkit for integrating critical thinking and information literacy in educational and professional settings. *Advances in Online Education: A Peer-Reviewed Journal*, 3(3), 247-273. <https://doi.org/10.69554/FMAI7138>
- McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology*, 52(1), 81-90. <https://doi.org/10.1037/0022-3514.52.1.81>
- Merchant, L., & Hepworth, M. (2002). Information literacy of teachers and pupils in secondary schools. *Journal of Librarianship and Information Science*, 34(2), 81-89. <https://doi.org/10.1177/096100060203400203>
- Mubashir, A. S., Altaf, W., & Kainaat, R. (2025). Personality traits and attitudes towards artificial intelligence among university students. *Social Science Review Archives*, 3(2), 1010-1019. <https://doi.org/10.70670/sra.v3i2.690>
- Ndungu, M. W. (2024). Integrating basic artificial intelligence literacy into media and information literacy programs in higher education: A framework for librarians and educators. *Journal of Information Literacy*, 18(2), 122-139. <https://doi.org/10.11645/18.2.641>
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 2, Article 100041. <https://doi.org/10.1016/j.caeai.2021.100041>
- Ng, D. T. K., Wu, W., Leung, J. K. L., & Chu, S. K. W. (2023). Artificial intelligence (AI) literacy questionnaire with confirmatory factor analysis. In *Proceedings of the 2023 IEEE International Conference on Advanced Learning Technologies* (pp. 233-235). IEEE. <https://doi.org/10.1109/ICALT58122.2023.00074>
- Ong, W. J. (1982). *Orality and literacy: The technologizing of the word*. Methuen. <https://doi.org/10.4324/9780203328064>
- Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the big five inventory in English and German. *Journal of Research in Personality*, 41(1), 203-212. <https://doi.org/10.1016/j.jrp.2006.02.001>
- Ronkainen, R., Kuusisto, E., & Tirri, K. (2019). Growth mindset in teaching: A case study of a Finnish elementary school teacher. *International Journal of Learning, Teaching and Educational Research*, 18(8), 141-154. <https://doi.org/10.26803/ijlter.18.8.9>
- Schneider, C., DeLuca, C., Pozas, M., & Coombs, A. (2020). Linking personality to teachers' literacy in classroom assessment: A cross-cultural study. *Educational Research and Evaluation*, 26(1-2), 53-74. <https://doi.org/10.1080/13803611.2021.1902354>
- Seker, O., Kwon, K., & Kocak, O. (2025). Exploring researchers' artificial intelligence (AI) literacy: The mediating role of digital literacy and data literacy between 21st century skills and AI literacy. *Information Development*. <https://doi.org/10.1177/02666669251336368>
- Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational Research Review*, 22, 142-158. <https://doi.org/10.1016/j.edurev.2017.09.003>
- Sing, C. C., Teo, T., Huang, F., Chiu, T. K., & Xing Wei, W. (2022). Secondary school students' intentions to learn AI: Testing moderation effects of readiness, social good and optimism. *Educational Technology Research and Development*, 70(3), 765-782. <https://doi.org/10.1007/s11423-022-10111-1>
- Stein, J. P., Messingschlager, T., Gnamb, T., Hutmacher, F., & Appel, M. (2024). Attitudes towards AI: measurement and associations with personality. *Scientific Reports*, 14(1), Article 2909. <https://doi.org/10.1038/s41598-024-53335-2>
- Street, B. V. (1984). *Literacy in theory and practice* (vol. 9). Cambridge University Press.
- Street, B. V. (2006). Understanding and defining literacy. *Maestra Productions*. <https://maestraproductions.org/wp-content/uploads/unesco-understandings-of-literacy.pdf>

- Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K-12: What should every child know about AI? *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(1), 9795-9799. <https://doi.org/10.1609/aaai.v33i01.33019795>
- Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological process*. Harvard University Press.
- Vygotsky, L. S. (1986). *Thought and language*. MIT Press.
- Wetzel, D. A., & Kani, J. (2024). Enhancing information literacy through generative AI in the library classroom. *Pennsylvania Libraries: Research & Practice*, 12(2). <https://doi.org/10.5195/palrap.2024.302>
- Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33-35. <https://doi.org/10.1145/1118178.1118215>
- Yeager, D. S., Carroll, J. M., Buontempo, J., Cimpian, A., Woody, S., Crosnoe, R., Muller, C., Murray, J., Mhatre, P., Kersting, N., Hulleman, C., Kudym, M., Murphy, M., Duckworth, A. L., Walton, G. M., & Dweck, C. S. (2022). Teacher mindsets help explain where a growth-mindset intervention does and doesn't work. *Psychological Science*, 33(1), 18-32. <https://doi.org/10.1177/09567976211028984>
- Zurkowski, P. G. (1974). *The information service environment relationships and priorities*. National Commission on Libraries and Information Science.

APPENDIX A

Table A1. Results of the EFA of the instrument PILS

Items	Scholarship as conversation	Searching as strategic exploration – mindset	Information creation as a process	Information has value	Research as inquiry	Authority is constructed and contextual	Searching as strategic exploration – tools	h ²
AUTHORITY_1	-.066	-.008	.042	-.056	.075	.792	.016	.639
AUTHORITY_2	.025	.041	-.037	.032	.005	.820	-.065	.715
AUTHORITY_3	.014	-.189	.169	-.028	.031	.634	.105	.656
AUTHORITY_4	-.037	.074	.075	.200	-.016	.623	-.119	.661
AUTHORITY_5	.207	.112	-.055	.171	.096	.467	.046	.461
AUTHORITY_6	.069	-.219	.085	.057	-.076	.501	-.106	.585
CREATION_1	.063	-.069	.758	.042	-.054	.010	-.026	.693
CREATION_2	.082	.029	.731	.018	-.001	.077	-.124	.750
CREATION_3	-.170	-.097	.653	.013	.202	.102	-.067	.801
CREATION_4	-.123	-.217	.447	.052	.093	.209	-.045	.660
INFO_VALUE_1	.051	-.162	.121	.448	.081	.105	-.040	.609
INFO_VALUE_2	-.031	.038	-.046	.799	.058	.061	.023	.661
INFO_VALUE_3	-.020	-.085	-.027	.844	.007	-.027	-.065	.762
INFO_VALUE_4	.012	-.185	.194	.418	-.028	.027	-.101	.509
INFO_VALUE_6	.219	.080	.219	.390	.099	.074	.061	.502
RESEARCH_INQUIRY_1	.362	-.081	.296	.062	.205	.116	.063	.639
RESEARCH_INQUIRY_2	.293	-.097	.275	-.019	.331	.050	-.038	.645
RESEARCH_INQUIRY_3	-.093	-.041	.002	.037	.950	-.015	-.023	.923
RESEARCH_INQUIRY_4	.134	-.045	-.049	.064	.656	.096	-.058	.731
SCHOLARSHIP_4	.329	-.230	.024	.055	.041	.238	-.242	.722
SCHOLARSHIP_6	.344	-.120	.057	.127	.156	.113	-.178	.641
SEARCH_TOOLS_1	.312	-.112	.058	.084	.349	.044	-.118	.655
SEARCH_TOOLS_2	.414	-.091	.055	.057	.160	.059	-.314	.739
SEARCH_TOOLS_3	.087	-.171	.050	.046	.080	.053	-.556	.698
SEARCH_TOOLS_5	-.059	-.107	.121	.015	.141	.036	-.653	.759
SEARCH_TOOLS_6	.056	.120	.212	.214	.110	.032	-.509	.670
SEARCH_TOOLS_7	.093	-.023	.133	.210	.035	.095	-.444	.636
SEARCH_MINDSET_1	.020	-.792	.097	.088	-.008	.003	.024	.761
SEARCH_MINDSET_2	-.032	-.811	.031	.034	.134	.035	.031	.827
SEARCH_MINDSET_3	.021	-.718	.090	.065	.074	-.020	-.028	.732
SEARCH_MINDSET_4	.187	-.502	-.109	-.030	.046	.093	-.325	.678
SEARCH_MINDSET_5	.009	-.530	.011	-.011	.091	.067	-.295	.691
Initial Eigenvalues	17.55	2.13	1.42	1.10	0.90	0.84	0.69	
Percentage of explained variance (%) (before rotation)	53.17	6.44	4.31	3.34	2.72	2.54	2.09	

APPENDIX B

Table B1. Results of the EFA and communalities after extraction for items of the instrument CTS

Items	1	2	3	4	5	h ²
CREATIVENESS_1	.830	.023	.065	.192	-.144	.751
CREATIVENESS_2	.860	.022	.069	.246	-.156	.830
CREATIVENESS_3	.683	.059	.167	.295	-.004	.585
ALGORITHMIC_1	.063	.657	.009	-.015	-.045	.438
ALGORITHMIC_2	-.007	.870	.128	.076	-.072	.785
ALGORITHMIC_3	.018	.785	.061	.169	-.055	.652
COOPERATION_1	.154	.002	.686	.191	-.022	.531
COOPERATION_2	.049	.117	.792	.053	.040	.648
COOPERATION_3	.053	.067	.828	.077	.052	.701
CRITICAL_1	.209	.077	.162	.591	-.066	.430
CRITICAL_2	.218	.000	.083	.810	-.162	.736
CRITICAL_3	.194	.128	.073	.579	-.017	.394
PROBLEM SOLVING_1	-.116	-.032	.036	-.095	.610	.397
PROBLEM SOLVING_2	-.039	-.320	-.054	-.072	.615	.490
PROBLEM SOLVING_3	-.065	.065	.063	-.031	.737	.557
Eigenvalues	2.08	1.96	1.89	1.62	1.39	
Percentage of explained variance (%)	13.84	13.05	12.59	10.79	9.24	

APPENDIX C

Table C1. Results of the EFA and communalities after extraction for items of the instrument DOMLA

Items	1	2	3	4	5	h ²
ETHICAL1	.315	-.036	.070	-.004	.072	.148
ETHICAL2	.006	.049	.246	.117	.245	.194
ETHICAL3	-.093	-.172	.696	-.079	-.108	.488
ETHICAL4	.261	.186	.653	.014	.060	.552
ETHICAL5	.363	.039	.333	.038	.123	.373
ACCESS1	-.028	.025	-.041	.681	-.057	.413
ACCESS2	.271	-.116	-.009	.301	.052	.306
ACCESS3	-.087	-.503	.073	.054	.081	.298
ACCESS4	.261	-.507	.085	-.058	.089	.468
ACCESS5	-.035	-.025	.128	.512	.081	.340
AWARENESS1	.008	-.064	.029	-.109	.526	.283
AWARENESS2	.439	-.152	.090	-.021	.203	.411
AWARENESS3	.421	-.073	.000	.138	.107	.329
AWARENESS4	.170	-.142	-.076	.117	.503	.451
AWARENESS5	-.062	-.079	.095	.203	.530	.441
EVALUATION1	.209	.136	-.049	.102	.552	.430
EVALUATION2	-.127	-.203	.278	.209	.176	.293
EVALUATION3	.157	-.291	.013	.168	.269	.391
EVALUATION4	.096	-.232	.096	-.026	.508	.467
EVALUATION5	.051	-.055	-.071	.521	-.012	.300
PRODUCTION1	.027	-.529	.011	.135	.028	.371
PRODUCTION2	.338	-.552	-.048	.035	-.023	.535
PRODUCTION3	.463	.179	.040	.185	.165	.373
PRODUCTION4	.488	-.270	-.046	-.018	.080	.415
PRODUCTION5	.349	-.176	.080	.183	-.269	.271
Eigenvalues	6.53	1.69	1.49	1.37	1.27	
Percentage of explained variance (%)	26.15	6.80	5.97	5.49	5.10	

APPENDIX D

Table D1. Correlations (Spearman's rho, Pearson's r) between PILS, SNAIL, DOMLA, CTS, TIPI, and mindset

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1.000															
2	.125*	1.000														
3	.411**	.333**	1.000													
4	.260**	-.026	.295**	1.000												
5	.152**	.385**	.112	.107	1.000											
6	.137*	.172**	.231**	.194**	.164**	1.000										
7	.331**	.097	.317**	.520**	.210**	.194**	1.000									
8	-.190**	.097	-.062	-.215**	-.158**	-.002	-.140*	1.000								
9	.352**	.101	.371**	.152**	.073	.120*	.261**	-.111	1.000							
10	.335**	.291**	.369**	.072	.194**	.064	.208**	-.059	.535**	1.000						
11	.271**	-.091	.373**	.378**	.051	.083	.347**	-.245**	.243**	.126*	1.000					
12	.214**	.035	.126*	.096	.062	.202**	.161**	-.155**	.194**	.163**	.010	1.000				
13	.266**	.030	.213**	.275**	.054	.115*	.322**	-.170**	.182**	.101	.198**	.263**	1.000			
14	-.089	-.137*	.016	-.036	-.065	-.132*	.001	.075	.065	.061	.075	-.238**	-.175**	1.000		
15	.162**	-.238**	.115	.171**	-.098	.071	.139*	-.103	.103	-.007	.325**	.173**	.290**	-.053	1.000	
16	.137*	-.109	.136*	.100	-.008	-.041	.143*	-.152**	.069	.013	.282**	-.020	.085	.244**	.127*	1.000

Note. 1 – PILS; 2 – SNAIL: Technical understanding; 3 – SNAIL: Critical application; 4 – CTS: Creativity; 5 – CTS: Algorithmic thinking; 6 – CTS: Cooperativity; 7 – CTS: Critical thinking; 8 – CTS: Problem-solving; 9 – DOMLA: Media access; 10 – DOMLA: Media production; 11 – Mindset; 12 – TIPI: Extraversion; 13 – TIPI: Conscientiousness; 14 – TIPI: Neuroticism; 15 – TIPI: Agreeableness; 16 – TIPI: Openness; **Correlation is significant at the 0.01 level (2-tailed); *Correlation is significant at the 0.05 level (2-tailed); Pearsons' r coefficients are in *italics*

