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The nexus between agility-fostering competences and AI literacy of higher education students

Abstract

Research background and purpose: The pace of artificial intelligence (AI) adoption in both organisations and higher education is accelerating, raising questions about whether students possess the competences required to engage with AI critically and effectively. Although adaptive capacity is frequently assumed to facilitate technology use, limited empirical evidence exists on whether such capacity translates into AI literacy. Drawing on the conceptualisation of student agility as a multidimensional metacapability comprising proactivity, adaptability, and resilience, this study examines the relationships between key competences, agility, and AI literacy in higher education.

Design/methodology/approach: The study is based on survey data collected from 224 management and finance students. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted to validate the measurement constructs used in the study. Structural modelling was applied to examine whether competences that foster agility also predict AI literacy.

Findings: The results indicate that agility and AI literacy follow partially distinct developmental pathways. While teamwork and cognitive competences significantly predict agility, AI literacy is primarily shaped by knowledge-skill competences and human-tool collaboration, while cultural competence does not show a statistically significant effect.

Value added and limitations: The findings challenge the assumption that generic student agility automatically fosters AI literacy and highlight the need to conceptually differentiate between adaptive capacity and AI-specific competence development in higher education. This study is subject to several limitations. The sample was relatively homogeneous, consisting of students from a single type of higher education institution within one national context, which may limit generalisability. Future research could extend this analysis to diverse institutional profiles and cross-national settings.

Keywords: *artificial intelligence literacy, student agility, competence development, human-AI collaboration, higher education*

JEL

Classification: I23, J24, M12, O33

Received: 2026-03-15; **Revised:** 2026-06-20; **Accepted:** 2026-08-28

1. Introduction

Rapid digital transformation is reshaping the nature of work and higher education. Emerging technologies not only redefine required skill sets but also transform career trajectories and work arrangements (Harney & Collings, 2021; Kossek et al., 2021). Nowadays the requirements of digital competence in the face of digitised work are increasing (Audrin et al., 2024; Cyfert et al., 2025; Gupta et al., 2022; Picatoste et al., 2018; Piwowar-Sulej et al., 2024), which is the rationale behind the research on competence of the future. As Tomczak et al. (2023) note, universities seem to compete in their ability to provide students with adequate skills in the context of digitalisation. In this aspect, higher education institutions face growing pressure to prepare students for technology-intensive environments characterized by uncertainty, automation, and continuous change. Employers increasingly report shortages in competences related to learning, communication, and collaboration, highlighting the need to better understand how universities foster work-relevant capabilities (Doherty & Stephens, 2023; Gawrysiak et al., 2024; Zahn et al., 2025).

The rapid advancement and diffusion of artificial intelligence (AI) in higher education further intensifies these challenges. AI adoption is currently outpacing institutional regulation and policy development (Beckman et al., 2025). While early debates focused on academic integrity, recent research emphasizes AI's transformative potential - as a "democratizing force," an assistive technology, and an enhancement across the instructional cycle (Pretorius et al., 2025; Zhao et al., 2025; Zhuang et al., 2025). However, the benefits of AI are not distributed evenly. Emerging evidence points to a growing 'GenAI divide,' where students differ substantially in their levels of AI literacy and capacity to engage critically with AI tools (Beckman et al., 2025). Effective AI use depends not only on technical skills but also on broader cognitive, ethical, and social competences (Al-Mamary & Abubakar, 2025).

Growing demands for digital competences have intensified scholarly attention to technology-related literacy in higher education (Audrin et al., 2024; Cyfert et al., 2025; Picatoste et al., 2018). As digitalisation advances, literacy in the use of emerging technologies has become a central educational objective (Ertl et al., 2020; Wan et al., 2023). With the rapid diffusion of AI, this focus has shifted toward AI-specific competences, which extend beyond technical proficiency to encompass critical understanding, contextual awareness, and responsible use (Celik, 2023). At the same time, functioning effectively in technology-rich environments requires broader adaptive capacities. Drawing on Cai et al. (2018), we conceptualize student agility as a multidimensional construct encompassing proactivity, adaptability, and resilience. Despite assumptions that such adaptive capacity facilitates technology use, the relationship between agility and AI literacy remains insufficiently examined.

Existing research has examined AI literacy and AI use in higher education primarily in relation to digital skills, ethical considerations, inclusion, and patterns of student adoption (Pretorius et al., 2025; Zhao et al., 2025; Zhuang et al., 2025). Recent work highlights issues such as the ‘GenAI divide,’ differential access, and the pedagogical affordances of AI tools, emphasizing variation in students’ engagement with generative technologies. Parallel streams of research have investigated adaptive capacity – such as proactivity, resilience, and agility – as predictors of performance in dynamic environments (Alavi et al., 2014; Cai et al., 2018). However, these bodies of literature have largely evolved independently. Consequently, it remains unclear whether adaptive capacity constitutes a meaningful antecedent of AI literacy, or whether AI-related competences develop through distinct mechanisms in higher education contexts.

This study addresses this gap by examining the relationships between key competences, student agility, and AI literacy in higher education. We investigate whether competences that contribute to agility also predict AI literacy, and whether agility itself enhances students’ ability to engage effectively with AI. By disentangling these relationships, the study contributes to a more nuanced understanding of competence development in AI-intensive educational environments.

The paper is structured as follows. Section 2 outlines the theoretical framework and hypotheses. Section 3 describes the research design and methodology. Section 4 presents the empirical findings, and Section 5 discusses implications, limitations, and directions for future research.

2. Theoretical background and hypothesis development

2.1. Key competences and agility

Considering work-relevant competences, their identification and analysis are often linked to educational reforms aimed at enabling students to develop these competences within the learning process (Barth et al., 2007; Falloon, 2010; Hutmacher, 1997). Existing conceptualisations commonly distinguish three interrelated areas of competences: (1) the relationship between people and tools (the ability to use technology in practice and communication skills), (2) interpersonal relationships (problem-solving skills), and the relationship between people and society (social communication competence) (Huang, 2021).

The development of new technologies necessitates the continuous development of skills and the ability to adapt to new conditions (Behrend et al., 2024). Key competences should not be limited to the mastery of basic knowledge and skills, but should also include the development of qualities that enable an individual to adapt to, function in and actively shape a changing society. Also important is the readiness for continuous

personal development (Hipkins, 2006). According to DeSeCo's basic definition (Rychen et al., 2003), students' key competences can be divided into three main areas: knowledge competence, team competence and learning competence. Each of these three areas consists of sub-constructs (sub-competences) (Wing, 2006).

Knowledge competence is divided into: (1) skill competence (includes mastery of basic knowledge and methods of application) and (2) cultural competence (understanding of different cultures and humanistic values). Team competence includes two sub-constructs: (1) teamwork competence (communication and relationship between students, especially in the area of joint problem solving) and (2) human-tool collaboration competence (skilful recognition and use of tools). The last category of competence - learning competence also includes two types of sub-competences, i.e. (1) cognitive competence (ability to perceive, analyse and draw conclusions) and (2) self-learning competence (independent acquisition of knowledge through analysis, practice, questioning and creation) (Huang, 2021).

Knowledge competence, team competence and learning competence are those key competences that a student should develop in the educational process. However, management practitioners emphasize that one of the key competences required of today's employees is agility (Alavi & Wahab, 2013; Cai et al., 2018; Sherehiy et al., 2007). It refers to the ability to react quickly and adapt to change flexibly and effectively, and use it to the organization's advantage (Alavi et al., 2014). Individuals characterized by a high level of agility are open to change, innovation and new technologies, which is manifested in their continuous involvement in learning and adaptation processes (Plonka, 1997).

The construct of agility can be described through three main dimensions: proactivity, adaptability and resilience (Cai et al., 2018). Proactivity means taking initiatives that support the organization in the face of dynamic change. Adaptability refers to the ability to modify one's behaviour or approach to better adapt to a new environment. Resilience, on the other hand, is the competence to function effectively despite pressures and stressful situations (Alviani et al., 2024). Each of these aspects of agility implies an employee's willingness to take on challenges and continually develop his or her competences through learning, exploring and acquiring new skills (Alavi et al., 2014; Eshlaghy et al., 2010; Vinodh & Prasanna, 2011). Thus, the question arises whether the competences acquired by students as a result of the various stages of education foster the development of the agility practitioner desired, and if so, which of the competences proposed by Wing (2006) positively influence the agility workforce. In an effort to find an answer to this question, the following hypotheses were proposed:

H1a: Skills competence has a positive impact on the agility of students in higher education.

H1b: Culture competence has a positive impact on the agility of students in higher education.

H1c: Teamwork competence has a positive impact on the agility of students in higher education.

H1d: Human-tool collaboration competence has a positive impact on the agility of students in higher education.

H1e: Cognitive competence has a positive impact on the agility of students in higher education.

H1f: Self-learning competence has a positive impact on the agility of students in higher education.

2.2. Key competences and AI literacy

The term literacy originally referred to the basic abilities and knowledge associated with books and print (McMillan, 1996). However, with the development of computer and digital technologies, the meaning of the term began to expand beyond the traditional understanding of literacy (Buckingham & Burn, 2007). There have been proposals of its variations, such as: television literacy (Buckingham, 1989), information literacy (Eisenberg, 2008), digital literacy (Tinmaz et al., 2022), game literacy (Buckingham & Burn, 2007) or media literacy (Potter, 2013). Over the past few years, the term AI literacy has emerged alongside the term digital literacy (Druga et al., 2019; Xiao & Bie, 2019). Artificial intelligence is developing at a rapid pace, and its applications and importance continue to grow. As a result, defining the precise competences that an AI-literate person should possess is difficult. This also seems to be justified by recent insights from Schiavo, Businaro and Zancanaro, who point out that the ability to use AI increases not only the perceived ease of use, but also the usability of AI (Schiavo et al., 2024). AI literacy should be viewed not as a separate set of skills, but as an important strategy in the context of a wide range of educational goals (Moore, 2011). Wang et al. (2023) define AI literacy as the ability to consciously perceive and understand its technology in the context of real-world applications, the ability to efficiently use AI to accomplish a variety of tasks, and the ability to critically analyse, select and evaluate information generated by artificial intelligence, while developing a sense of responsibility and respect for the rights and responsibilities of others. Based on this definition, the authors identify four constructs that make up AI literacy: (1) awareness - refers to the ability to identify and understand AI technologies, (2) usage - refers to the use of AI technologies to perform tasks efficiently, this construct has an operational dimension involving easy access, proficiency in use, and the ability to integrate various AI applications and tools, (3) evaluation - refers to the ability to analyse, select, and critically evaluate AI applications and the effects of their use, and (4) ethics - refers to awareness of the risks associated with the use of AI and taking responsibility for them.

Artificial intelligence is playing an increasingly important role in user technologies, but the public's knowledge of these solutions is still sometimes insufficient. More research

is needed in the field of human-computer interaction to identify the skills needed to use AI effectively and to consciously assess the effects of this collaboration (Annapureddy et al., 2024; Kelly et al., 2023; Long & Magerko, 2020). This raises the question of what competences will be needed in a future where artificial intelligence transforms the way we communicate, work, and coexist with both people and machines.

Adopting the division of student competences proposed by Wing (2006), the paper will undertake a consideration, both theoretical and empirical, of the impact of each category of competences on students' AI literacy (Table 1,2,3) (Cetindamar et al., 2024; Laupichler et al., 2022; Long & Magerko, 2020; So-Hyun & Suh, 2021).

Table 1. The impact of knowledge competences on students' AI literacy

Knowledge competence	
Type of subcompetence	How it supports AI literacy
Skill competence	Students with a solid foundation of knowledge and well-developed analytical skills (logical, abstract, and critical thinking) better understand how AI works and can effectively use it for learning and problem-solving.
Cultural competence	Understanding different cultural backgrounds and humanistic values enables students to use AI responsibly and ethically. It also helps them reflect critically on the social impact of AI and apply it thoughtfully in various life contexts.

Source: own study

Taking into account the above considerations, two hypotheses can be proposed regarding the relationship between knowledge competence and AI literacy.

H2a. Skill competence has a positive impact on the AI literacy of students in higher education.

H2b. Culture competence has a positive impact on the AI literacy of students in higher education.

Table 2. The impact of team competences on students' AI literacy

Team competence	
Type of subcompetence	How it supports AI literacy
Teamwork competence	Students who can effectively communicate and collaborate in teams are better equipped to complete AI-related projects. Their ability to solve problems together through discussion and negotiation enhances their practical use of AI.
Human-tool collaboration competence	The ability to recognize and properly use tools is crucial in the AI environment. Students learn to work harmoniously with intelligent machines, approaching AI development rationally and ethically. This competence enables them to responsibly use AI and participate in building an intelligent society.

Source: own study

On this basis, two hypotheses relating to team competences can be formulated, according to which:

- H2c. Teamwork competence has a positive impact on the AI literacy of students in higher education.*
H2d. Human-tool collaboration competence has a positive impact on the AI literacy of students in higher education.

Table 3. **The impact of learning competences on students' AI literacy**

Learning competence	
Type of subcompetence	How it supports AI literacy
Cognitive competence	Students who develop the ability to perceive, analyze, and draw conclusions better understand how machines observe the world. This enables them to use AI more consciously and effectively in various contexts.
Self-learning competence	The ability to independently acquire knowledge through analysis, exploration, practice, questioning, and creation helps students understand how AI algorithms learn and how machine learning methods work. This competence fosters a deeper understanding of self-learning and allows students to effectively leverage AI.

Source: own study

With regard to Table 3, two hypotheses can be formulated, taking into account the relationship between learning competences and AI literacy.

- H2e. Cognitive competence has a positive impact on the AI literacy of students in higher education.*
H2f. Self-learning competence has a positive impact on the AI literacy of students in higher education.

2.3. Agility and AI literacy

Nowadays, both technology exploitation and agility are expected to become increasingly important as one of the core competences (Audrin et al., 2024). As Alavi et al. (2014) note, agility is a necessity, not a strategy or a goal. The rationale for research into generational characteristics and differences in terms of overall use of AI comes from the impending changes in workplace circumstances (Mahmoud et al., 2021). Considering organisational agility with IT capabilities is one of significant research directions (Tanushree et al.,

2024). A study conducted in the context of the use of enterprise social media indicates that the psychological characteristics of the workforce, translate into agility (considered in terms of proactivity, adaptability and resilience)(Cai et al., 2018).

Research by Wut et al. (2025) shows that AI literacy can translate into getting a job, suggesting the growing importance of building competences that foster AI literacy. AI literacy refers to the skills involved in critically evaluating and using AI technologies (Maddowell et al., 2024). Brock and von Wangenheim (2019) argue that agility is a key success factor for implementing and using AI in an organisation. There are links between student adaptability and critical thinking and AI literacy, however Imjai et al. (2025) consider this relationship in the direction of AI literacy-adaptability and AI-critical thinking. Research of Abdo-Salloum and Al-Mousavi (Abdo-Salloum & Al-Mousawi, 2025) suggests that today's students have a basic competence in AI. Interestingly, it appears that information literacy, rather than digital comportment, is important in the adoption of AI. Based on the discussion above, we hypothesise as follows.

H3: The agility of the students in higher education has a positive impact on their AI literacy.

Figure 1 presents the theoretical diagram.

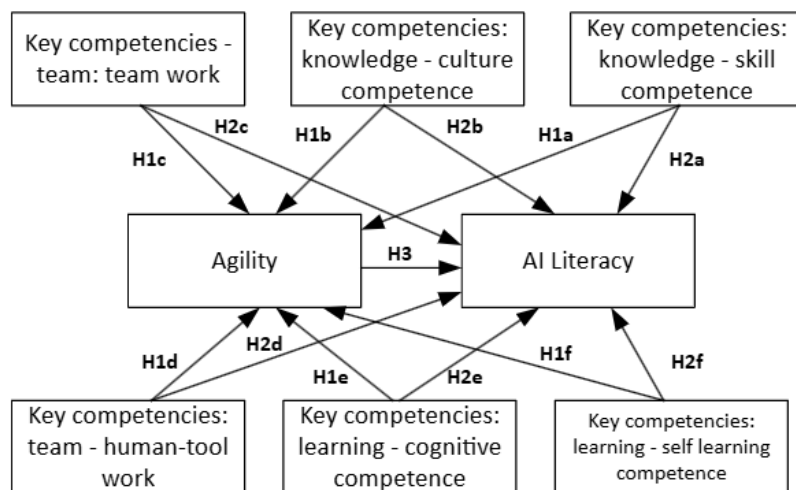


Figure 1. Theoretical diagram

Source: own study

3. Methods

The study focuses on a specific group of students and does not aim at population-level generalisation. Data were collected between February and April 2025 at a public university of economics in Poland. The survey was conducted using the computer assisted web interview (CAWI) method on a group of 224 students of Management and Finance. Participation in the survey was voluntary and the research questionnaire was approved by the university's ethics committee. The survey questionnaire was distributed to students via Microsoft Forms. The sample selection was purposive. The assumption was made that the students of economics faculties are oriented towards working in services that involve and adopt solutions based on artificial intelligence. The questionnaire used three reversed questions to ensure the reliability of the material collected (i.e., to verify the reliability of the respondent's answers).

Female students constituted 62% of the sample, while male students accounted for 38%. The characteristics of the sample are shown in Table 4.

Table 4. **Sample characteristics**

Faculty	
Finance	51%
Management	49%
Gender	
Female	62%
Male	38%

Source: own study

Validated scales exploring artificial intelligence literacy (Wang et al., 2023) were used as the survey instrument - these questions were set on a Likert scale, where 1 indicated a very low level of a skill and 7 indicated a very high level of a skill; student agility was considered as a construct including proactivity, adaptability and resilience, in this case the Likert scale was 5-point, where 1 indicated very low and 5 very high (Cai et al., 2018). The particular key competences were also examined on a 5-point Likert scale (Huang, 2021), where 1 was very low and 5 was very high. The measurement items for each of the constructs are summarised in Table 5.

Table 5. Measurement items (constructs and measurement)

Student Agility Scale (Cai et al., 2018)	
1. Proactivity	1. I look for the opportunities to make improvements at work. 2. I am trying to find out more effective ways to perform my job. 3. I let time take care of things that I have to do. 4. At work, I stick to what I am told or required to do. 5. I find new ways to obtain or utilize resources when resources are insufficient to do my job.
2. Adaptability	1. In my work, I can change my behavior to work more effectively with other people. 2. In my work, I can accept critical feedback. 3. In my work, I can adjust to new work procedures. 4. Use new equipment at work. 5. Keep up-to-date at work. 6. I can quickly adapt to switch from one project to another.
3. Resilience	1. I am able to perform my job efficiently in difficult or stressful situations. 2. I am able to work well when faced with a demanding workload or schedule. 3. When a different situation occurs, I react by trying to manage the problem. 4. I drop everything and take an alternate course of action to deal with an urgent problem.
Artificial Intelligence Literacy Scale (Wang et al., 2023)	
1. Awareness	1. I can distinguish which products use AI technology and which do not. 1. I can tell when I am using an AI-enabled product or service. 2. I know that many technologies I use in daily life are powered by AI.
2. Usage	1. I know how to use AI products or services in my daily life. 2. I can use AI technologies to assist me in completing tasks. 3. I feel confident using AI-enabled applications.
3. Evaluation	1. I can judge whether AI-generated results are reliable. 1. I can critically evaluate the output produced by AI systems. 2. I can recognize limitations or errors in AI systems.
4. Ethics	1. I am aware that AI may raise ethical issues. 2. I understand that AI can have negative social consequences. 3. I think AI should be used responsibly and ethically.
Students' Key Competencies Scale (Huang, 2021)	
Knowledge competence	
Skill competence	1. My logical thinking is strong 2. My abstract thinking is strong 3. My critical thinking is strong 4. I am good at observing 5. I am good at analyzing

Cultural competence	1. I understand the various cultural backgrounds and activities in my life 2. I understand various kinds of humanistic ideas 3. I am capable of analyzing emotions 4. I am capable of appreciating human values
Team competence	
Teamwork competence	1. I would like to collaborate with others 2. I would like to shoulder responsibility in the collaborative projects 3. I can identify problems in collaborative projects 4. I would like to discuss and solve problems together with other members in cooperative projects
Human-tool collaboration competence	1. I can use tools to help me solve problems 2. I am dependent on the use of tools 3. I can select suitable tools 4. Tools are helpful in improving my abilities
Learning competence	
Cognitive competence	1. I would like to perceive things 2. I would like to represent things 3. I would like to judge concepts 4. I would like to reason 5. I would like to summarize
Self-learning competence	1. I would like to analyze the problems independently 2. I would like to explore independently 3. I would like to practice independently 4. I would like to ask myself questions 5. I would like to create independently

Source: own elaboration based on: Cai et al. (2018), Wang et al. (2023), Huang (2021)

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted to validate the measurement constructs used in the study. EFA was applied to explore the underlying factor structure, while CFA was used to confirm the measurement model. Based on these results, composite indicators were computed for each construct and used in subsequent analysis.

In the next step, a structural model was estimated using TIBCO Statistica (version 13.3). The analysis was conducted as a path model based on aggregated indicators representing each construct, rather than a full structural equation model with latent variables. The model was estimated using the maximum likelihood (ML) method. Model fit was assessed using multiple goodness-of-fit indices, including the chi-square statistic (χ^2), the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI), the Normed Fit Index (NFI), the Comparative Fit Index (CFI), and the Standardized Root

Mean Square Residual (SRMR), following commonly accepted thresholds reported in the literature.

4. Results and discussion

In the first step of data analysis, an exploratory analysis of the proposed constructs was carried out. For each construct, methods such as the Kaiser criterion, Cattell's scree plot, and principal component analysis were used. The PCA results indicated that, despite the use of validated measurement scales, not all items contributed adequately to the intended constructs. A one-factor structure was indicated for the following constructs: AI literacy, skill competence, culture competence, teamwork competence, human-tool collaboration competence, cognitive competence, and self-learning competence. In the case of the agility construct, a three-factor structure consistent with the original scale was retained.

In the next step (considering the previously obtained results), confirmatory factor analyses (CFA) of the measurement constructs were conducted. The results of these analyses are presented in Table 6 and Table 7.

Table 6. Confirmatory factor analysis results for one-factor constructs

Construct	Item	Std. Factor loadings	Composite reliability	SRMR	Goodness-of-fit indices
AI literacy	AIL4	0.79**	0.84	0.03	GFI=0.98 NFI=0.97 CFI=0.98 IFI=0.98
	AIL5	0.60**			
	AIL6	0.85**			
	AIL7	0.60**			
	AIL8	0.60**			
	AIL9	0.69**			
Skill competence	KC_KSC1	0.51**	0.67	0.03	GFI=0.99 NFI=0.97 CFI=0.99 IFI=0.99
	KC_KSC3	0.40**			
	KC_KSC4	0.62**			
	KC_KSC5	0.78**			
Culture competence	KC_KCC1	0.61**	0.66	0.03	GFI=0.99 NFI=0.97 CFI=0.98 IFI=0.99
	KC_KCC2	0.69**			
	KC_KCC3	0.49**			
	KC_KCC4	0.51**			

Teamwork competence	KC_TTW1	0.66**	0.69	0.09	GFI=0.92 NFI=0.79 CFI=0.79 IFI=0.79
	KC_TTW2	0.43**			
	KC_TTW3	0.50**			
	KC_TTW4	0.77**			
Human-tool collaboration competence	KC_THT1	0.65**	0.67	0.04	GFI=0.98 NFI=0.96 CFI=0.97 IFI=0.97
	KC_THT2	0.16* (REMOVED)			
	KC_THT3	0.82**			
	KC_THT4	0.62**			
Cognitive competence	KC_LCC1	0.53**	0.83	0.03	GFI=0.98 NFI=0.97 CFI=0.98 IFI=0.98
	KC_LCC2	0.69**			
	KC_LCC3	0.79**			
	KC_LCC4	0.76**			
	KC_LCC5	0.74**			
Self-learning competence	KC_LSLC1	0.64**	0.83	0.06	GFI=0.93 NFI=0.90 CFI=0.91 IFI=0.91
	KC_LSLC2	0.68**			
	KC_LSLC3	0.71**			
	KC_LSLC4	0.66**			
	KC_LSLC5	0.79**			

Source: own study

Table 7. **Confirmatory factor analysis results for the multidimensional agility construct**

Agility dimension	Item	Std. Factor loadings	Composite reliability	SRMR	Goodness-of-fit indices
Proactivity	AGI_Pro1	0.94**	0.88	0.05	GFI=0.97 NFI=0.96 CFI=0.99 IFI=0.99
	AGI_Pro2	0.80**			
	AGI_Pro5	0.62**			
Adaptability	AGI_Ad2	0.67**			
	AGI_Ad3	0.70**			
	AGI_Ad5	0.56**			
Resilience	AGI_Res1	0.84**			
	AGI_Res2	0.79**			
	AGI_Res3	0.63**			
				AGI_Pro	AGI_Ad
			AGI_Ad	0.56**	
			AGI_Res	0.46**	0.52**

Source: own study

The CFA results provided support for the factorial validity and acceptable internal consistency of most retained scales. In most cases, the goodness-of-fit indices were within acceptable ranges. However, the ‘teamwork competence’ construct showed weaker model fit and should therefore be interpreted with caution. In the case of the ‘human-tool collaboration competence’ construct, one item was removed from the measurement scale due to a very low standardized factor loading.

Following the evaluation of the measurement models, composite scores were computed as the arithmetic means of the retained items and used as observed variables in the structural model to test the research hypotheses. For agility, the composite score used in the structural model was computed as the mean of the three retained dimension scores (proactivity, adaptability, and resilience).

In the next step, a structural model based on observed composite scores was estimated. Following the estimation of the initial model, non-significant paths were sequentially removed in order to obtain a more parsimonious final model, while preserving the theoretical interpretability of the relationships. For the final model (see Figure 2), the goodness-of-fit indices were as follows: GFI = 0.99, AGFI = 0.96, NFI = 0.99, CFI = 0.99, and IFI = 0.99. The model p-value was 0.42 and SRMR equalled 0.02, indicating an acceptable-to-good model fit.

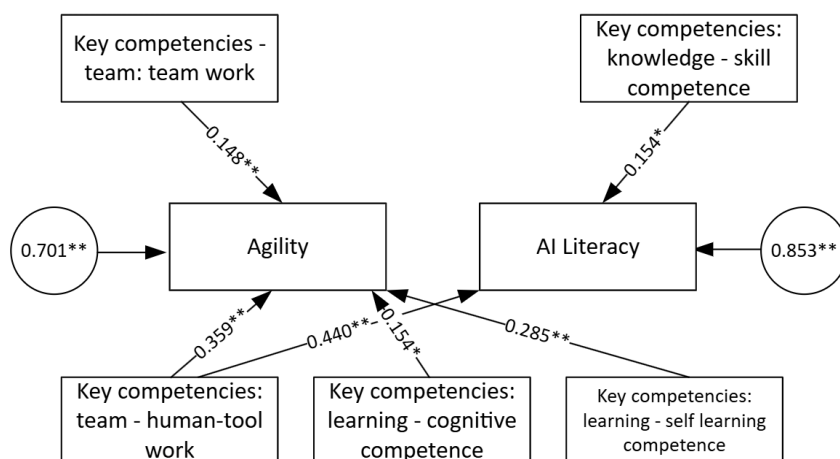


Figure 2. Final results of SEM analysis (* p -value<0.05; ** p -value<0.01)

Source: own study

When adapting to digital transformation, it is important to consider the soft aspects of management, such as competence categories (Cyfert et al., 2025). Our study adopts a human perspective, focusing on competences and identifying those that are particularly relevant to AI literacy and adaptive capacity (agility). Disruptive technologies such as AI have transformed multiple domains, including teaching and learning, thereby increasing the importance of AI-related competences (Ukwandu et al., 2025). Literacy in the use of new technologies is emerging as a key competence in modern societies and can determine the success of individuals (Ertl et al., 2020). Prior research highlights the need to create conditions that enable students to engage in self-directed and informal ICT learning in rapidly evolving technological contexts (Picatoste et al., 2018). Beyond technical skills, contemporary digital environments also require interpersonal competences, including teamwork and communication (Pater et al., 2022), as well as broader competence development aligned with digitally transforming work environments (Szelągowska-Rudzka et al., 2025). Effective AI use therefore depends not only on technical expertise but also on broader soft skills, such as critical thinking and communication (Calma & Davies, 2025; Chiu et al., 2021; Jatobá et al., 2023; Mohamed Saad, 2024; Skrzek-Lubasińska & Malik, 2023).

However, the results indicate that competences do not uniformly influence agility and AI literacy, suggesting that the constructs are shaped by partially distinct mechanisms. Knowledge-skill competence significantly predicted AI literacy (H2a supported), but did not influence agility (H1a not supported). Although knowledge-related

competences have been linked to workforce agility in organizational contexts (Alavi et al., 2014; Das et al., 2023), their direct contribution to student agility appears limited in this setting. This finding suggests that AI literacy relies on structured knowledge and analytical capabilities rather than on general adaptive capacity. It also highlights the importance of human-specific competences, particularly in areas where AI systems lack inherently human capabilities such as creativity and contextual judgment (Kong et al., 2023). Contrary to initial expectations, knowledge-culture competence did not significantly predict either agility or AI literacy (H1b and H2b not supported). This may indicate that cultural awareness, while conceptually important, does not directly translate into measurable competence in AI use or adaptive behaviour in the analysed context.

However, teamwork competence predicted agility (H1c supported), it did not predict AI literacy (H2c not supported). This result is consistent with the conceptualisation of agility as a socially embedded capability, developed through interaction, communication, and role flexibility. In contrast, AI literacy appears to depend less on interpersonal interaction and more on domain-specific knowledge and engagement with technology, including understanding algorithms, AI ethics, and data processes (Annapureddy et al., 2024). The absence of a direct relationship between teamwork and AI literacy may also reflect the influence of unexamined mediating factors, such as motivation or epistemic engagement.

Human-tool collaboration competence emerged as one of the most robust predictors, significantly influencing both agility and AI literacy (H1d and H2d supported). This finding underscores the importance of direct interaction with technological tools. Practical engagement with AI systems may simultaneously enhance adaptive responsiveness and deepen understanding of technological processes, including critical evaluation and ethical awareness (Aydin, 2021; Haitao et al., 2024; Karpińska & Owczarczuk, 2024; Fang & Deng, 2025).

In contrast, learning-related competences showed a more differentiated pattern. Cognitive competence predicted agility (H1e supported) but did not influence AI literacy (H2e not supported). Similarly, self-learning competence did not significantly affect either agility or AI literacy (H1f and H2f not supported). These findings suggest that general learning orientation and cognitive engagement may support adaptability but are insufficient for developing AI literacy without more targeted, domain-specific knowledge and technological interaction. This contrasts with some prior studies suggesting that self-directed learning may enhance AI-related competences (Gupta & Jaiswal, 2024), and may indicate the need for more structured learning environment when developing AI-related skills. Future research may consider the potential role of mediating factors such as technostress or technology-related beliefs (Lin & Yu, 2024).

Overall, the findings highlight the differentiated nature of competence development in AI-intensive environments. They suggest that AI literacy and agility should not be

treated as interchangeable outcomes of generic competence development, but rather as constructs grounded in partially distinct competence configurations. This distinction raises important questions regarding how higher education conceptualizes and supports competence development in digitally transforming contexts.

Contrary to our initial expectations, no statistically significant association was found between student agility and AI literacy (H3 not supported). While some prior studies suggest a relationship between adaptability and AI use (Imjai et al., 2025), much of the existing literature conceptualizes adaptability as an outcome of AI capabilities rather than as their antecedent (Dubey et al., 2022; Sullivan & Fosso Wamba, 2024). Our findings suggest that, at the student level, agility and AI literacy may develop along partially independent pathways. One possible explanation is that agility-related competences, such as teamwork and learning orientation, are primarily shaped through social and collaborative experiences, which students may encounter to a limited extent within formal higher education contexts. In contrast, AI literacy appears to depend more strongly on knowledge-skill competences and human-tool interaction, which can be directly cultivated through structured curricular and technological engagement.

This interpretation aligns with prior research indicating that workforce agility is often fostered through organizational practices such as leadership support and talent management rather than through technical skill acquisition alone. From a higher education perspective, this raises an important question regarding the extent to which universities provide opportunities for students to simultaneously develop adaptive capacity and AI-specific competences. Addressing both dimensions may be particularly relevant in light of growing concerns about resistance to AI adoption in organizations (Golgeci et al., 2025). Developing AI-related competences in a reflective and context-sensitive manner may therefore contribute not only to higher AI literacy but also to a more constructive orientation toward AI use in future professional roles.

5. Conclusions

The increasing integration of artificial intelligence into higher education has reconfigured competence requirements, particularly in relation to human-AI collaboration. In this context, understanding which competences support AI literacy – and how they relate to broader adaptive capacity – represents an important research challenge. The findings of this study demonstrate that key competences play differentiated roles in shaping AI literacy and student agility. Competences related to knowledge-skill, and human-tool collaboration emerged as particularly significant predictors of AI literacy, whereas cultural competence did not show a statistically significant effect. Conversely, competences that significantly supported agility –

such as teamwork and cognitive competence – did not show a statistically significant relationship with AI literacy.

The results further indicate that teamwork-related competences, including interpersonal collaboration and human–tool cooperation, as well as learning competences such as cognitive engagement and self-directed learning, are especially relevant for the development of student agility. This is consistent with the conceptualisation of agility as a multidimensional adaptive capacity requiring collaboration, flexibility, and responsiveness to change. Agile functioning typically involves shifts in roles, tasks, and team configurations, underscoring the importance of communication, cooperation, and continuous learning.

From a higher education perspective, these findings highlight the need to conceptually distinguish between adaptive capacity and AI literacy rather than treating them as interchangeable outcomes of competence development. While exposure to digital technologies may support familiarity with AI tools, it does not automatically translate into AI literacy. The development of AI-related competences appears to require deliberate engagement with knowledge-based, contextual, and human–technology interaction dimensions. At the same time, fostering agility may rely more strongly on collaborative and experiential learning environments. Recognising this distinction may help clarify how competence development unfolds in AI-intensive educational contexts.

This study is subject to several limitations that also point to directions for future research. First, the sample was relatively homogeneous, consisting of students from a single type of higher education institution within one national context, which may limit generalisability. This homogeneity may also help explain the lack of significance of cultural competence, as limited diversity in students' backgrounds (e.g., nationality or cultural experience) may reduce variability in this dimension. Moreover, the observed relationships may partly reflect the specific educational profile of the respondents, as Management and Finance students may differ from students in other disciplines with regard to their exposure to digital technologies and AI-related issues. Future research could extend this analysis to diverse institutional profiles and cross-national settings. Second, the study focused on a selected set of competences and did not account for broader institutional factors, such as pedagogical approaches, AI integration strategies, or organisational support structures. Third, the cross-sectional design does not capture the dynamic nature of competence development. Longitudinal studies could provide deeper insight into how agility and AI literacy evolve over time. Finally, future research may explore potential mediating and moderating mechanisms –such as epistemic beliefs, digital mindsets, or technology-related self-efficacy – that could further explain the relationship between key competences, agility, and AI literacy in higher education. Overall, the findings suggest that competence development in AI-intensive higher education contexts requires greater conceptual precision in distinguishing between adaptive capacity and AI-specific literacy.

Authors' contribution

A.Ch.-K./K.M./W.Sz.: article conception, theoretical content of the article, research methods applied, conducting the research, data collection, analysis and interpretation of results, draft manuscript preparation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors did not use Generative AI and AI-assisted technologies in the writing process.

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