

Article

Artificial Intelligence (AI) in Higher Education: Digital Adaptability, General Self-Efficacy, and Student Attitudes

Aniella Mihaela Vieriu ¹ and Gabriel Petrea ^{2,*}

¹ The Department of Teacher Training and Social Sciences, The National University of Science and Technology POLITEHNICA Bucharest, 060042 Bucharest, Romania; aniella.vieriu@upb.ro

² Faculty of Industrial Engineering and Robotics, The National University of Science and Technology POLITEHNICA Bucharest, 060042 Bucharest, Romania

* Correspondence: gabriel.petrea@upb.ro

Abstract

Artificial intelligence (AI) has become increasingly visible in higher education, making it important to understand how students in this context evaluate AI in general. Although students' attitudes toward AI have been widely examined, less is known about the relative roles of broad psychological resources and technology-related adaptive capacities in shaping these attitudes. This study examined whether digital adaptability and general self-efficacy were associated with students' general attitudes toward AI and whether they showed distinct comparative associations within the tested model. Using a cross-sectional design, data were collected from 550 undergraduate and master's students enrolled in technical programs at a large university. Correlational analyses, group comparisons, and hierarchical regression analyses were conducted, controlling for faculty and year of study. The findings showed that both digital adaptability and general self-efficacy were positively associated with students' attitudes toward AI; however, only digital adaptability showed a statistically significant unique association within the regression model. This comparative pattern should be interpreted as association-based rather than as evidence of explanatory superiority. The results suggest that students' general attitudes toward AI are associated with adaptive digital resources, although the findings should not be interpreted as direct evidence regarding AI-supported learning environments, curriculum design, instructional strategies, or actual AI use.

Keywords: artificial intelligence in higher education; digital adaptability; students' attitudes toward AI; general self-efficacy; general AI attitudes



Academic Editor: Sergio Miranda

Received: 13 May 2026

Revised: 25 June 2026

Accepted: 26 June 2026

Published: 6 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The accelerated integration of artificial intelligence (AI) into higher education has transformed teaching, learning, and assessment practices. However, the present study does not directly measure students' attitudes toward these specific educational uses of AI; rather, it examines students' general attitudes toward AI within a higher education sample. Beyond its role as a technological tool, AI is increasingly becoming part of the epistemic and pedagogical infrastructure of higher education, influencing how students access information, interpret knowledge, and engage with learning tasks. Recent literature emphasizes that AI should not be viewed solely as an instrument of efficiency or automation, but also as a technology that shapes how learning is designed, supported, and experienced in higher education (OECD, 2021; Zhai et al., 2021). This perspective aligns with broader calls in

educational technology research to examine learners' subjective evaluations of emerging digital systems, as such evaluations influence whether new technologies are perceived as useful, trustworthy, and pedagogically meaningful (Selwyn, 2022; Long & Magerko, 2020). Systematic reviews further reinforce the view that artificial intelligence should be conceptualized as an educational technology embedded in learning design and pedagogical mediation rather than as a neutral digital tool (Holmes & Tuomi, 2022; Wang et al., 2024).

The integration of artificial intelligence into higher education also reflects a broader structural transformation of universities as educational institutions. The use of AI-based systems has been discussed in relation to curriculum design, assessment practices, the roles of educational stakeholders, and institutional strategies for digital development. Technological progress has also been shown to reshape young people's learning trajectories, professional expectations, and adaptive responses to rapid innovation (Neagu & Vieriu, 2019). Research on artificial intelligence in higher education suggests that AI contributes to redefining academic functions and reshaping how universities organize teaching, support student learning, and pursue their educational mission in increasingly digitalized contexts (Ouyang & Jiao, 2021). From an educational technology perspective, this transformation positions AI within a broader sociotechnical reconfiguration of learning processes (Kirkwood & Price, 2014; Selwyn, 2010). Recent evidence indicates that students' attitudes toward AI influence adoption intentions, trust, and engagement (Merino-Campos, 2025).

Students' attitudes toward artificial intelligence represent more than a simple indicator of technology acceptance. In the present study, they are understood as broad evaluative orientations toward AI rather than as direct indicators of students' attitudes toward AI use in teaching, learning, assessment, feedback, or academic support. Existing research shows that positive attitudes are associated with greater openness to innovation, more reflective orientations toward educational technologies, and greater willingness to engage with AI-based tools and emerging digital systems. In contrast, negative or ambivalent attitudes may foster resistance to change, technological anxiety, and avoidance of AI-based tools in educational contexts (Sáez-Velasco et al., 2025). Educational technology research increasingly conceptualizes attitudes as mediating mechanisms between technological affordances and learning practices (Nazaretsky et al., 2025).

A central construct for understanding how students respond to contemporary technological transformations is digital adaptability, defined as the capacity to respond flexibly to changing technological demands, learn and integrate new digital tools, and manage the uncertainty associated with technological innovation. Recent studies indicate that higher levels of digital adaptability are associated with more effective adjustment to digital learning environments, the use of more functional learning strategies, and more favorable evaluations of emerging technologies. Within higher education, digital adaptability can be conceptualized as both an individual resource and a learning-relevant capability in universities undergoing continuous digital transformation (Ren et al., 2025). Recent research conducted among technical university students further suggests that digital engagement is closely linked to psychological well-being and adaptive functioning in highly technologized educational environments, highlighting the importance of examining broader psychological resources in digitalized academic contexts (Neagu & Vieriu, 2025). In the context of artificial intelligence, digital adaptability may play a particularly important role, given the opacity, rapid evolution, and perceived unpredictability of AI-based systems (Ng et al., 2021; Garzón et al., 2025). Although the present study did not measure students' experiences with AI-mediated learning environments directly, research on such environments suggests that students may be required to interpret algorithmic outputs and adjust their learning strategies, highlighting the importance of adaptive capacities that extend beyond traditional digital skills (Chiu, 2024). This interpretation is supported by recent

empirical research showing that digital literacy and digital competence are associated with students' self-efficacy and academic functioning in technology-rich learning environments. [Zakir et al. \(2025\)](#), for instance, found that digital literacy was positively associated with digital competence and self-efficacy among university students, suggesting that students' ability to navigate digital environments is connected to broader psychological resources relevant to academic adaptation.

In addition to digital adaptability, self-efficacy represents an essential psychological resource for understanding how students relate to artificial intelligence in educational contexts. General self-efficacy reflects students' broad confidence in their ability to manage challenges, cope with unexpected situations, and persist when facing difficulties. In educational technology research, this construct may help explain students' general orientations toward technological change. However, it should be distinguished from academic self-efficacy, technology self-efficacy, and AI-specific self-efficacy, none of which were directly measured in the present study. Research on technology adoption suggests that students with higher levels of self-efficacy demonstrate greater willingness to use advanced digital technologies, including AI-based tools, and tend to evaluate them more favorably ([Tseng, 2025](#)). Within educational technology research, self-efficacy has frequently been treated as a central explanatory construct for students' engagement with digital systems and is often assumed to operate uniformly across different technological contexts ([Schiff, 2022](#)). This assumption reflects generalized technology acceptance frameworks, such as TAM and UTAUT, which posit that motivational beliefs, including self-efficacy, constitute universal drivers of attitudes toward educational technologies. However, in AI-mediated higher education environments, it remains important to examine whether such generalized beliefs retain their explanatory power when compared with more context-specific adaptive capacities.

The literature further highlights that digital adaptability, digital competence, and self-efficacy are interconnected constructs in digitalized educational contexts. Recent studies show, for example, that digital literacy significantly influences ICT self-efficacy ([Yuan & Li, 2025](#)). Similarly, research on digital competencies and general self-efficacy has identified significant correlations between students' digital skills and perceived self-efficacy, reinforcing the interdependence between these psychological resources and the acceptance of educational technologies ([González-Prida et al., 2024](#)).

Despite the extensive research on artificial intelligence in higher education, the literature on students' attitudes toward artificial intelligence has expanded rapidly, particularly in relation to AI literacy, digital competence, self-efficacy, technology acceptance, and AI adoption. Therefore, the contribution of new empirical studies should not be framed simply as demonstrating that students' attitudes toward AI are associated with another learner-related variable. Rather, a more precise contribution lies in clarifying how different learner-related resources are conceptually positioned and whether they show distinct associations with students' evaluations of artificial intelligence. This distinction is theoretically important because learner-related resources do not operate at the same level of specificity. General psychological resources, technology-facing adaptive capacities, and AI-specific forms of competence may relate differently to students' evaluations of artificial intelligence. Treating these resources as interchangeable risks obscuring whether students' attitudes toward AI are associated with broad perceived competence, with adaptability to technological change, or with more specific AI-related knowledge and experience. First, existing studies predominantly rely on generalized technology acceptance frameworks that emphasize broad motivational predictors, such as self-efficacy, while offering limited differentiation between generalized psychological beliefs and technology-specific adaptive capacities when applied to AI-mediated learning contexts ([Zawacki-Richter et al., 2019](#);

[Scherer et al., 2020](#)). Although both self-efficacy and digital adaptability have been associated with positive responses to technology-rich environments, they represent conceptually distinct learner-related resources. Self-efficacy reflects a broad belief in one's ability to manage challenges successfully, whereas digital adaptability focuses more specifically on perceived readiness to adjust to changing technological demands, uncertainty, and novelty. Because these constructs operate at different levels of specificity, it remains necessary to examine whether they show similar or different associations with students' attitudes toward artificial intelligence. The purpose of this distinction is not to establish that one resource is inherently more important than the other, but to clarify how domain-general and technology-facing resources should be theoretically positioned when studying attitudes toward AI.

Second, although digital adaptability and self-efficacy are frequently identified as relevant psychological resources, they are typically examined in isolation or within fragmented explanatory approaches, leaving their relative and unique contributions to students' evaluations of artificial intelligence insufficiently clarified ([Getenet et al., 2024](#); [Matos et al., 2025](#)). Third, empirical studies that directly compare generalized self-efficacy with technology-facing adaptive resources within a single explanatory framework remain scarce, particularly among students in technical fields characterized by sustained exposure to advanced digital technologies ([Liang & Reiss, 2025](#)).

This gap is particularly relevant in the context of artificial intelligence, where learning environments are increasingly shaped by dynamic, algorithmically mediated systems that require continuous adaptation from learners. It remains unclear whether broad psychological resources and technology-focused adaptive resources contribute similarly or differently to students' attitudes toward artificial intelligence ([Ouyang & Jiao, 2021](#); [Kasneci et al., 2023](#); [Alfredo et al., 2024](#)). Thus, the added value of the present study lies in its comparative focus: digital adaptability and general self-efficacy are examined simultaneously, allowing their associations with students' attitudes toward artificial intelligence to be interpreted in relation to one another rather than as isolated predictors. This framing addresses a specific issue in the current literature: the need to distinguish between broad psychological resources and technology-facing adaptive capacities when examining students' orientations toward AI. At the same time, this comparison must be interpreted cautiously because digital adaptability and attitudes toward AI are both technology-facing constructs. Therefore, the stronger association between digital adaptability and AI attitudes should be interpreted cautiously because it may reflect greater conceptual proximity between a technology-facing predictor and a technology-oriented outcome, rather than a substantively different explanatory role. The contribution of the study is therefore not to claim explanatory superiority for digital adaptability, but to make explicit how construct specificity and conceptual proximity affect the interpretation of learner-related predictors in AI attitude research.

Conceptually, the present study is based on the assumption that students' attitudes toward artificial intelligence may be associated with both broad motivational resources and more technology-facing adaptive capacities. General self-efficacy reflects students' overall confidence in their ability to manage challenges and cope with difficult or unexpected situations, whereas digital adaptability reflects their perceived readiness to respond flexibly to technological novelty, uncertainty, and change. From this perspective, general self-efficacy may support students' overall confidence when encountering complex technologies, whereas digital adaptability may be more directly connected to how students evaluate AI as a rapidly evolving digital technology. The study therefore does not propose a causal mechanism but instead examines whether these two theoretically distinct resources show different patterns of association with students' general attitudes toward AI. This theoretical distinction matters because it helps situate the present findings within a broader

continuum of learner-related resources, ranging from domain-general psychological beliefs to technology-facing adaptive capacities and, in future research, AI-specific self-efficacy, AI literacy, and direct experience with AI tools.

In this context, the present study examines how students' psychological resources—specifically digital adaptability and self-efficacy—are associated with attitudes toward artificial intelligence in higher education. More specifically, the study investigates whether a technology-facing adaptive resource, namely digital adaptability, is associated with students' attitudes toward AI when examined alongside generalized self-efficacy, while accounting for faculty and year of study. The study therefore addresses a narrower but more precise question: whether students' attitudes toward artificial intelligence are more closely associated with a broad belief in personal competence or with their perceived ability to adapt to changing digital conditions. By directly comparing these two resources within the same empirical model, the study provides a comparative examination of their relative associations with attitudes toward artificial intelligence. The intended contribution is thus not to claim that AI attitudes are an underexplored topic, but to clarify the relative role of digital adaptability within an already developed literature on AI attitudes, self-efficacy, and technology acceptance. More specifically, the study clarifies that the observed stronger association of digital adaptability should be understood as a modest comparative association within the tested model, which may partly reflect construct proximity, not as evidence of causal influence, explanatory superiority, or construct independence.

By doing so, the study offers a limited and association-based contribution to the literature, providing a focused comparison between a broad motivational resource and a technology-facing adaptive capacity in relation to students' general evaluations of AI. This contribution should be understood narrowly: the study does not establish a new explanatory model, resolve the issue of construct overlap, or provide direct evidence about students' attitudes toward specific educational uses of AI. Rather, it clarifies how two learner-related resources are comparatively associated with broad AI attitudes within one higher education sample.

Based on this conceptual rationale and the associative, cross-sectional design of the study, the following hypotheses were tested:

- H1.** *There is a positive association between digital adaptability and attitudes toward artificial intelligence among students.*
- H2.** *There is a positive association between self-efficacy and attitudes toward artificial intelligence among students.*
- H3.** *There is a positive association between self-efficacy and digital adaptability among students.*
- H4.** *Exploratory analyses examine whether students differ with respect to digital adaptability, general self-efficacy, and attitudes toward artificial intelligence across faculties.*
- H5.** *Exploratory analyses examine whether digital adaptability, general self-efficacy, and attitudes toward artificial intelligence vary across years of study.*
- H6.** *Digital adaptability and general self-efficacy are associated with students' attitudes toward artificial intelligence, above and beyond relevant educational variables (faculty and year of study).*

2. Materials and Methods

2.1. Variables and Research Design

The present study employed a quantitative, cross-sectional, correlational design aimed at investigating the relationships between students' psychological resources and their attitudes toward artificial intelligence in the context of higher education.

Independent Variable 1: Digital adaptability assessed using the Digital Adaptability Scale (DAS).

Independent Variable 2: General self-efficacy, assessed using the Self-Efficacy Scale (SES).

Independent Variable 3: Faculty.

Independent Variable 4: Year of study.

Dependent variable: Attitudes toward artificial intelligence, assessed using the Artificial Intelligence Attitude Scale (AIAS).

2.2. Participants

The sample consisted of 550 undergraduate and master's students enrolled at the National University of Science and Technology POLITEHNICA Bucharest. Participants included students of both genders.

Participants were recruited voluntarily through an institutional distribution strategy targeting undergraduate and master's students enrolled in technical programs. All respondents were enrolled in technical study programs, ensuring the relevance of the sample to the objectives of the study. Technical universities represent highly technologized educational environments in which students are frequently exposed to advanced digital systems, making them a relevant context for examining psychological resources associated with students' general attitudes toward AI.

2.3. Procedure

The study was conducted entirely online using Google Forms as the data collection platform. Participants received a secure survey link distributed through institutional channels and were asked to complete the questionnaire in a single session.

Prior to participation, respondents were informed about the purpose of the study, the voluntary nature of participation, and the anonymity and confidentiality of their responses. Data were collected anonymously. Informed consent was provided through the voluntary completion and submission of the online questionnaire. To strengthen data protection and privacy management, no personally identifiable information, such as names, student identification numbers, institutional email addresses, IP addresses, or contact details, was collected or retained. The dataset was stored in a password-protected digital file accessible only to the research team. Responses were analyzed only in aggregate form, and no individual participant could be identified in the reporting of the results. Because the study focused on students' attitudes toward artificial intelligence but did not involve AI-based profiling, automated decision-making, or behavioral tracking, no AI-generated personal data or algorithmic monitoring data were collected.

2.4. Data Collection, Research Instruments, and Statistical Analyses

Three instruments were used: (1) the Digital Adaptability Scale (DAS), used to assess perceived adaptability to changing digital and technological demands; (2) the Self-Efficacy Scale (SES), used to measure general self-efficacy, defined as a global perception of personal competence; and (3) the Artificial Intelligence Attitude Scale (AIAS), used to evaluate students' general attitudes toward artificial intelligence. The scale captures broad evaluative orientations toward AI rather than attitudes specifically directed toward AI use in higher education, assessment, feedback, academic integrity, or actual AI-supported

learning practices. The instruments were selected because they corresponded directly to the constructs examined in the hypotheses and allowed the assessment of technology-related adaptive capacity, broad perceived competence, and general evaluative attitudes toward AI. The Digital Adaptability Scale included positively and negatively worded items designed to capture students' perceived flexibility, persistence, help-seeking, and openness when learning or using new technologies. The Artificial Intelligence Attitude Scale was used as a concise measure of broad positive and negative evaluations of AI, whereas the Self-Efficacy Scale was interpreted as a measure of general self-efficacy because its items assess perceived capability to manage problems, unexpected events, and difficult situations. Full item wording and scoring procedures are provided in Appendix A.

All instruments were administered using Likert-type scales, with higher scores indicating higher levels of the assessed constructs. Internal consistency was evaluated using Cronbach's alpha. The Digital Adaptability Scale demonstrated good reliability ($\alpha = 0.817$), the Self-Efficacy Scale showed very good internal consistency ($\alpha = 0.853$), and the Artificial Intelligence Attitude Scale, consisting of four items, exhibited satisfactory reliability ($\alpha = 0.720$), which was adequate for the analysis. These coefficients indicate acceptable to very good internal consistency for the instruments used in the study. The reliability of the Artificial Intelligence Attitude Scale was considered adequate given its concise four-item structure and the exploratory nature of the analysis. In addition, the conceptual distinction among the instruments was supported by their different theoretical focuses, item content, scoring procedures, and the correlational pattern observed among the variables, which indicated related but non-equivalent constructs. However, no formal confirmatory factor analysis, convergent validity analysis, or discriminant validity test was conducted in the present study.

Statistical analyses were conducted using IBM SPSS Statistics (Version 26). Descriptive statistics were computed for all study variables. Subsequently, relationships between digital adaptability, self-efficacy, and attitudes toward artificial intelligence were examined using Pearson and/or Spearman correlation coefficients, depending on the distributional characteristics of the variables, to test hypotheses H1–H3. Group differences based on faculty and year of study were analyzed using one-way ANOVA, corresponding to hypotheses H4 and H5.

The selection of statistical tests was guided by the level of measurement, the distributional characteristics of the variables, and the structure of the hypotheses. Correlation analyses were used for H1–H3 because these hypotheses examined associations among continuous scale scores. Spearman's rho was preferred when normality assumptions were not met, whereas Pearson's correlation was also reported, where appropriate, to examine the robustness of the associations. One-way ANOVA was used for H4 and H5 because these hypotheses involved comparisons of mean scores across categorical educational groups. For H6, hierarchical linear regression was selected because it allowed the associations of digital adaptability and general self-efficacy with attitudes toward artificial intelligence to be examined after accounting for faculty and year of study. In interpreting the findings, statistical significance was considered together with the magnitude of the associations and the proportion of variance accounted for by the model.

For comparative analyses across faculties, faculty affiliation was used as the grouping factor. Because participants came from 21 faculties and many faculties had small numbers of respondents, it was not methodologically appropriate to compare all faculties separately. Therefore, only faculties with enough respondents to allow valid statistical comparisons were included as separate groups. Specifically, the Faculty of Industrial Engineering and Robotics ($n = 95$), the Faculty of Aerospace Engineering ($n = 80$), and the Faculty of Applied Sciences ($n = 61$) were analyzed individually, whereas faculties with smaller sample sizes

were aggregated into a separate category (“other faculties”). This aggregation was used as a pragmatic analytical solution to avoid highly unbalanced and underpowered group comparisons. However, the “other faculties” category is heterogeneous and should not be interpreted as a substantively coherent disciplinary group. Consequently, faculty-related findings were treated as exploratory and interpreted with caution.

For the year-of-study analyses, the original variable included several categories corresponding to undergraduate years 1–4 and master’s years 1–2. Because some categories had small numbers of respondents, the variable was recoded into broader educational-cycle groups. Undergraduate students from years 1–4 were grouped into an “undergraduate” category, whereas master’s students from years 1–2 were grouped into a “master’s” category. Consequently, year-of-study findings should be interpreted as exploratory comparisons between broader educational cycles rather than as detailed comparisons among individual years of study.

To test H6, a hierarchical multiple linear regression model was employed to assess the associations of digital adaptability and self-efficacy with attitudes toward artificial intelligence while controlling for year of study and faculty affiliation. The level of statistical significance was set at $p < 0.05$. Given the cross-sectional and self-report nature of the study, as well as the correlational analytical approach, the findings should be interpreted as reflecting students’ perceived psychological resources and evaluative orientations toward artificial intelligence rather than objective or behavioral indicators of AI use or evidence of causal mechanisms.

3. Results

This section presents the results of the hypothesis testing regarding the relationships between digital adaptability, self-efficacy, and attitudes toward artificial intelligence, including exploratory group comparisons and regression analyses.

3.1. Relationship Between Digital Adaptability and Attitudes Toward Artificial Intelligence (H1)

To test Hypothesis H1, which posited a positive association between digital adaptability (DAS) and attitudes toward artificial intelligence (AIAS), correlation analyses were conducted.

Preliminary analyses of the variable distributions indicated that scores for attitudes toward artificial intelligence (AIAS) did not meet the assumption of normality, as assessed by the Kolmogorov–Smirnov test ($Z = 2.314$, $p < 0.001$). In contrast, scores for digital adaptability (DAS) approximated a normal distribution ($p = 0.093$). Given these distributional characteristics, both Spearman’s rho and Pearson’s correlation coefficient were computed to ensure the robustness of the findings.

Spearman’s correlation analysis revealed a positive and statistically significant association between digital adaptability (DAS) and attitudes toward artificial intelligence (AIAS) ($\rho = 0.288$, $p < 0.001$; see Table 1), indicating that students with higher levels of digital adaptability tended to report more favorable attitudes toward artificial intelligence.

Table 1. Correlations among Digital Adaptability, Self-Efficacy, and Attitudes toward Artificial Intelligence.

Variable	1	2	3
1. Digital Adaptability (DAS)	—		
2. Self-Efficacy (SES)	0.277 **	—	
3. Attitudes toward AI (AIAS)	0.288 **	0.254 **	—

Note. Values represent Spearman correlation coefficients. ** $p < 0.01$. $N = 550$.

This association was also observed in the Pearson correlation analysis, which showed a significant positive relationship between the two variables ($r = 0.254$, $p < 0.001$), suggesting a stable and consistent pattern of association. Overall, these findings are consistent with Hypothesis H1.

3.2. Relationship Between Self-Efficacy and Attitudes Toward Artificial Intelligence (H2)

To test Hypothesis H2, which proposed a positive association between self-efficacy and attitudes toward artificial intelligence, correlational analyses were conducted.

Distributional analyses indicated that scores for attitudes toward artificial intelligence (AIAS) did not meet the assumption of normality, as assessed by the Kolmogorov–Smirnov test ($Z = 2.314$, $p < 0.001$). In addition, self-efficacy (SES) scores also deviated from normality ($p < 0.001$). Consequently, Spearman’s rank-order correlation coefficient was used to test this hypothesis.

The Spearman correlation analysis revealed a positive and statistically significant association between self-efficacy (SES) and attitudes toward artificial intelligence (AIAS) ($\rho = 0.254$, $p < 0.001$; see Table 1), indicating that students who reported higher levels of self-efficacy tended to hold more favorable attitudes toward artificial intelligence. The magnitude of the correlation suggests a small-to-moderate effect size.

These findings are consistent with Hypothesis H2 by indicating a positive association between general self-efficacy and attitudes toward artificial intelligence.

3.3. Relationship Between Self-Efficacy and Digital Adaptability (H3)

To test Hypothesis H3, which posited a positive association between self-efficacy (SES) and digital adaptability (DAS), correlational analyses were conducted.

Distributional analyses indicated that self-efficacy (SES) scores did not meet the assumption of normality, as assessed by the Kolmogorov–Smirnov test ($p < 0.001$). In contrast, scores for digital adaptability (DAS) approximated a normal distribution ($p = 0.093$). Based on these distributional characteristics, Spearman’s rank-order correlation coefficient was used to test this hypothesis.

The Spearman correlation analysis revealed a positive and statistically significant association between self-efficacy (SES) and digital adaptability (DAS) ($\rho = 0.277$, $p < 0.001$; see Table 1), indicating that students who reported higher levels of self-efficacy also tended to exhibit higher levels of digital adaptability. This association suggests an interdependence between psychological resources relevant to academic functioning in digitalized learning environments. At the same time, the strength of the correlation indicates that digital adaptability cannot be reduced to general self-efficacy, thereby supporting their conceptual distinction.

This relationship complements the observed correlational pattern, indicating systematic associations among the examined psychological resources and attitudes toward artificial intelligence. Overall, these findings are consistent with Hypothesis H3, indicating a positive association between general self-efficacy and digital adaptability.

The correlation coefficients corresponding to hypotheses H1–H3 are summarized in Table 1.

Taken together, the correlational analyses indicate that digital adaptability and self-efficacy are related yet non-equivalent psychological resources, both of which are associated with students’ attitudes toward artificial intelligence. Although the correlations were statistically significant, their magnitude indicates small-to-moderate associations. Therefore, these results should be interpreted as evidence of consistent but limited relationships among the examined constructs rather than as evidence of strong associations.

3.4. Exploratory Differences Among Students in Digital Adaptability, Self-Efficacy, and Attitudes Toward Artificial Intelligence (H4)

To test Hypothesis H4, formulated as an exploratory analysis, one-way ANOVA analyses were conducted to examine whether students differed in terms of digital adaptability (DAS), self-efficacy (SES), and attitudes toward artificial intelligence (AIAS) across faculties. Descriptive statistics and the results of the one-way ANOVA analyses are presented in Table 2.

Table 2. Differences across Faculties in Attitudes toward Artificial Intelligence (AIAS), Digital Adaptability (DAS), and Self-Efficacy (SES).

Variable	Faculty	N	M	SD	F	p
Attitudes toward AI (AIAS)	Applied Sciences	61	14.3279	3.3947	3.853	0.010
	Aerospace Engineering	80	13.9875	2.9958		
	Industrial Engineering and Robotics	95	15.5368	2.8725		
	Other faculties	314	14.5032	3.3576		
Digital Adaptability (DAS)	Applied Sciences	61	71.0328	9.4569	2.341	0.072
	Aerospace Engineering	80	68.8125	9.6549		
	Industrial Engineering and Robotics	95	70.0211	11.1451		
	Other faculties	314	67.8248	10.2769		
Self-Efficacy (SES)	Applied Sciences	61	21.8033	5.3846	0.602	0.614
	Aerospace Engineering	80	22.0125	5.9075		
	Industrial Engineering and Robotics	95	21.3053	5.6814		
	Other faculties	314	22.2389	6.3071		

Note. M = Mean; SD = Standard Deviation. One-way ANOVA results are reported; $N = 550$.

Comparisons were performed among the three faculties included in the analysis—Industrial Engineering and Robotics, Aerospace Engineering, and Applied Sciences—as well as the aggregated category of other faculties. Because the “other faculties” category combined respondents from multiple faculties with smaller subsamples, the faculty comparison should be interpreted as an exploratory descriptive analysis rather than as a robust test of disciplinary differences.

With regard to attitudes toward artificial intelligence (AIAS), the ANOVA results indicated statistically significant differences across faculties, $F(3, 546) = 3.853$, $p = 0.010$. Levene’s test indicated that the assumption of homogeneity of variances was met ($p = 0.235$). Descriptive means suggested moderate variation across faculties, with slightly higher AIAS scores observed among students from the Faculty of Industrial Engineering and Robotics.

For digital adaptability (DAS), the ANOVA did not reveal statistically significant differences between groups, $F(3, 546) = 2.341$, $p = 0.072$.

Similarly, the ANOVA conducted for self-efficacy (SES) showed no statistically significant differences across faculties, $F(3, 546) = 0.602$, $p = 0.614$.

Overall, this pattern suggests that faculty-related differences are selective and specific to attitudes toward artificial intelligence, whereas the psychological resources examined display a relatively homogeneous distribution across groups. These findings are consistent with the exploratory formulation of Hypothesis H4, indicating selective faculty-related differences only in attitudes toward artificial intelligence.

To facilitate the interpretation of faculty-level differences, Figure 1 presents the mean scores for attitudes toward artificial intelligence across the analyzed faculty groups.

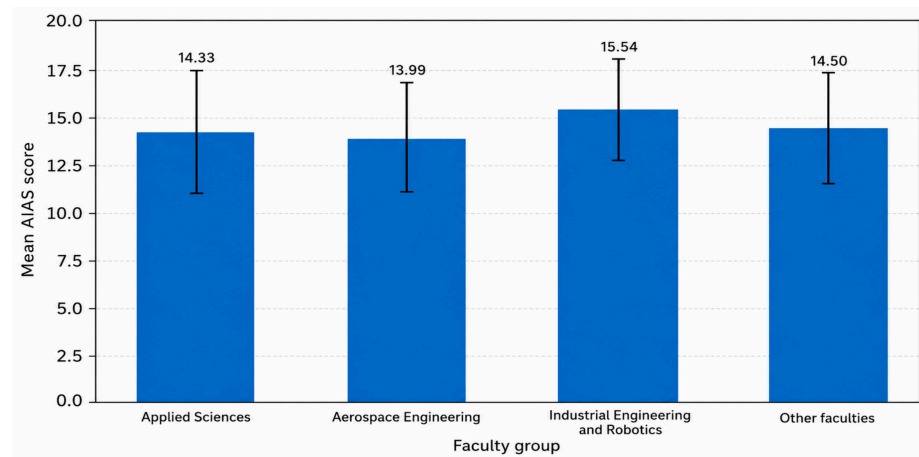


Figure 1. Mean scores for attitudes toward artificial intelligence across faculty groups.

3.5. Exploratory Differences Between Students by Year of Study in Digital Adaptability, Self-Efficacy, and Attitudes Toward Artificial Intelligence (H5)

To test Hypothesis H5, formulated as an exploratory analysis, one-way ANOVA analyses were conducted to examine whether digital adaptability (DAS), self-efficacy (SES), and attitudes toward artificial intelligence (AIAS) varied according to educational level (undergraduate vs. master's).

With regard to attitudes toward artificial intelligence (AIAS), the ANOVA results did not indicate statistically significant differences between undergraduate and master's students, $F(1, 548) = 0.205$, $p = 0.651$. The ANOVA examining digital adaptability (DAS) also revealed no statistically significant differences between undergraduate and master's students, $F(1, 548) = 1.963$, $p = 0.162$.

Similarly, the ANOVA conducted for self-efficacy (SES) did not reveal statistically significant differences between undergraduate and master's students, $F(1, 548) = 0.099$, $p = 0.754$, indicating comparable levels of self-efficacy across educational levels.

Overall, these results indicate a high degree of homogeneity in the examined variables with respect to educational level. Consistent with its exploratory formulation, Hypothesis H5 was not supported.

To provide a clearer visualization of the comparison across educational levels, Figure 2 presents the mean scores for digital adaptability, general self-efficacy, and attitudes toward artificial intelligence among undergraduate and master's students.

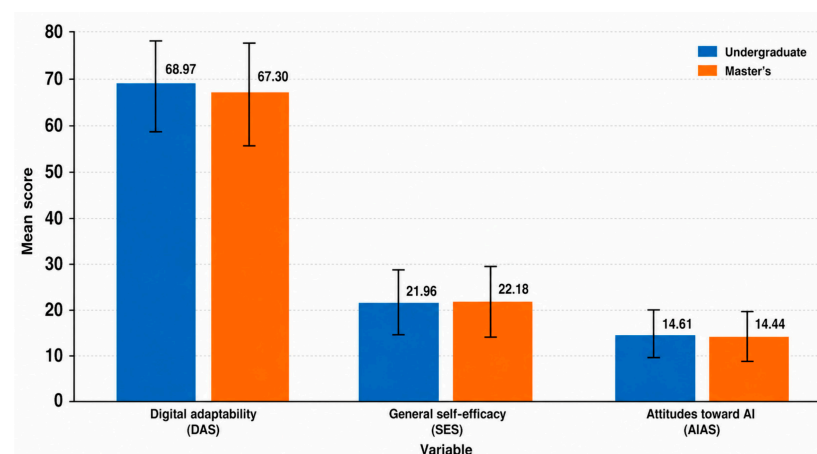


Figure 2. Mean scores for digital adaptability, general self-efficacy, and attitudes toward artificial intelligence by educational level.

3.6. Regression Analysis of Digital Adaptability, Self-Efficacy, and Attitudes Toward Artificial Intelligence (H6)

To integrate the previous correlational findings and examine whether the psychological resources included in the model were associated with attitudes toward artificial intelligence after accounting for faculty and year of study, a hierarchical multiple linear regression analysis was conducted to test Hypothesis H6, with attitudes toward artificial intelligence (AIAS) specified as the dependent variable (see Table 3).

Table 3. Hierarchical Multiple Linear Regression Predicting Attitudes toward Artificial Intelligence (AIAS).

Predictor	B	SE B	β	t	p
Model 1					
Faculty	0.112	0.137	0.036	0.82	0.413
Year of study	−0.263	0.395	−0.030	−0.67	0.507
Model 2					
Faculty	0.179	0.133	0.058	1.35	0.178
Year of study	−0.179	0.382	−0.020	−0.47	0.641
Digital Adaptability (DAS)	0.087	0.014	0.274	6.34	<0.001
Self-Efficacy (SES)	0.029	0.023	0.054	1.25	0.210

Note. Dependent variable: AIAS. Model 1: $R^2 = 0.002$; Model 2: $R^2 = 0.071$; $\Delta R^2 = 0.069$, $p < 0.001$; $N = 550$.

In the first block of the analysis, the control variables—faculty and year of study—were entered. The resulting model was not statistically significant, $F(2, 547) = 0.44$, $p = 0.646$, and explained a negligible proportion of the variance in AIAS scores ($R^2 = 0.002$).

The inclusion of psychological resources in the second block significantly increased the variance accounted for by the model. Specifically, after digital adaptability (DAS) and self-efficacy (SES) were entered, the model became statistically significant, $F(4, 545) = 10.35$, $p < 0.001$, accounting for 7.1% of the variance in AIAS scores ($R^2 = 0.071$; $\Delta R^2 = 0.069$).

Regression coefficient analyses showed that digital adaptability was positively and statistically significantly associated with attitudes toward artificial intelligence ($\beta = 0.274$, $t = 6.34$, $p < 0.001$), indicating a modest but statistically reliable association with unique variance in AIAS scores within the hierarchical model. In contrast, self-efficacy was not significantly associated with unique variance in AIAS scores ($\beta = 0.054$, $t = 1.25$, $p = 0.210$). This result indicates that, once digital adaptability is taken into account, general self-efficacy does not show a statistically significant association with unique variance in attitudes toward artificial intelligence.

Overall, the regression analysis indicates that digital adaptability showed a statistically significant, although still modest, unique association within the examined model, whereas self-efficacy did not show a significant unique association. This result should be interpreted as a comparative association within the model, not as evidence that digital adaptability has superior explanatory value. These findings are consistent with the associative formulation of Hypothesis H6, indicating that digital adaptability accounted for a statistically significant but modest proportion of variance in attitudes toward artificial intelligence after accounting for faculty and year of study.

Although the proportion of variance accounted for by the model is limited ($R^2 = 0.071$), this value is comparable to those reported in research on attitudes toward emerging educational technologies. Accordingly, the regression findings should be understood as indicating a statistically reliable but modest association within the tested model. Digital adaptability was the only psychological variable significantly associated with unique variance in students' attitudes toward AI, but the model also indicates that most of the variance remains unaccounted for by the variables included in the present analysis.

Overall, the findings indicate a coherent pattern of relationships among digital adaptability, self-efficacy, and attitudes toward artificial intelligence, characterized by consistent small-to-moderate associations. Comparative analyses suggest homogeneity in the examined constructs across educational levels, whereas faculty-related differences emerged selectively and exclusively for attitudes toward artificial intelligence. The regression analysis further indicates that digital adaptability accounts for a statistically significant, yet modest and partial, proportion of variance in attitudes toward artificial intelligence, suggesting a limited association with unique variance within the examined model while also highlighting the multifactorial nature of students' evaluative responses to AI.

4. Discussion

The study examined the relationship between digital adaptability, self-efficacy, and students' attitudes toward artificial intelligence in higher education. The findings indicate that students' attitudes toward artificial intelligence were modestly but consistently associated with the psychological resources examined. Digital adaptability showed a slightly stronger association with attitudes toward artificial intelligence than self-efficacy within the tested model, whereas faculty-related differences emerged selectively for attitudes toward AI. However, this comparison should be interpreted as an association-based pattern that may partly reflect conceptual proximity between a technology-facing predictor and a technology-oriented outcome measure. From an educational technology perspective, these findings suggest that adaptive digital resources may be relevant to understanding students' general attitudes toward AI, but this relevance remains limited by the general nature of the AI attitude measure, the small-to-modest associations, the limited explained variance, and the possibility of construct proximity. They should be understood as correlational evidence of comparative association rather than as evidence of comparative explanatory superiority or as a strong basis for causal, psychological, educational, or institutional claims.

4.1. Digital Adaptability as a Context-Relevant Correlate of Attitudes Toward Artificial Intelligence

A key finding concerns the role of digital adaptability in accounting for variation in students' attitudes toward artificial intelligence. Although both digital adaptability and self-efficacy were positively associated with AIAS at the bivariate level, only digital adaptability showed a statistically significant unique association in the hierarchical regression model. This pattern suggests that scores on digital adaptability were more closely associated with general AI attitudes than scores on general self-efficacy within the present model. In this sense, the findings indicate that students' evaluations of artificial intelligence were somewhat more closely associated, within the tested model, with perceived adaptability to technological novelty, uncertainty, and complexity than with generalized confidence. This interpretation is also consistent with recent empirical evidence indicating that students' AI-related attitudes are associated with digital competence and AI literacy rather than with exposure to digital technologies alone (Baum & Trzcińska-Król, 2024; Mansoor et al., 2024). Therefore, the present findings contribute to this empirical line of research by suggesting that adaptive readiness for technological change may represent an additional learner-related resource associated with students' general evaluations of AI.

Digital adaptability may be considered a technology-facing correlate of attitudes toward artificial intelligence, consistent with prior research identifying digital competencies as important determinants of students' responses to emerging educational technologies (Nazaretsky et al., 2025). This finding indicates an association between students' general evaluations of AI and their self-reported adaptability to technological change, new digital tools, and uncertainty. However, this interpretation should remain cautious. The present regression model does not demonstrate that digital adaptability is theoretically central to

AI attitudes, nor does it establish a psychological mechanism explaining such attitudes. A plausible alternative interpretation is that digital adaptability shows a somewhat stronger association in the present model because its content is more closely related to technology-oriented evaluations than that of a broad self-efficacy measure. Therefore, the result should be understood as evidence of a slightly stronger and still modest association within the tested model rather than as proof that digital adaptability has a central explanatory status in AI acceptance. Importantly, the present data cannot determine whether this pattern reflects a substantively distinct role of digital adaptability or greater conceptual proximity between the predictor and the outcome.

Recent studies show that digital competencies shape how students interact with advanced technologies, such as AI-based tools, and may mediate both attitudes and usage intentions (Yaseen et al., 2025). Although the present study did not directly measure students' experiences with AI-mediated learning environments, prior research suggests that students are increasingly required to interpret algorithmically generated outputs and adjust their learning strategies, reinforcing the importance of examining adaptive capacities such as digital adaptability.

From a higher education perspective, digital adaptability may be examined not merely as an individual characteristic but as a learning-relevant outcome that future studies could investigate in relation to curriculum design and activities requiring students to interpret, question, and revise AI-assisted work. The fact that digital adaptability showed a statistically significant unique association with attitudes toward artificial intelligence, whereas self-efficacy did not, represents a limited empirical distinction within the present model. However, the findings should not be interpreted as sufficient to revise or advance AI acceptance models on their own. Rather, they suggest that future research should examine more directly whether technology-facing adaptive resources show distinct associations beyond broader motivational constructs, using AI-specific measures and designs appropriate for testing explanatory mechanisms when such mechanisms are of interest. The limited proportion of explained variance is consistent with the multifactorial nature of attitudes toward emerging educational technologies. The fact that the model explained only 7.1% of the variance further indicates that most of the variation in students' attitudes toward AI remains unaccounted for by the present predictors. This unexplained variance may reflect factors not included in the current model, such as students' direct hands-on experience with generative AI tools, the frequency and purpose of AI use, perceived usefulness, trust in AI-generated outputs, perceived risk, AI literacy, AI-specific self-efficacy, prior exposure to AI-related coursework, and discipline-specific learning experiences. Therefore, the present findings should be interpreted as identifying a modest learner-related association rather than offering a comprehensive explanatory model of students' attitudes toward AI. Future research should incorporate these context-specific and AI-specific predictors to provide a more complete understanding of how students evaluate artificial intelligence in higher education.

4.2. General Self-Efficacy and AI-Related Attitudes

The results of the study revealed a positive and statistically significant association between self-efficacy and attitudes toward artificial intelligence, indicating that students who perceive themselves as competent and capable tend to express more favorable evaluations of AI-based technologies. However, the absence of a significant unique association for self-efficacy in the multivariate model suggests that this result should be interpreted cautiously when more technology-facing learner resources are considered simultaneously.

The lack of a statistically significant unique association for general self-efficacy should not be interpreted as evidence that this construct is irrelevant to students' attitudes toward

AI. Rather, it indicates only that, in the present model, general self-efficacy did not account for unique variance in AI attitudes after digital adaptability was included.

Accordingly, the present findings do not allow conclusions about whether self-efficacy functions as a conditional, indirect, or standalone resource in relation to AI attitudes. Although self-efficacy is theoretically understood as a general belief in one's capability to manage challenges (Bandura, 1997), the present data only show that general self-efficacy was positively associated with AI attitudes at the bivariate level but did not show a statistically significant unique association in the hierarchical regression model.

Recent research links general self-efficacy to digital competence and experience with digital tools (Javier-Aliaga et al., 2024; González-Prida et al., 2024), while studies on advanced technologies suggest that digital competence may be related to perceptions of AI through technology-specific forms of self-efficacy (Ren et al., 2025). In the case of artificial intelligence, prior research suggests that attitudes may be more closely related to AI-specific self-efficacy and perceived competence in interacting with AI systems than to general self-efficacy (Bewersdorff et al., 2025). The present findings are consistent with this broader distinction, but they cannot directly test it because AI-specific self-efficacy was not measured. At the same time, the positive association between general self-efficacy and digital adaptability suggests that these resources are related, but the present study cannot determine the direction, sequence, or process underlying this relationship. Therefore, the findings should be interpreted as evidence of observed associations among the measured constructs rather than as evidence of indirect effects, mediation, or explanatory pathways.

From a higher education perspective, these findings indicate that general self-efficacy, as measured in the present study, was associated with students' general attitudes toward AI at the bivariate level but did not remain uniquely associated with AI attitudes in the regression model. Future studies should examine AI-specific self-efficacy and students' direct experiences with AI-based systems using designs that can test explanatory processes more appropriately. Recent literature likewise emphasizes that self-efficacy relevant to AI use is connected to authentic, guided, and reflective educational experiences involving meaningful interaction with AI-based systems (Tlili et al., 2023; Schutte, 2025).

4.3. Stability Across the Educational Trajectory and Context-Specific Differences

Comparative analyses revealed a high degree of homogeneity in digital adaptability, self-efficacy, and attitudes toward artificial intelligence across years of study, suggesting the relative stability of these constructs throughout university cycles. This stability challenges the assumption that prolonged exposure to higher education environments automatically leads to the progressive development of adaptive or evaluative capacities related to emerging technologies. From an educational technology perspective, this pattern suggests that students do not necessarily become more adaptively prepared for AI simply by progressing through university. Instead, these results suggest that learner-related resources connected to AI may remain relatively stable unless they are intentionally addressed through educational experiences and technology-rich learning activities (Novikova et al., 2023).

Moreover, evidence points to a positive relationship between digital competence and self-efficacy in interactions with digital and AI-based tools, suggesting that these psychological resources tend to stabilize and be maintained through accumulated university experience (Ren et al., 2025). In the absence of deliberate pedagogical interventions, differences observed across years of study are more likely to be attributable to individual factors and learning experiences than to fundamental shifts in orientations toward technology and digital competence (Zhao et al., 2021).

From a higher education perspective, this finding may have tentative implications, as it suggests that universities should not automatically assume the natural, progressive

development of digital adaptability or attitudes toward artificial intelligence as students advance through their years of study. On the contrary, the observed stability suggests that these resources may need to be examined in future research as potential educational objectives related to curriculum design, pedagogy, and structured educational experiences. Research on digital transformation in higher education emphasizes that prolonged exposure to technology alone does not guarantee the development of adaptive competencies or reflective attitudes toward technology; rather, these outcomes require intentionally designed educational contexts (Kirkwood & Price, 2014; Selwyn, 2022).

This finding is particularly relevant because it suggests that progression from the undergraduate to the master's level should not, in itself, be assumed to produce greater digital adaptability or more favorable attitudes toward AI. Rather than treating technological maturity as an automatic outcome of time spent in higher education, future research and educational practice should examine how structured learning experiences, guided AI use, reflective activities, and discipline-specific exposure to AI tools may contribute to the development of adaptive and critical orientations toward AI. However, such implications should be interpreted cautiously, as the present study did not directly measure curricular interventions, instructional practices, or students' actual engagement with AI tools.

In contrast to the stability observed across years of study, the differences identified between faculty groups—limited exclusively to attitudes toward artificial intelligence—should be interpreted cautiously. Because the largest comparison category consisted of an aggregation of multiple smaller faculties, the faculty variable does not provide a precise basis for substantive disciplinary interpretation. These differences may suggest that the educational context is relevant for future investigation, but the present analysis cannot determine which specific disciplinary, curricular, or institutional factors account for variation in students' attitudes toward AI.

Descriptively, students from the Faculty of Industrial Engineering and Robotics reported the highest mean score for attitudes toward AI. However, this pattern should be interpreted cautiously because the present study did not directly measure curricular content, AI-related coursework, technological exposure, instructional practices, or students' actual use of AI tools within each faculty. Therefore, the observed difference should not be attributed directly to specific disciplinary or curricular characteristics. Rather, it should be understood as an exploratory finding that points to the need for future research using more balanced faculty samples and direct measures of educational and technological exposure.

This cautious interpretation is consistent with prior research showing that students in different academic fields may engage with educational technologies in different ways (Pumptow & Brahm, 2023). It also aligns with the educational technology literature emphasizing that students' attitudes toward technology may be shaped by pedagogical experiences and institutional practices, although the present study cannot identify these mechanisms directly (Selwyn, 2010).

The absence of significant faculty-level differences in digital adaptability and self-efficacy, combined with selective differences in attitudes toward AI, suggests that disciplinary context may be relevant for future research on students' general AI-related orientations. However, these findings do not provide a sufficient basis for strong claims about differentiated institutional strategies for AI integration.

4.4. Cautious Implications for Future Research and Educational Practice

From a practical educational perspective, the findings should be interpreted cautiously because the study measured general attitudes toward artificial intelligence rather than students' direct experiences with AI-supported learning environments, assessment practices, feedback systems, academic integrity issues, or actual AI use. Therefore, the implications

of the study are indirect. They suggest that digital adaptability may be relevant to students' general orientations toward AI, but they do not provide direct evidence regarding the effectiveness of specific curricular interventions, instructional strategies, or institutional AI policies. Nevertheless, this cautious interpretation remains consistent with the broader literature on AI literacy, which emphasizes that a predominantly technical approach is insufficient to support informed and responsible orientations toward AI (Long & Magerko, 2020; Ng et al., 2021), as well as with critiques of instrumental approaches to AI integration in education (Schiff, 2022). Accordingly, the practical relevance of the present findings should be understood primarily as a basis for formulating future research questions rather than as a basis for immediate educational recommendations. Given the limited proportion of variance explained by the regression model, the applied significance of the findings is modest: they help identify digital adaptability as a learner-related variable for future research, rather than as a basis for immediate educational intervention or institutional decision-making.

Taken together, the findings contribute to future educational research by suggesting that students' orientations toward AI should not be explained solely through broad motivational constructs or general technology acceptance variables. Instead, the results indicate the need to examine technology-facing adaptive capacities, such as digital adaptability, as distinct resources that may shape how students respond to rapidly changing AI-based systems.

Future studies should therefore examine whether digital adaptability is related to more specific aspects of AI engagement, including AI literacy, AI-specific self-efficacy, trust in AI-generated outputs, perceived risk, feedback-related and assessment-related experiences, academic integrity concerns, and actual patterns of AI use. In relation to curriculum design, the present findings should be viewed only as an exploratory starting point for future inquiry. Because the study measured general attitudes toward AI rather than students' actual use of AI tools or their experiences with AI-supported learning activities, it cannot determine which instructional strategies are most effective.

Within this cautious interpretive framework, digital adaptability may be considered a relevant construct for future research on students' general orientations toward AI, particularly in relation to their perceived ability to cope with the change, uncertainty, and complexity associated with AI-based systems (Long & Magerko, 2020). Future studies should examine whether, and under what conditions, digital adaptability supports meaningful engagement with AI-mediated learning processes. However, such questions require more specific measures and stronger designs than those used in the present study.

Accordingly, future research should examine whether students' direct AI-related educational experiences are associated with the development of adaptive capacities. Such claims require studies that directly measure AI-related learning experiences, instructional practices, and students' actual engagement with AI-based systems. Recent systematic reviews of artificial intelligence in education highlight that guided, reflective, and contextualized educational experiences are essential for fostering a balanced and responsible relationship with AI-based systems (Garzón et al., 2025). For this reason, these points should be understood as directions for future empirical investigation rather than as practical recommendations derived from the present data.

Furthermore, the observed stability of digital adaptability and attitudes toward artificial intelligence across years of study suggests that these resources do not develop automatically through exposure to digital technologies or natural progression through university cycles. This finding may inform future research and institutional reflection, but it should not be interpreted as direct evidence supporting specific digitalization policies. Recent literature shows that assumptions regarding the implicit development of

digital competencies and attitudes are often unjustified in the absence of intentional pedagogical interventions, making “one-size-fits-all” approaches particularly problematic (Pumptow & Brahm, 2023).

Faculty-level differences in attitudes toward artificial intelligence may indicate that students’ general evaluations of AI vary across educational contexts. However, because the dependent variable measured broad attitudes toward AI rather than discipline-specific educational uses of AI, these differences should be interpreted cautiously (Qu et al., 2024). Overall, the findings suggest that digital adaptability may be relevant to understanding students’ general AI-related orientations, but they do not directly establish how artificial intelligence should be integrated into specific curricula, assessment practices, or university learning environments. Consequently, the practical implications of the study should remain limited to identifying future research questions about how learner-related resources, educational contexts, and actual AI-related experiences are associated in higher education.

4.5. Limitations and Directions for Future Research

The findings should be interpreted in light of several limitations. The cross-sectional design of the study does not allow causal inferences regarding the relationships between psychological resources and attitudes toward artificial intelligence. In addition, the use of self-report measures may introduce biases related to social desirability or subjective perceptions.

These limitations are not peripheral qualifications but define the scope of the contribution of the study. In particular, the cross-sectional design, the use of broad self-report measures, the modest explained variance, and the possible conceptual proximity between digital adaptability and attitudes toward AI mean that the findings should be interpreted as limited comparative associations rather than as evidence of explanatory mechanisms or strong educational implications.

First, the analytical scope of the study was limited. The analyses included correlations, group comparisons, and hierarchical regression, which are appropriate for examining associations among variables but do not allow complex theoretical models to be tested. The present study did not include structural equation modeling, mediation or moderation analyses, a measurement model, or formal tests of construct validity, convergent validity, or discriminant validity. It also did not control for students’ actual AI use, AI literacy, or behavioral outcomes. Consequently, the findings should be interpreted as exploratory and correlational evidence regarding associations among digital adaptability, general self-efficacy, and general attitudes toward AI, rather than as evidence supporting a comprehensive technology acceptance model or a mechanism explaining AI-mediated learning. Future studies should employ confirmatory factor analysis or structural equation modeling to examine the factorial structure of the instruments and test convergent and discriminant validity more rigorously, particularly when comparing closely related constructs such as digital adaptability, digital competence, technology self-efficacy, and AI-specific self-efficacy.

Second, the possible content proximity between the Digital Adaptability Scale and the Artificial Intelligence Attitude Scale should be considered central to the interpretation of the main comparative finding. Although the two instruments assess different constructs, digital adaptability is more closely related to technology-oriented experiences than general self-efficacy. Therefore, its stronger association with attitudes toward artificial intelligence may partly reflect greater topical alignment with the outcome measure rather than a deeper explanatory mechanism. The present study cannot determine whether the stronger association of digital adaptability reflects a substantively different explanatory role or greater conceptual proximity to the outcome measure. For this reason, the findings should be interpreted as evidence of comparative association, not comparative explanatory superi-

ority. Future studies should address this issue by including more specific measures of AI attitudes, AI literacy, AI self-efficacy, and actual AI use, as well as analyses designed to examine construct distinctiveness more directly.

Third, the measurement of self-efficacy represents another important limitation. Although the manuscript initially referred to academic self-efficacy, the items assess broad perceived capability to solve problems, cope with unexpected events, and manage difficult situations. Therefore, the construct was revised throughout the manuscript to general self-efficacy. The scale does not measure academic self-efficacy, technology self-efficacy, or AI-specific self-efficacy. Consequently, the findings should not be interpreted as evidence regarding these more specific forms of self-efficacy. Future research should include domain-specific measures to examine whether academic, technology-related, or AI-specific self-efficacy explains students' AI-related attitudes more precisely.

Fourth, students' attitudes toward artificial intelligence were operationalized using a concise four-item scale. The items assess broad positive and negative evaluations of AI rather than attitudes toward AI specifically in higher education, learning, assessment, academic integrity, feedback, or actual use. Although the Artificial Intelligence Attitude Scale demonstrated acceptable internal consistency ($\alpha = 0.720$), this measure captures a deliberately parsimonious and evaluative representation of attitudes toward AI rather than a multidimensional or context-specific attitudinal profile.

Fifth, the treatment of faculty affiliation limits the interpretation of group differences. Although respondents came from 21 faculties, only the three faculties with the largest numbers of respondents were analyzed as separate groups, whereas the remaining faculties were aggregated into an "other faculties" category. This category included more than half of the sample and was heterogeneous by design. Therefore, the significant faculty effect observed for attitudes toward AI should be interpreted as exploratory and descriptive rather than as evidence of clear disciplinary differences. Future studies should use more balanced sampling across faculties or disciplinary fields to allow more meaningful comparisons and stronger conclusions regarding contextual or disciplinary variation in AI-related attitudes.

Finally, the treatment of year of study also requires caution. Because the original year-of-study variable included several categories with uneven numbers of respondents, corresponding to undergraduate years 1–4 and master's years 1–2, it was recoded into broader educational-cycle groups for analysis. Therefore, the comparison should be interpreted as an exploratory analysis of undergraduate versus master's students rather than as a detailed test of differences across individual years of study. Future studies should use more balanced samples across educational levels to examine developmental or progression-related differences more precisely.

Future research could employ longitudinal and mixed-methods designs, incorporate behavioral indicators of AI use, and extend the investigation to other institutional settings and fields of study. It should also examine AI-specific self-efficacy, distinct from general self-efficacy, and explore how instructional design, disciplinary context, and actual patterns of AI use interact with learner-related psychological resources, including through classroom-based implementations that clarify when digital adaptability becomes most relevant to meaningful and responsible AI use in higher education.

Another limitation concerns the exclusively quantitative nature of the data. Although the use of standardized scales allowed the systematic measurement of the constructs, the study did not include qualitative methods such as interviews, focus groups, or classroom observations. Therefore, it could not capture in-depth explanations of how students interpret AI, how they experience AI tools in concrete learning situations, or how institutional and pedagogical contexts shape their attitudes. Future research should integrate qualita-

tive or mixed-methods approaches to provide a deeper interpretation of the contextual meanings associated with students' AI-related evaluations.

5. Conclusions

This study provides a limited contribution to educational technology research by examining associations between students' psychological resources and their general evaluation of artificial intelligence within a higher education sample. At the theoretical level, the findings suggest that broad motivational constructs, such as self-efficacy, showed a weaker unique association with students' general attitudes toward AI when examined alongside a technology-facing adaptive resource in the present model. Digital adaptability showed a statistically significant unique association with attitudes toward artificial intelligence within the tested model, whereas general self-efficacy did not; however, this finding should be interpreted as evidence of a comparative association that may partly reflect construct proximity, rather than as proof of a central explanatory mechanism or explanatory superiority. Methodologically, the study contributes by directly comparing digital adaptability and self-efficacy within a single analytical model, highlighting the value of more differentiated and construct-sensitive approaches in educational technology research on emerging technologies such as AI, while also showing the need for greater caution when interpreting technology-facing predictors in relation to technology-oriented outcomes.

Overall, the findings suggest that digital adaptability is associated with students' general attitudes toward artificial intelligence and may represent a relevant construct for future research on AI-related orientations in higher education, provided that this relevance is understood as association-based and exploratory rather than explanatory or practice-directing. Accordingly, the findings should not be interpreted as showing that digital adaptability or general self-efficacy causes students to develop more favorable attitudes toward AI.

However, because the dependent variable captured broad attitudes toward AI rather than attitudes toward specific educational uses of AI, the results should not be interpreted as direct evidence regarding curriculum design, instructional strategies, assessment practices, or institutional AI policies. Future research should examine these issues using more specific measures of AI-related learning experiences, AI literacy, AI-specific self-efficacy, academic integrity concerns, feedback practices, and actual patterns of AI use.

Author Contributions: Conceptualization, A.M.V. and G.P.; methodology, A.M.V. and G.P.; software, A.M.V. and G.P.; validation, A.M.V. and G.P.; formal analysis, A.M.V. and G.P.; investigation, A.M.V. and G.P.; resources, A.M.V. and G.P.; data curation, A.M.V. and G.P.; writing—A.M.V. and G.P.; writing—review and editing, A.M.V. and G.P.; visualization, A.M.V. and G.P.; supervision, A.M.V. and G.P.; project administration, A.M.V. and G.P.; funding acquisition, A.M.V. and G.P.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of The National University of Science and Technology POLITEHNICA Bucharest. The ethical approval for the study was obtained from the Institutional Review Board, approval number 150/23.05.2025.

Informed Consent Statement: Informed consent was obtained implicitly from all participants through the voluntary completion and submission of the online questionnaire. Prior to participation, respondents were informed about the purpose of the study, the voluntary nature of participation, and the anonymity and confidentiality of their responses. No personally identifiable information was collected or retained.

Data Availability Statement: The datasets generated and analyzed during the current study are not publicly available due to participant confidentiality but are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1. Digital Adaptability Scale (DAS)

Please indicate how much each statement describes you using a 6-point Likert scale, where

1 = Not at all like me

6 = Very much like me.

Item	Statement
1	When learning to use a new technology, I do not think about the purpose for which it was designed.
2	I always know where to look for help when I encounter difficulties in using technology.
3	When learning technology frustrates me, I prefer to give up or let others do it instead of me.
4	I constantly look for faster ways to use technology, such as shortcuts, keyboard commands, or quick-access menus.
5	I usually fail to learn how new technologies work, so I avoid using them.
6	When learning to use a new technology, I try to connect it to other technologies I already know.
7	When learning to use new technology, I compare my needs with the purpose for which the technology was created.
8	Even when using technology frustrates me, I keep trying and do not give up.
9	I am open to learning new technologies, even if I do not succeed on the first attempt.
10	I usually do not invest time in learning faster ways to use technology.
11	I do not always know where to look for help when I experience difficulties using technology.
12	When learning to use technology, I take into account the purpose for which it was designed.
13	It is important to me to learn tips and tricks that help me use technology more efficiently.
14	I avoid using new technologies because I am afraid of making mistakes and not knowing how to fix them.
15	Even when the process of learning technology feels boring, I continue and do not give up.

Scoring Instructions

To calculate the total Digital Adaptability score, items 1, 3, 5, 10, 11, and 14 must be reverse-coded (i.e., responses are recorded from 6 to 1). After reverse coding the specified items, all 15 item scores are summed. The total score ranges from 15 to 90, with higher scores indicating higher levels of perceived digital adaptability. Reverse-coded items may also be used to identify response patterns (e.g., acquiescence bias). For instance, if a respondent provides similar answers across all items, reverse-coded items should yield opposite scores compared to positively worded items within the same conceptual category. To compute scores for each digital adaptability habit, the items corresponding to each habit are summed, applying reverse coding where indicated (*). Items measuring the same habit are intentionally similar in content in order to triangulate the measurement of the construct through multiple indicators.

Appendix A.2. Artificial Intelligence Attitude Scale (AIAS)

Instructions

Please indicate the extent to which you agree with the following statements using a 5-point Likert scale, where:

1 = Strongly disagree

5 = Strongly agree

Item	Statement
1	I believe that artificial intelligence will improve my life.
2	I believe that artificial intelligence will be beneficial for society.
3	Artificial intelligence makes me feel uncomfortable. (reverse-coded)
4	I believe that artificial intelligence represents a threat to humans. (reverse-coded)

Items 3 and 4 are reverse coded prior to analysis. A total attitude score is computed by summing the four items, with higher scores indicating more positive attitudes toward artificial intelligence.

Appendix A.3. Self-Efficacy Scale (SES)

Appendix A.3.1. Instructions

Please read the instructions carefully. Below is a series of statements referring to your professional or academic activity. Read each statement carefully and indicate the extent to which you agree with it, always referring to your own activity. For each statement, please select one single response option that best represents you.

Responses are rated on a 4-point Likert scale:

1 = Not at all true of me

2 = Mostly not true of me

3 = Mostly true of me

4 = Exactly true of me

Although the instructions refer to professional or academic activity, the items assess broad perceived capability to manage problems, unexpected events, and difficult situations. Therefore, the scale was interpreted in the present study as a measure of general self-efficacy.

Item	Statement
1	I can always manage to solve difficult problems if I try hard enough.
2	If someone opposes me, I can find the means and ways to get what I want.
3	It is easy for me to remain persistent in order to achieve my goals.
4	I am confident that I could successfully deal with unexpected events.
5	Thanks to my abilities, I know how to handle unforeseen situations.
6	I can solve most problems if I invest the necessary effort.
7	I can remain calm when facing difficulties because I can rely on my problem-solving abilities.
8	When I am confronted with a problem, I can usually find several solutions.
9	When I face a delicate problem, I usually know what needs to be done to solve it.
10	I am generally prepared to cope with any situation or problem I may encounter.

Appendix A.3.2. Scoring

The total self-efficacy score is obtained by summing the scores of all 10 items. Possible total scores range from 10 to 40, with higher scores indicating higher levels of perceived self-efficacy.

References

- Alfredo, R., Echeverria, V., Jin, Y., Yan, L., & Swiecki, Z. (2024). Human-centred learning analytics and AI in education: A systematic literature review. *Computers & Education: Artificial Intelligence*, 6, 100215. [\[CrossRef\]](#)
- Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.
- Baum, A., & Trzcińska-Król, M. (2024). Students' attitudes towards artificial intelligence and their digital competence [Special Issue]. *The New Educational Review*, 5, 142–157. [\[CrossRef\]](#)
- Bewersdorff, A., Hornberger, M., Nerdel, C., & Schiff, D. S. (2025). AI advocates and cautious critics: How AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy. *Computers and Education: Artificial Intelligence*, 8, 100340. [\[CrossRef\]](#)
- Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, 100197. [\[CrossRef\]](#)
- Garzón, J., Patiño, E., & Marulanda, C. (2025). Systematic review of artificial intelligence in education: Trends, benefits, and challenges. *Multimodal Technologies and Interaction*, 9(8), 84. [\[CrossRef\]](#)
- Getenet, S., Cante, R., Redmond, P., & Albion, P. (2024). Students' digital technology attitude, literacy and self-efficacy and their effect on online learning engagement. *International Journal of Educational Technology in Higher Education*, 21, 3. [\[CrossRef\]](#)
- González-Prida, V., Chuquin-Berrios, J. G., Moreno-Menéndez, F. M., Sandoval-Trigos, J. C., Pariona-Amaya, D., & Gómez-Bernaola, K. O. (2024). Digital competencies as predictors of academic self-efficacy: Correlations and implications for educational development. *Societies*, 14(11), 226. [\[CrossRef\]](#)
- Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, 57(4), 542–570. [\[CrossRef\]](#)
- Javier-Aliaga, D., Silva Neyra, O. R., Calizaya-Milla, Y. E., & Saintila, J. (2024). Academic self-efficacy and digital competence in a sample of university students. *Contemporary Educational Technology*, 16(4), ep540. [\[CrossRef\]](#)
- Kasneji, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Kasneji, G., Krusche, S., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Spannagel, C., . . . Kasneji, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, 103, 102274. [\[CrossRef\]](#)
- Kirkwood, A., & Price, L. (2014). Technology-enhanced learning and teaching in higher education: What is “enhanced” and how do we know? A critical literature review. *Learning, Media and Technology*, 39(1), 6–36. [\[CrossRef\]](#)
- Liang, H., & Reiss, M. J. (2025). The associations between students' attitudes toward AI and learning engagement: Serial mediating roles of perceived autonomy and learning enjoyment. *Frontiers in Psychology*, 16, 1681635. [\[CrossRef\]](#) [\[PubMed\]](#)
- 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). ACM. [\[CrossRef\]](#)
- Mansoor, H. M. H., Bawazir, A., Alsabri, M. A., Alharbi, A., & Okela, A. H. (2024). Artificial intelligence literacy among university students—a comparative transnational survey. *Frontiers in Communication*, 9, 1478476. [\[CrossRef\]](#)
- Matos, T., Santos, W., Zdravevski, E., Coelho, P. J., Pires, I. M., & Madeira, F. (2025). A systematic review of artificial intelligence applications in education: Emerging trends and challenges. *Decision Analytics Journal*, 15, 100571. [\[CrossRef\]](#)
- Merino-Campos, C. (2025). The impact of artificial intelligence on personalized learning in higher education: A systematic review. *Trends in Higher Education*, 4(2), 17. [\[CrossRef\]](#)
- Nazaretsky, T., Mejia-Domenzain, P., Swamy, V., Frej, J., & Käser, T. (2025). The critical role of trust in adopting AI-powered educational technology for learning: An instrument for measuring student perceptions. *Computers and Education: Artificial Intelligence*, 8, 100368. [\[CrossRef\]](#)
- Neagu, S. N., & Vieriu, A. M. (2019). The impact of technological progress on young people. In *Proceedings of the 15th international conference eLearning and software for education: New technologies and redesigning learning spaces* (Vol. 2, pp. 351–358). Carol I National Defence University Publishing House. [\[CrossRef\]](#)
- Neagu, S. N., & Vieriu, A. M. (2025). Digital and psychological well-being among technical university students: Exploring the impact of digital engagement in higher education. *Education Sciences*, 15(9), 1192. [\[CrossRef\]](#)
- Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). AI literacy: Definition, teaching, evaluation and ethical issues. *Proceedings of the Association for Information Science and Technology*, 58(1), 504–509. [\[CrossRef\]](#)
- Novikova, I. A., Bychkova, P. A., Shlyakhta, D. A., & Novikov, A. L. (2023). Attitudes towards digital educational technologies scale for university students: Development and validation. *Computers*, 12(9), 176. [\[CrossRef\]](#)
- OECD. (2021). *OECD digital education outlook 2021: Pushing the frontiers with artificial intelligence, blockchain and robots*. OECD Publishing. [\[CrossRef\]](#)
- Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, 2, 100020. [\[CrossRef\]](#)
- Pumptow, M., & Brahm, T. (2023). Higher education students differ in their technology use. *Computers and Education Open*, 5, 100149. [\[CrossRef\]](#)

- Qu, Y., Tan, M. X. Y., & Wang, J. (2024). Disciplinary differences in undergraduate students' engagement with generative artificial intelligence. *Smart Learning Environments*, 11, 51. [\[CrossRef\]](#)
- Ren, J., Guo, J., & Li, H. (2025). Linking digital competence, self-efficacy, and digital stress to perceived interactivity in AI-supported learning contexts. *Scientific Reports*, 15, 33182. [\[CrossRef\]](#) [\[PubMed\]](#)
- Sáez-Velasco, S., Alaguero-Rodríguez, M., Rodríguez-Cano, S., & Delgado-Benito, V. (2025). Students' attitudes towards AI and How they perceive the effectiveness of AI in designing video games. *Sustainability*, 17(7), 3096. [\[CrossRef\]](#)
- Scherer, R., Siddiq, F., & Tondeur, J. (2020). All the same or different? Revisiting measures of teachers' technology acceptance. *Computers & Education*, 143, 103656. [\[CrossRef\]](#)
- Schiff, D. (2022). Education for AI, not AI for education: The role of ethics in national AI education strategies. *International Journal of Artificial Intelligence in Education*, 31(4), 527–555. [\[CrossRef\]](#)
- Schutte, N. S. (2025). The role of self-efficacy and curiosity in student use of artificial intelligence. *International Journal of Educational Technology in Higher Education*, 22, 73. [\[CrossRef\]](#)
- Selwyn, N. (2010). Looking beyond learning: Notes towards the critical study of educational technology. *Journal of Computer Assisted Learning*, 26(1), 65–73. [\[CrossRef\]](#)
- Selwyn, N. (2022). *Education and technology: Key issues and debates* (3rd ed.). Bloomsbury Academic.
- Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, 10, Article 15. [\[CrossRef\]](#)
- Tseng, S.-M. (2025). Determinants of the intention to use digital technology. *Information*, 16(3), 170. [\[CrossRef\]](#)
- Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications*, 252, 124167. [\[CrossRef\]](#)
- Yaseen, H., Mohammad, A. S., Ashal, N., Abusaimeh, H., Ali, A., & Sharabati, A.-A. A. (2025). The impact of adaptive learning technologies, personalized feedback, and interactive AI tools on student engagement: The moderating role of digital literacy. *Sustainability*, 17(3), 1133. [\[CrossRef\]](#)
- Yuan, J., & Li, X. (2025). How digital literacy and ICT self-efficacy shape student perceived post-editing competence. *Acta Psychologica*, 259, 105409. [\[CrossRef\]](#) [\[PubMed\]](#)
- Zakir, S., Hoque, M., Susanto, P., Nisaa, V., Alam, M., Khatimah, H., & Mulyani, E. (2025). Digital literacy and academic performance: The mediating roles of digital informal learning, self-efficacy, and students' digital competence. *Frontiers in Education*, 10, 1590274. [\[CrossRef\]](#)
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, 16, 39. [\[CrossRef\]](#)
- Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence (AI) in education from 2010 to 2020. *Complexity*, 2021, 8812542. [\[CrossRef\]](#)
- Zhao, Y., Sánchez Gómez, M. C., Pinto Llorente, A. M., & Zhao, L. (2021). Digital competence in higher education: Students' perception and personal factors. *Sustainability*, 13(21), 12184. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.