Fostering AI Literacy in Higher Education

The Role of Students' Usage Patterns[1]

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The expanding use of AI in education has driven governmental initiatives underlining the need for critical, ethical, and effective AI use. The TAM model suggests that more AI use could improve students' AI literacy, and evidence shows that promoting AI literacy among university students benefits their well-being and learning outcomes. However, research on key preconditions of AI literacy remains unclear. Moreover, there is a need to distinguish between self-reported and actual skills. In a survey (N = 247), we found that three frequent AI usage patterns (write essays, prepare presentations, organize workflows) were linked to certain dimensions of self-reported AI literacy and to specific facets of a knowledge test. Academic uses of AI may foster confidence, while not necessarily enhancing real proficiency. Results suggest the way students use AI matters more than how often.

Förderung von AI Literacy in der Hochschulbildung.
Die Rolle studentischer Nutzungsmuster
Die zunehmende Nutzung von KI im Hochschulbereich hat politische Initiativen hervorgebracht, die einen kritischen, ethischen und effektiven Einsatz fordern. Das TAM-Modell legt nahe, dass schon die intensive Nutzung von KI die AI Literacy von Studierenden fördern könnte. Empirische Befunde deuten darauf hin, dass AI Literacy mit Wohlbefinden und besseren Lernerfolgen einhergeht. Welche Prädiktoren dabei eine Rolle spielen, ist unklar. Außerdem ist es notwendig, selbstberichtete Kompetenzen von tatsächlichen Fähigkeiten zu unterscheiden. In einer Befragung (N = 247) zeigte sich, dass drei Nutzungsmuster (Essays verfassen, Präsentationen vorbereiten, Arbeitsabläufe organisieren) mit Dimensionen von AI Literacy im Selbstbericht als auch mit Facetten eines Wissenstests zusammenhingen. Die

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Ergebnisse deuten darauf hin, dass die Qualität der Nutzung wichtiger ist als die Häufigkeit.

Background

Relevance in education and in higher education

The development of artificial intelligence (AI) has accelerated rapidly, leading to its widespread integration into education, from elementary schools to universities and vocational training. This expansion has strengthened the importance of AI literacy, i.e., the knowledge and ability to use AI effectively, critically, ethically, and responsibly (Ng/Leung/Chu/Qiao 2021). Policymakers have explicitly emphasized this need as well. For example, the EU AI Act requires all actors involved in operating and using AI systems (European Commission 2025). In Germany, both the Federal Ministry of Education and Research (BMBF) and the Standing Conference of the Ministers of Education and Cultural Affairs (KMK) have published guidelines since 2023 that highlight the need for AI literacy in school and higher education contexts (BMBF 2023; KMK 2024). This policy emphasis underscores the necessity of equipping educators and students with competencies to handle both opportunities and risks of AI. Beyond policy, international organizations such as UNESCO IITE and SOU (2023) have similarly called for AI literacy as a cornerstone of digital citizenship, arguing that the ability to engage critically with AI is a prerequisite for democratic participation and social inclusion in increasingly digital societies.

AI Literacy

Past research has broadly defined AI literacy as the set of knowledge, skills, and attitudes that enable individuals to interact with AI systems in an effective, critical, and ethical manner (e.g., Carolus et al. 2023; Long/Magerko 2020). Additionally, scholars have emphasized that AI literacy should be viewed not only as a technical competence but also as a socio-technical and ethical capacity, encompassing awareness of issues such as bias, fairness, and accountability in AI systems (Tuomi/Cachia/Villar-Onrubia 2023). From an educational policy perspective, the OECD AI Literacy Framework (AILit) postulates that AI literacy includes technical understanding (e.g., how AI systems process data), the ability to use AI tools responsibly, and the capacity to evaluate AI outputs critically (OECD 2025). Importantly, AI literacy also requires practical competencies such as prompt engineering to improve the accuracy and usefulness of AI responses, as well as the skill to identify and mitigate hallucinations, i.e., AI-generated but factually incorrect information (Kasneci et al. 2023).

Assessment of AI Literacy

In recent years, researchers have proposed a wide range of instruments to assess AI literacy (for an overview, see the meta-analysis by Lintner 2024). These assessments typically cover dimensions such as technological knowledge, ethical considerations, problem-solving abilities, and the use of AI applications. Most existing instruments rely on self-reported skills, with only a few including performance-based tests. Lintner et al. (2024) identified thirteen self-report scales and three performance-based measures. This imbalance is problematic, as self-reports often overestimate competencies. Indeed, prior research found a negative connection between AI tool usage and critical thinking skills (Gerlich 2025), suggesting that frequent AI use may boost confidence without necessarily improving proficiency. Consequently, distinguishing between perceived (self-reported) abilities and actual abilities is essential for valid assessment. Furthermore, the sample for which an instrument has been validated must be taken into account, differentiating between university students, K-12 students, teachers, or the general population.

Antecedents and Consequences of AI Literacy

Promoting AI literacy has been associated with positive outcomes for university students, including enhanced well-being and improved academic performance (Xiao et al. 2024). Yet, the conditions that foster AI literacy are not fully understood. The Technology Acceptance Model (TAM; Davis 1989) suggests that frequent use of technology enhances related skills, implying that more AI usage could naturally improve AI literacy. However, evidence is mixed. The International Computer and Information Literacy Study (ICILS 2023) found that years of computer experience correlated positively with ICT literacy, whereas academic-media multitasking was negatively associated (Fraillon 2024). These findings indicate that how technology is used matters more than how often it is used. Similarly, in higher education, little is known about the usage patterns students follow when using AI tools for academic purposes and how these relate to AI literacy.

Aims

The present study aimed to (a) explore usage patterns of AI tools in study-related activities among university students and (b) examine how these patterns are connected to AI literacy, distinguishing between self-reported abilities and actual knowledge. By integrating insights from prior research with new empirical evidence, this work contributes to understanding how AI use in higher education shapes students' competencies for responsible and effective AI engagement.

Methods

Sample & Procedure

Analyses in the present study were based on data from the project »Studis-KI« (Studis-KI 2025). An online survey using SoSciSurvey was conducted. Data collection took place between November 2024 and August 2025. Ethical approval was obtained prior to the start of the survey. A total of $N = 247$ university students (80 % female, $M_{age} = 23.06$, $SD = 4.39$) who indicated using AI for study purposes participated in this survey. Sixty-two percent of students had a background in psychology (64 % Bachelor, 11 % Master) and 23 % in teacher education. Participants perceived either participant minutes ($n = 149$) or a voucher ($n = 98$).

Measures

In this section, we describe the measurement instruments used to assess students' study-related experiences with AI tools, as well as different measures of AI literacy, including both self-report scales and a knowledge test. Where applicable, we used Cronbach's alpha to estimate internal consistency. An alpha value of ≥ 0.70 is generally considered satisfactory (Tavakol/Dennick 2011).

AI Literacy (Self-report)

Self-reported AI literacy was assessed using four subscales of the META AI Literacy Scale (MAILS; Carolus et al. 2023), with an 11-point rating scale. The original MAILS subscales focus on AI use in a general context. In the present study, we specifically examined AI use in higher education. Therefore, we adapted the items to fit the higher education context, for example, by adding phrases such as »my studies« where applicable (e.g., »I can use AI tools to make <u>my studies</u> more efficient.«). The four subscales included Use and Apply (4 items; $\alpha = .91$), Know and Understand (4 items; $\alpha = .69$), Detect AI (4 items; $\alpha = .78$), and AI Ethics (4 items; $\alpha = .77$). It must be noted that the internal consistency of the Know and Understand subscale was below .70. Item–total correlations suggested deleting one item, which would have improved the internal consistency to .72. However, to preserve content validity, we decided not to delete this item, as the subscale has previously been shown to be reliable in a large sample.

AI Literacy (knowledge test)

For an objective measure of AI literacy, we developed a short knowledge test consisting of six single-choice items with four answer options for critical AI use based on recommendations of Tancredi (2024). We developed each item for six of the seven proposed strategies; the strategy »implement retrieval-augmented generation« was not addressed because it is less applicable in students' everyday use. Each item had one correct answer. All items had item difficulty indices (*p*) that fell within the recommended range: (a) increase awareness/attention (.79), (b) use a more advanced model (.48), (c) provide explicit instruction (.89), (d) provide sample answers (.81), (e) provide full context (.31), and (f) verify outputs (.84).[6]

Quantity of AI Use for Study-Related Activities (Usage Patterns, UP)

As a proxy for the quantity of AI use in study-related activities (see Table 1), we asked students to rate how often they engaged in 14 types of AI-supported study practices: »*How often do you use AI tools for the following study-related activities?*« Responses were given on a 5-point scale (1 = *never*, 5 = *every day*). The scale was adapted from an instrument originally developed to assess students' use of ICT for study purposes in ICILS 2018 (Vennemann et al. 2021). For this study, the items were revised to reflect AI-specific applications rather than general ICT use.

Background Variables

Students were asked to provide demographic information (e.g., gender, age, study program) and self-reported data on their Abitur GPA and the frequency of use of 51 different AI tools. In addition, they were asked to indicate their prior knowledge (yes/no) in 13 different areas of AI (e.g., machine learning, deep learning, neural networks) or to state that they had no prior knowledge of the topic.

Results

Descriptives and Correlational Analyses

Descriptive analyses showed that, among 51 AI tools, most students reported frequently using ChatGPT (92 %), followed by DeepL (30 %), and Canva (15 %), respectively. Almost half of the students (46 %) reported having no knowledge about AI concepts, while about a third reported some understanding of advanced AI topics: 33 %

6 The scale is available from the first author for research purposes upon request.

machine learning, 27 % deep learning, and 26 % neural networks. Correlational analyses revealed positive associations among the dimensions of self-reported AI literacy (AIL). Guided by prior research (Gerlich 2025) that self-perceived AI competencies and actual knowledge do not necessarily align, this study did not aim to identify latent AI literacy constructs but rather to examine how predefined and conceptually distinct dimensions of self-reported AIL and knowledge-based performance relate to one another. Consistent with these assumptions, the dimensions of self-reported AIL and those of the knowledge test were largely uncorrelated (see Table 1).

Table 1: Correlations between Dimensions of AI Literacy (AIL): Self-Report versus Knowledge Test

AIL Measures	*N*	*M*	*SD*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Self-Report													
(1) Use & Apply	243	8.45	1.83	—									
(2) Know & Understand	243	7.80	1.64	.67**	—								
(3) Detect AI	243	6.33	2.05	.40**	.59**	—							
(4) AI Ethics	243	7.36	1.90	.42**	.70**	.57**	—						
Knowledge Test													
(5) Increase Awareness	241	0.79	0.41	.01	.10	.02	.04	—					
(6) Advanced Model	241	0.48	0.50	.01	.00	.04	.03	.02	—				
(7) Explicit Instruction	241	0.89	0.31	.17**	.20**	.01	.14*	.25**	.07	—			
(8) Example Answers	241	0.81	0.39	.00	.04	.02	.05	.17**	.05	.14*	—		
(9) Full Context	241	0.32	0.47	.07	.08	.14*	.14*	.01	.03	.12	.10	—	
(10) Verify Outputs	241	0.84	0.37	.13*	.11	.04	.08	.51**	-.06	.33**	.25**	.10	—

Note: $^{*}p < .05$. $^{**}p < .01$.

Exploring Usage Patterns of AI Tools For Study Purposes Among University Students

Table 2 shows descriptive statistics for fourteen AI usage patterns among university students. The results showed that students used AI most often for research and information gathering ($M = 3.47$, $SD = 1.17$) and for preparing research papers and essays ($M = 3.16$, $SD = 1.14$), whereas AI tools were rarely employed for creative tasks such as video content ($M = 1.48$, $SD = 0.93$) or audio production ($M = 1.47$, $SD = 0.93$).

Table 2: Descriptive Statistics for AI Usage Patterns among University Students

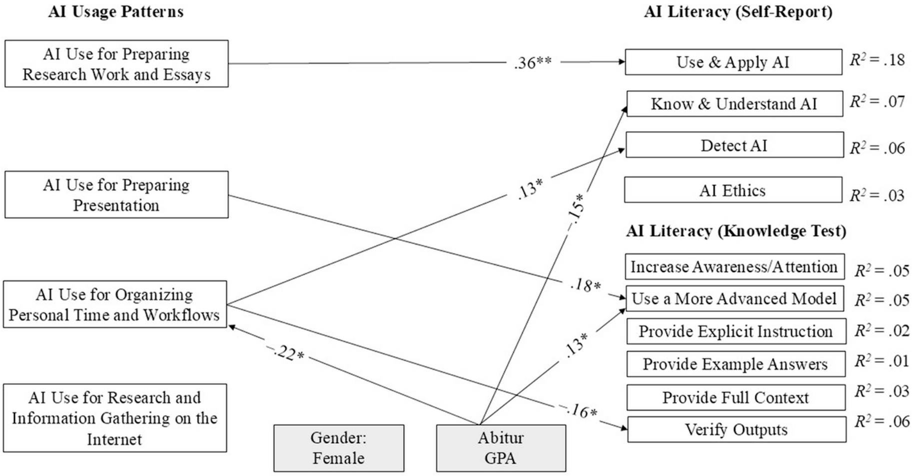
AI Usage Patterns (1 = *never*, 5 = *every day*)	***N***	***M***	***SD***
Research and information gathering on the internet*	247	3.47	1.17
Preparation of research papers and essays*	247	3.16	1.14
Working on worksheets and exercises*	247	3.06	1.27
Preparation of presentations	247	2.67	1.26
Working on exams and quizzes	247	2.35	1.33
Research and preparation of information for long-term projects	247	2.31	1.24
Use of software or applications to develop specific skills or for a subject (e.g., math tutoring)	247	2.30	1.32
Structuring of information, e.g., as lists, tables, or mind maps	247	2.23	1.25
Use of programming environments to work on tasks (e.g., programming projects)	247	2.21	1.35
Organization of one's own time and work processes**	247	2.19	1.32
Analysis and presentation of data, e.g., in charts and graphs	247	2.06	1.24
Working online with other students	247	2.00	1.19
Creation of videos to explain study content	247	1.48	1.02
Creation of video or audio productions	247	1.47	0.93

Note: * patterns with the highest frequencies selected for analyses; **pattern selected for analyses

AI Usage Patterns Associated with AI Literacy Among University Students

Among the 14 AI usage patterns, we selected four as predictors of AI literacy. We chose *AI use for research and information gathering*, *AI use for preparation of research papers and essays*, and *AI use for preparation of presentations*, as the most frequently reported activities among the 14 patterns. *AI use for working on worksheets and exercises* ranked third in frequency, but was not included because it substantially overlaps conceptually with *AI use for preparation of research papers and essays* and thus could introduce redundancy in the analysis. Instead, we selected *AI use for organization of one's own time and work processes*, not because of its frequency of use, but due to its conceptual relevance for self-regulated learning skills (e.g., Zimmerman 2002), which are central to understanding students' AI literacy.

Figure 1: Path Model for AI Usage Patterns Associated with AI Literacy Among University Students



Note. $N = 247$. $*p < .05$. $**p < .01$.
For simplicity, correlations among usage patterns and among AI literacy indicators were estimated but are not displayed.

A path analysis was conducted using Mplus 8.8 (Muthén & Muthén 1998–2022) to examine the hypothesized associations while controlling for gender and Abitur GPA in a sample of 247 participants. It must be noted that Abitur GPA was included as a control variable to account for general academic achievement, thereby ensuring that the associations between AI usage patterns and AI literacy are examined independently of prior educational performance.

All study variables were specified as manifest variables; grouping labels are included solely for conceptual clarity. Model fit indices indicated a mixed fit, $\chi^2(2, N = 247) = 19.17$, CFI = .98, SRMR = .03, RMSEA = .19. Overall, model fit was acceptable, with strong support from CFI and SRMR; although RMSEA indicated poor fit, this index is unreliable in low-df models (Kenny et al., 2015), so findings should be interpreted with caution. Three of the four AI usage patterns (UP, reported in Table 1) were significantly related to certain dimensions of self-reported AIL as well as some knowledge test dimensions: Regarding self-reported AIL, the UP *AI use for preparing research papers and essays* was positively associated with the perceived ability to use and apply AI, while the UP *AI use for organizing workflows* was positively associated with the perceived ability to detect AI. No significant associations for UPs were found with perceived knowledge and understanding of AI or with perceived AI ethics. Interestingly, Abitur GPA was negatively associated with perceived knowledge and understanding of AI. Likewise, it was negatively associated with the UP *AI use for organizing workflows*. The UP *AI use for research and information gathering* showed no significant associations with any literacy dimensions. For the knowledge test items, the UP *AI use for preparing presentations* and Abitur GPA were positively associated with knowledge of recognizing when an advanced model is needed. In contrast, the UP *AI use for organizing workflows* was negatively associated with knowledge of validating AI output. Gender was unrelated to both AI usage and literacy dimensions.

Discussion

Summary & Discussion of Results

The study identified four patterns of AI use in higher education. Three were most frequently employed among students: using AI tools to research and information gathering on the internet, to prepare research papers or essays, and to prepare presentations. The fourth pattern is relevant to self-regulated learning skills as it involves organizing personal time and workflows. Three of these patterns were found to be associated with specific dimensions of AI literacy, both self-reported (e.g., Use and Apply AI, and Detect AI) and knowledge test (e.g., Use a More Advanced Model, and Verify Outputs). Notably, AI use for information gathering showed no connection to either self-reported or tested AI literacy. Furthermore, a negative relationship was observed between Abitur GPA and the pattern of using AI for organizing personal time and workflows, as well as knowledge and understanding of AI.

In the three patterns that showed associations, students interact more actively with the AI tools and typically require multiple feedback loops, which in turn could explain why they are linked to AI literacy. In contrast, using AI for quick information searches involves less active engagement and critical evaluation. Interestingly, we found students with lower Abitur GPA appeared to rely more on AI, while those with higher Abitur GPA report being more critical in their AI usage. This interpretation aligns with prior research showing that students' engagement with generative AI is heterogeneous and task-dependent, ranging from low overall reliance to extensive use for assignment-related activities (Stojanov et al. 2024)

The findings suggest that while academic uses of AI may foster confidence in handling these tools, such usage does not automatically translate into actual proficiency. This highlights the crucial point that *how* students use AI matters more than *how often* they use it. Moreover, the distinction between self-reported and tested AI literacy becomes essential in both research and practice: confidence alone cannot be equated with competence. Designing curricula and interventions should therefore aim at promoting measurable skills, not merely self-perceptions.

Limitations

The study sample consisted mainly of female students and students of psychology, which limits the generalizability of the results. In addition, the strong focus on the Goethe University Frankfurt context (93 % of participants) limits the transferability to other institutions or subject areas. It must be noted that the working model consisted of many study variables. Increasing the sample size would allow us to gain information about the robustness of the model. Finally, the knowledge test requires further development, due to its limited number of items to measure each strategy for critical AI evaluation skill and some items that were rather easy. Strategies to increase the test's reliability and depth include particularly the inclusion of more items per strategy and an in-depth analysis of the quality of distractors.

Further Investigation of the Dataset

Theoretical frameworks from psychology will be employed to explain antecedents and consequences of AI literacy. Ongoing work will therefore examine additional predictors of AI literacy, including further usage patterns, personality traits (e.g., Paulhus/Williams 2002), and motivational beliefs (e.g., self-determination theory, Deci/Ryan 2000). Moreover, future studies will extend the focus to other groups, such as school students and the elderly. In addition to antecedents, consequences of AI literacy will be explored in relation to achievement, well-being, and mental health in future analyses based on the Studis-KI dataset.

Practical Implications & Outlook

The findings provide empirical evidence to inform the development of interventions that foster AI literacy in higher education. For students, guidelines should focus on activities and usage patterns that strengthen critical engagement with AI and foster competence beyond surface-level interaction. For university lecturers, the study underscores that the use of AI is not homogeneous among students; targeted training and clear guidelines are necessary to support reflective and responsible use. This could be reflected in adaptation of curriculum designs (e.g., seminars, study programs, workshops) to systematically strengthen critical AI skills, or adaptation of assessment strategies to fit the new curricula (Digital Education Council 2025). To date, the link from AI literacy to student success (e.g., achievement, motivation, well-being) is still underexplored. A meta-analysis (e.g., Deng et al. 2024) demonstrated that the use of AI in education was connected with diverse educational outcomes. However, this connection should be further investigated systematically.

Scientific Significance of the Study

This study advances the understanding of how specific AI usage patterns relate to AI literacy, demonstrating that certain types of use can foster competence while others may undermine critical evaluation. For educators, the findings provide valuable guidance on integrating AI tools into teaching and learning, enabling targeted support to address both opportunities and challenges. Moreover, the insights gained can serve as a foundation for developing seminar and workshop concepts that strengthen AI literacy. By highlighting how diverse patterns of AI use contribute to academic activities, the study underscores the importance of promoting responsible and informed engagement with AI tools in higher education.

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