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Uncovering structural relationships between AI literacy, AI ethics, AI problem-solving, and self-regulated learning

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Abstract
The study aimed to explore how dimensions of AI literacy, specifically, AI technical understanding, AI critical appraisal, and AI practical application affect university students' AI ethics, their ability to solve problems using AI tools, and their self-regulated learning. Structural equation modelling (SEM) was conducted using AMOS to examine the research model. The findings indicated that AI technical understanding and AI ethics are significant predictors of students' self-regulated learning. In addition, AI critical appraisal and AI practical application significantly predicted AI ethics, while AI practical application emerged as a significant predictor of AI-supported problem-solving. Other AI literacy dimensions had no significant effects on AI problem-solving and self-regulated learning. The study highlights the necessity of embedding AI literacy into educational policy and curricula not only as a technical skill but also as a multidimensional competence tied to autonomy and ethical reasoning. We emphasize that using AI effectively requires going beyond simple tool proficiency and instead fostering reflective, value-based, and strategic engagement with AI in learning environments. These findings may also contribute to a more nuanced theoretical understanding of AI literacy by identifying components which are most relevant to students' AI ethics, problem-solving, and self-regulated learning.

Keywords Artificial intelligence, AI literacy, AI ethics, Self-regulated learning, AI practical application, AI problem solving

1 Introduction

The rapid development of artificial intelligence (AI) and its integration into various aspects of social life are reshaping the processes through which information is acquired, processed, and applied. In educational settings, AI is emerging not only as a technological tool but also as a challenge that has introduced a new form of literacy, known as AI literacy. AI literacy is widely acknowledged as a multidimensional construct that refers to an individual's ability to understand, evaluate, utilize, and reflect on artificial intelligence technologies across their technical, ethical, and social dimensions [1, 2].

With the increasing prevalence of AI-driven tools in educational contexts, a growing body of research has examined their implications for teaching and learning processes, particularly with regard to academic performance [3–5], institutional AI policies [6, 6, 7, 7], faculty experiences [8], and the use of AI systems as tutors or learning assistants [9, 10]. Empirical studies have indicated that AI-supported learning environments can influence student motivation, self-efficacy, and engagement [11–14].

Despite the growing use of generative AI tools such as ChatGPT, Gemini, Claude, DeepSeek, or Perplexity, empirical research examining how specific dimensions of AI literacy shape students' learning behavior, competencies, and ethical orientations remains limited, particularly in non-technical higher education contexts. While several conceptual frameworks of AI literacy have been proposed [1, 2], there remains a relative lack of quantitative studies investigating how AI literacy relates to students' AI-supported problem-solving, ethical decision-making, and learning autonomy. In particular, the interrelations between AI literacy, AI ethics, AI problem-solving, and self-regulated learning have not yet been comprehensively examined.

Unlike traditional digital resources, generative AI systems do not merely deliver information but actively participate in the construction of knowledge. This requires students to actively plan, monitor, and evaluate both their own reasoning and AI-generated outputs. Such demands are closely aligned with the principles of self-regulated learning, which place emphasis on goal setting, strategic action, monitoring, and reflection in learning processes [15]. From a theoretical standpoint, this study is grounded primarily in the concept of AI literacy as its core analytical framework. Self-regulated learning serves as a complementary construct that helps explain how AI literacy translates into learning-related behaviors. Recent studies show that effective use of AI tools requires well-developed self-regulation skills, including learner autonomy, goal setting, metacognitive monitoring, and reflection, which help to prevent cognitive offloading and support meaningful learning [16–18]. Empirical evidence further suggests that AI technologies can actively support reflective and self-regulated learning when used in cognitively appropriate ways. For example, Holmes et al. [19] underscore the role of AI in fostering reflective and self-regulated learning, while Sardi et al. [20] argue that cognitively appropriate interaction with AI can promote reflection, self-confidence, and strategic learning. At the same time, technical knowledge of AI alone is insufficient for developing ethical awareness, which requires value anchoring, social context, and pedagogical facilitation [21, 22]. Self-Determination Theory (SDT) [23–25] is employed as an interpretive lens rather than as a causal explanatory model in our study. SDT helps clarify why dimensions of AI literacy—such as technical understanding or ethical awareness—may reflect more autonomous and competent forms of engagement with AI-enhanced learning environments. Examining the relationship between AI literacy and self-regulated learning is, thus, theoretically important for understanding how students manage their autonomy, control, and motivation in AI-supported learning environments.

Most existing studies tend to focus either on technical skills or ethical awareness separately, without examining how these aspects interact within educational settings that are not primarily STEM-oriented (e.g., [1, 26, 27]). Thus, to date, no empirical research has comprehensively examined these concerns, specifically within the framework of Slovak higher education. Although AI tools are now widely employed by students in Slovakia, including those in economics and business study programs, there is a lack of data that would enable educators, researchers, and decision-makers to make informed and evidence-based curricular or pedagogical decisions. Without such data, it is challenging to accurately assess students' AI literacy levels, their patterns of AI tool use, and the impact of this use on their critical thinking, ethical awareness, and self-regulated learning.

Accordingly, the aim of this study is to empirically examine how individual dimensions of AI literacy influence students' AI ethics, ability to solve problems using AI, and their self-regulated learning in a non-technical higher education context. The central research question is: Which dimensions of students' AI literacy significantly predict AI ethics, AI-supported problem-solving, and self-regulated learning in non-STEM academic environments? Given the limited empirical evidence on how AI literacy relates to ethical practices in the use of AI-powered tools, students' AI-supported problem-solving, and learning autonomy, particularly self-regulated learning [18], this study addresses an important gap in the existing literature. As students are now widely expected to act autonomously in AI-enhanced learning environments, understanding the interplay among AI literacy, AI ethics, AI-supported problem-solving, and self-regulated learning becomes essential for the responsible and meaningful integration of AI into educational practice.

Therefore, in addition to contributing to the professional literature in this academic field, the findings of this study may inform the development and revision of educational policies, curriculum redesign and design, and enhancements to instructors' teaching approaches in higher education. These improvements aim to strengthen students' AI literacy, AI ethics, problem-solving skills, and self-regulation strategies in response to the growing impact of AI technology on education. Additionally, the results may help students develop AI literacy, adopt ethical strategies for using AI, apply AI tools effectively to solve problems, and cultivate effective self-regulated learning within AI-enhanced educational settings.

2 Literature review

The use of AI-powered tools is becoming increasingly evident across various professional fields, where they enhance and streamline many processes [3–5]. This trend is particularly visible in education, where student engagement with AI is growing more pronounced [28]. However, numerous challenges are associated with this trend, including improper use and misuse of AI tools, which violate ethical standards in educational settings [6, 7]. Although the use of AI is relatively recent in the educational environment, several studies have already addressed its implementation in teaching and learning [3–7, 28, 29]. The following section firstly introduces and describes the research model of the present study, and then discusses prior research, focusing on the research problem and variables under investigation.

Digital literacy encompasses not only the fundamental skills of reading and writing but also the capacity to utilize and engage properly with contemporary digital tools [2, 30]. Similarly, the concept of AI literacy is nowadays significant in student learning contexts and refers to the ability to use AI tools effectively [31]. This definition can be expanded to include the area of responsibility related to the critical evaluation of the use of AI tools among students [32]. AI literacy is a key factor that may influence other variables related to the use of AI technology. As such, it has been addressed in recent research [1, 3–5, 33, 34], and is central to our study as well.

2.1 The research model

The research model of this inquiry (Fig. 1) is based on frameworks developed by Laupichler et al. [34], Carolus et al. [35, 36], and Li et al. [37]. More specifically, this study employs the framework proposed by Laupichler et al. [34], which was designed to assess non-experts' AI literacy, and is perfectly well suited to the present study research sample. Within the "Scale for the Assessment of Non-experts' AI Literacy," Laupichler et al. [34] outline a set of items developed through an expert Delphi study to assess individuals' literacy, emphasizing three important variables: technical understanding, critical appraisal, and practical application. The current study examines the effects of the three aforementioned variables on AI ethics and AI-supported problem-solving, based on the Meta-Artificial Intelligence Literacy Scale (MAILS) [35, 36]. Additionally, the study examines how these variables, together with AI ethics and AI-supported problem-solving, influence self-regulated learning, as conceptualized by Li et al. [37]. Self-regulated learning focuses on how students deliberately define objectives within their academic domain and make thoughtful choices that impact their assignments and help them acquire educational experiences [38]. Therefore, the research model of this study examines the relationships among three dimensions of AI literacy, namely: AI technical understanding, AI critical appraisal, and practical application of AI [34], on the one hand, and AI ethics [35, 36], AI-supported problem-solving [35, 36], and self-regulated learning [37], on the other hand. The rationale for incorporating each variable in the present research model, along with the proposed interrelationships among them, is outlined in the subsequent subsections. Although AI literacy is generally regarded as a multifaceted construct encompassing technical, critical, and practical elements [34], these components are here treated as independent first-order predictors. This decision reflects our aim to identify the distinct contributions of each dimension, while acknowledging their conceptual interrelation within the broader framework of AI literacy.

2.2 Theoretical background

To provide a stronger theoretical rationale for the hypothesized relationships among the constructs, this study draws upon Self-Determination Theory (SDT [23]), which highlights three fundamental psychological needs—autonomy, competence, and relatedness—as essential for intrinsic motivation and effective learning. One of the SDT subtheories, basic psychological needs, helps distinguish between intrinsic and extrinsic

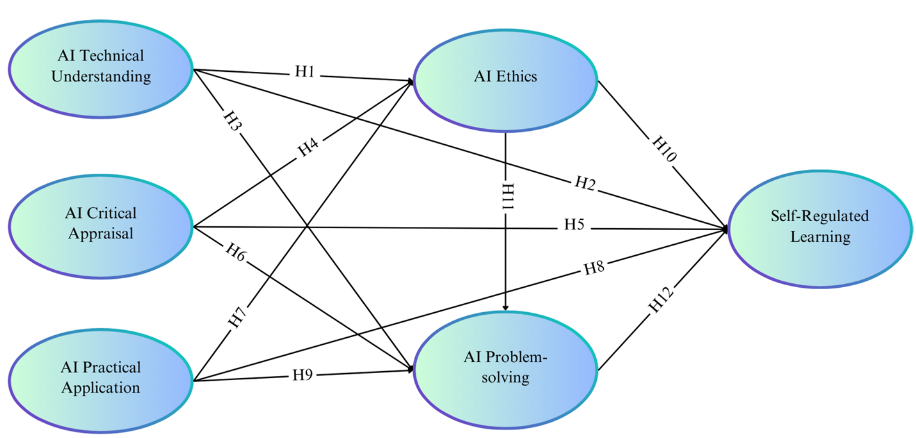

Fig. 1 The research model

motivation. SDT holds that autonomous (intrinsic) motivation, which is regarded as an individual's driving force, rises when these fundamental psychological needs are satisfied [23–25]. Research consistently shows that individuals who perceive themselves as competent and autonomous in using digital tools tend to hold more positive views of technology [39–41]. Intrinsic motivation to use technology also depends on the satisfaction of basic psychological needs—autonomy, competence, and relatedness [40, 42]. Online learning environments that allow flexibility and user control can strengthen students' sense of autonomy and competence [41]. Thus, attitudes toward technology might be seen as a key factor shaping behavioral adaptation [43, 44].

Building on these foundations, SDT has been increasingly applied to technology-enhanced and AI-supported learning [45, 46]. Although SDT is well established in educational psychology, its connection to AI literacy remains insufficiently explored [47, 48]. While the theory effectively explains motivation and engagement in digital learning, few studies have examined how the fulfillment of psychological needs contributes specifically to AI literacy. However, the existing evidence indicates that satisfying these needs enhances students' digital competencies [49], with autonomy and competence positively influencing AI literacy and emotional engagement mediating this relationship [50, 51]. The intersection of SDT, self-regulated learning, and AI literacy has also received limited attention. Although SDT supports motivation and self-regulated learning improves learning outcomes [52–54], few studies have integrated these perspectives. Wang et al. [47, 48] found that autonomy, competence, and relatedness are central to developing AI literacy, with four SRL strategies—cognitive engagement, metacognitive knowledge, resource management, and motivational beliefs—mediating this link. These findings underscore that both the satisfaction of psychological needs and the use of effective self-regulatory strategies are essential for fostering students' AI literacy and adaptive learning.

While SDT traditionally explains how the fulfillment of autonomy, competence, and relatedness drives intrinsic motivation and learning behavior, in the present study, it serves as an interpretative framework rather than a causal model. The three dimensions of AI literacy—technical understanding, critical appraisal, and practical application—reflect manifestations of perceived competence and autonomy in AI-supported contexts. Therefore, rather than positioning SDT's psychological needs as antecedents, this study empirically examines how the cognitive and practical expressions of these needs (operationalized through AI literacy) influence ethical awareness, problem-solving, and self-regulated learning. In other words, students who experience greater competence and autonomy in their engagement with AI tools (core needs in SDT) are believed to demonstrate higher levels of AI literacy, which in turn enhances their ethical awareness, problem-solving capacity, and self-regulation.

2.3 AI technical understanding

With the rapid development of AI technologies and their increasing use in educational environments, students are expected to possess a sufficient understanding of how AI tools operate and how they are used ethically and effectively. These skills can be defined as AI literacy, which encompasses various dimensions, such as the ability to apply AI technologies and critically evaluate them [1]. This can be achieved in higher education through collaborative interactions between students and teachers, aimed at fostering a deeper understanding of AI tools, not only from a technological perspective but also critically and ethically, through mutual discussion [33]. AI literacy research is a relatively new topic. Recently, AI literacy has emerged as a supporting theme within several studies discussing its implications in student environments [3–5, 55–58]. For example, Bećirović et al. [46, 59, 60] indicate that understanding AI technology significantly impacts not only AI self-efficacy and AI output quality but also students' overall academic performance. Assessing AI ethical reflection, Wang et al. [47, 48] also demonstrate a positive relationship between AI literacy and AI Ethics. Similar findings were reported in the study by Ng et al. [61]. Therefore, we predict a significant association between AI technical understanding and three other variables: AI ethics, self-regulated learning, and AI-supported problem-solving. Based on that, the following three hypotheses are formulated:

H1: AI technical understanding significantly predicts AI ethics.

H2: AI technical understanding significantly predicts self-regulated learning.

H3: AI technical understanding significantly predicts AI problem-solving.

2.4 AI critical appraisal

When it comes to using AI tools, several ethical concerns arise, including issues related to privacy and data protection. Students' use of AI-powered tools should be linked to their ability to critically evaluate these aspects of AI usage [34], so several studies [20, 62, 63] have focused on the relationship between artificial intelligence and critical thinking. Sardi et al. [20] point out that artificial intelligence tools positively impact critical thinking and self-regulated learning, which was confirmed in an empirical study by Shanto et al. [63]. The authors argue that the use of ChatGPT enhances students' cognitive abilities, positively affecting their critical thinking skills [20, 63]. Conversely, a negative relationship between critical thinking and the use of artificial intelligence tools can also be observed [64]. For example, Bećirović et al. [46, 59, 60] identified a significant negative relationship in the Austrian educational setting between the critical appraisal of AI and the quality of AI output, as well as between critical AI appraisal and self-efficacy in AI. However, an insignificant association was noticed between critical AI appraisal and the practical application of AI. The current study aims to draw attention to the correct application of artificial intelligence tools in the learning process, with the aim of minimizing the potential threats associated with their use. Therefore, the following hypotheses are proposed:

H4: AI critical appraisal significantly predicts AI ethics.

H5: AI critical appraisal significantly predicts AI problem-solving

H6: AI critical appraisal significantly predicts self-regulated learning

2.5 AI practical application

Zawacki-Richter et al. [65] emphasize that the use of AI tools will become an integral part of teaching in the coming decades. It is crucial to consider that the implementation of AI-powered technology requires substantial human oversight and control. Consequently, educational institutions should ensure that students' competencies in the application of AI tools are appropriately aligned. Kamalov et al. [66] highlight that the practical application of AI tools must be accompanied by AI literacy and an awareness of the ethical implications of using AI tools.

Previous research has explored the practical application of AI tools from various perspectives [11, 67, 68]. Pratama and Hastuti [68] found a positive impact of AI usage on students' writing skills. Bewersdorff et al. [11] suggested that educational strategies should emphasize not only AI literacy but also the practical application of AI tools. A similar conclusion and recommendations were made by Asirit and Hua [67], who, in their study combining quantitative survey data with qualitative responses, highlight the importance of teaching practical AI tool usage in schools. In this context, our study focuses on the relationship between the practical application of AI tools and three other variables: AI ethics, self-regulated learning, and AI-supported problem-solving. Taking that into account, the following hypotheses are proposed:

H7: AI practical application significantly predicts AI ethics.

H8: AI practical application significantly predicts AI problem-solving.

H9: AI practical application significantly predicts self-regulated learning.

2.6 AI ethics

The application of AI technologies raises several ethical concerns, including data security and privacy, transparency, and the morality of AI use [69]. AI ethics can be defined as a set of rules and standards that users should follow to avoid potential unlawful behavior while using AI models [69]. Numerous studies have already been conducted on AI ethics (e.g., [3, 26, 27, 47, 70–72]). By investigating the effects of AI models in classrooms, Tang and Su [72] explore the ethical concerns associated with using AI tools. Kajiwara and Kawabata [70] highlight specific benefits of using chatbots in teaching while adhering to ethical principles. Other studies have addressed the issue of AI ethics in general [27] or within student environments [26, 59, 71]. Wang et al. [47, 48] examine the ethics of AI use from three perspectives: ethical awareness, critical evaluation, and AI for social good. They point out the necessity of including education about the ethical use of AI in the curriculum [47, 48]. Alam [26] proposes a curriculum for students divided into four areas: safety, fairness, privacy, and AI ethics. He underscores that students should be well-versed not only in the technical aspects but also in the ethical issues surrounding AI technology. Ranade and Saravia [71] present a three-level framework (institutional, course, and instructional levels) for implementing AI ethics in education. They argue that a systematic approach to AI pedagogy is crucial for enhancing students' skills in AI ethics. The European Union is also paying increasing attention to the ethical use of artificial intelligence in school education. The legal framework for this effort is provided by the EU Artificial Intelligence Act (European [73]) and the Ethics Guidelines for Trustworthy AI [74]. This legislation, adopted at the European level, highlights the importance of using AI in a trustworthy manner based on the following key dimensions: legality, by ensuring compliance with EU law; by upholding fundamental ethical principles; and social responsibility, by considering the broader impact on society and the educational environment [75]. From the perspective of AI ethics, the following hypotheses are proposed:

H10: AI ethics significantly predict self-regulated learning.

H11: AI ethics significantly predict AI problem-solving.

2.7 AI-supported problem-solving

Students' use of AI tools is closely linked to their ability to solve complex problems in the current AI era. They face various challenges during their studies, including numerous projects and assignments [76]. Most of these tasks can be handled by AI tools, which provide users with a variety of options rather than just one [77]. Several studies [77, 78] have already examined the role of AI tools in problem-solving within educational contexts. For instance, Joksimovic et al. [79] investigate how AI-powered tools support the solving of complex problems by reviewing previously published works, thereby providing a comprehensive overview of recent findings in this area. Urban et al. [77] studied the impact of ChatGPT on complex problem-solving and showed that students' collaboration with artificial intelligence, specifically ChatGPT, improves creative problem-solving performance. Other studies in this field explore the connection between artificial intelligence and problem-solving, either directly [78] or indirectly by assessing research on critical thinking [62, 64, 76, 80]. According to Chen, Xiang et al. [81, 82], the relationship between AI problem-solving and self-regulated learning is closely linked to learners' help-seeking strategy, based on which students decide whether to use human sources when searching for information, or alternative methods, including artificial intelligence tools. Their findings indicate that learners´ help-seeking processes differ significantly when using a large-language model (LLM) like ChatGPT compared to a human expert. When learners seek help from ChatGPT, their sequences of activity form non-linear patterns. In contrast, with a human expert, learners more often follow linear help-seeking models. In this context, we propose the final hypothesis:

H12: AI problem-solving significantly predicts self-regulated learning.

2.8 Self-regulated learning

Self-regulated learning is defined as students' ability to purposefully set goals within their academic scope while making conscious decisions that reflect on their assignments and contribute to gaining educational experiences [38]. This concept has consistently attracted significant attention within the academic community. Consequently, recent research has indicated a positive impact of AI use on self-regulated learning [20]. In a similar vein, Lai [18] examined the relationship between self-regulated learning and the use of chatbots as AI tools that provide users with answers to a wide range of questions. In his work, Lai [18] describes not only the extent of this connection but also the methodologies and mechanisms through which interactions with chatbots can positively affect students' learning processes and educators' teaching methods. The integration of AI into the learning process is also explored by Kong and Yang [83]. Their research, conducted within the Chinese educational context, emphasizes the use of suitable methods for integrating AI tools to enhance not only student concentration but also overall engagement in learning, thereby optimizing their learning satisfaction [83]. Self-regulated learning has been further investigated in studies examining how personality traits influence students' self-regulated learning performance when learning with ChatGPT [60]. In parallel, Dahri et al. [84] explored the effects of using AI-powered tools on educators' self-regulated learning. Their findings reveal that a significant proportion of teachers hold positive perceptions of artificial intelligence, particularly ChatGPT, as a learning tool [84].

3 Methods

3.1 Participants

The current study involved 531 students from the Bratislava University of Economics and Business (EUBA). The participants were randomly selected, and their participation was voluntary EUBA is the largest public university in Slovakia, focused on economics, business, management, marketing, and economic diplomacy. The university comprises seven faculties and maintains strong international partnerships, participating in Erasmus +, Horizon Europe, and other strategic initiatives. EUBA is part of the global business education network AACSB [85] and holds HRS4R [86] certification. As part of the European project ENRICH (Enhancing Teaching and Research through Innovative Digital Technologies), the participants were selected using convenience sampling, the most common form of nonprobability sampling [87]. Convenience sampling has its advantages and disadvantages. Since this study was funded by the European Commission initiative, it had to adhere to the project's guidelines, which affected the sampling method. Still, "non-probability convenience samples are the standard within developmental science, and likely will remain so" ([88], p. 13), and "most research is conducted on convenience and purposive samples that may be randomly or non-randomly drawn" ([89], p. 86). In this case, developmental science refers to the use of AI in education, an emerging area in teaching and learning. Additionally, convenience sampling is used when "either time or resources are in short supply" ([90], p. 3). The European ENRICH project determined both the time and the resources, and, since most research is conducted on convenience and purposive samples [89], despite their known limitations, this study offers valuable theoretical and practical contributions.

With a mean age of 21.2 and a standard deviation of 2.16, the participants ranged in age from 17 to 37. This study comprised 342 female (64.4%) and 186 male students (35%), with two individuals (0.4%) choosing not to declare their gender and one student (0.2%) selecting the "other" category. The research sample included students from the following fields of study: International Economic Relations ($N = 266$; 50.7%), Economic Diplomacy ($N = 119$; 22.5%), International Business ($N = 90$; 17.2%), Accounting ($N = 18$; 3.4%), Data Science ($N = 10$; 2%), Accounting and Auditing ($N = 7$; 1.3%), Economic Informatics ($N = 7$; 1.3%), and 14 students in other academic fields (2.8%). Furthermore, the study sample comprised 207 first-graders (39%), 83 s-graders (15.6%), 92 third-graders (17.3%), 61 fourth-graders (11.5%), 85 fifth-graders (16%), and 3 PhD students (0.6%). The comprehensive descriptive analysis of the study participants is displayed in Table 1.

3.2 Instruments and procedures

An online survey was used to collect data. The survey began with questions regarding students' demographic characteristics, including gender, year of study, usage of AI, types of AI-powered technologies used, field of study, and age. The rest of the survey comprised statements with a Likert scale with seven points, with seven indicating strong agreement and one strong disagreement. The survey included the following variables: AI technical understanding, AI ethics, the practical application of AI, AI-supported problem-solving, AI critical appraisal, and self-regulated learning. Validated scales were used to investigate these factors. Cronbach's alpha was employed to assess the reliability of the data. The reliability test indicated that each Cronbach's alpha coefficient was

Table 1 Descriptive analysis of the study sample and AI-powered tools used

Categories	Classification	N	%
	Male	186	35
	Female	342	64.4
Gender	Other	1	0.2
	Prefer not to say	2	0.4
	First	207	39
	Second	83	15.6
Year of the study	Third	92	17.3
	Fourth	61	11.5
	Fifth	85	16
	Doctorand	3	0.6
	Yes	515	97
AI Use	No	16	3
	ChatGPT only	226	42.6
	All other single tools (e.g., Claude, Deep AI, DeepSeek, Perplexity, Scholarcy) were each used by 0.2–0.4% of students (1–2 respondents each)		
	ChatGPT + Gemini	62	11.7
	ChatGPT + Grammarly	48	9
AI Tools	ChatGPT + Gemini + Grammarly	37	7
	ChatGPT + Perplexity	17	3.2
	ChatGPT + DeepSeek	11	2.1
	ChatGPT + DeepSeek + Grammarly	4	.8
	ChatGPT + Perplexity + Grammarly	9	1.7
	ChatGPT + Gemini + Perplexity	4	.8
	≈ 30 other unique small-n combinations (each ≤ 0.4%)		
	International Economic Relations	266	50.7
	Economic Diplomacy	119	22.5
	International Business	90	17.2
Field of Study	Accounting	18	3.4
	Data Science	10	2
	Accounting and Auditing	7	1.3
	Economic Informatics	7	1.3
	Other	14	2.8
Total		531	100

Table 2 Instruments for data collection and reliability coefficients

No.	Variables included in the study	Cronbach's	Sources of the instruments
1	AI Technical Understanding (AITU)	0.953	Laupichler et al. [34]
2	AI Critical Appraisal (AICA)	0.932	Laupichler et al. [34]
3	AI Practical Application (AIPA)	0.884	Laupichler et al. [34]
4	AI Ethics (AIETH)	0.772	Carolus et al. [35, 36]
5	AI problem solving (AIPS)	0.927	Carolus et al. [35, 36]
6	Self-regulated learning (SRL)	0.853	Li et al. [37]

acceptable, ranging from 0.77 to 0.95. All variables are presented in Table 2, along with their reliability coefficients and corresponding sources.

The original survey was developed and validated in English. However, it was translated into Slovak by bilingual experts, familiar with digital and AI technologies, to ensure a complete understanding of the survey items because the participants were Slovak students. Additionally, to verify translation accuracy, the Slovak version was reviewed by the bilingual research team, which discussed, revised, and approved the translation.

After this stage, the survey was back-translated into English. This back-translation was compared with the original English version to identify discrepancies and clarify meaning. Any differences noted were discussed and resolved collaboratively by the bilingual research team. Finally, the Slovak survey was pilot-tested with a group of university students at EUBA University, and necessary further refinements were made based on their feedback regarding clarity. Such systematic, multi-stage approach ensured that the translated instrument achieved both linguistic and conceptual equivalence [91].

Data were collected using Google Forms. Participation in the survey was voluntary, and all students who met the inclusion criteria were invited to participate in the study. Before data collection, ethical approval for this study was obtained from the Ethics Committee of the Bratislava University of Economics and Business (Ref. no. EKEUBA-RRP09103-03-V04-00523/4/2024). Additionally, prior to data collection, informed consent was obtained from both the university administration and the students. The questionnaire's aims, instructions for completion, and information regarding volunteer participation were outlined at the beginning of the survey. Students were informed that they could withdraw from the study at any time. The participants completed the survey in approximately 15–20 min.

3.3 Data analysis

The gathered data were analyzed using SPSS and AMOS, both versions 29.0. Means, standard deviations, frequencies, and correlations were computed before testing the proposed research model. Additionally, the reliability of the data was evaluated using the Cronbach's alpha reliability test, and skewness and kurtosis were calculated to test the normality of the distribution. Confirmatory factor analyses (CFA) were performed in order to evaluate the proposed research model [92]. The following indicators were used to evaluate the goodness of model fit: $\chi 2/df$, Tucker–Lewis index (TLI), standardised root mean square residual (SRMR), root mean square error of approximation (RMSEA), and comparative fit index (CFI) [93]. Covariance-based structural equation modeling (CB-SEM) was employed to examine the structural model after discriminant and convergent validity, and an appropriate model fit was confirmed. SEM was selected due to its ability to evaluate conceptualization models formed from previous theoretical inferences [94], to accurately forecast complex models [95], and to evaluate prediction and estimation [96]. Furthermore, SEM is a strong statistical method that can find connections in social science studies that other approaches could miss [95]. According to Kosiba et al. [97], it is particularly well-suited to models incorporating second-level constructs or model development, which fits perfectly with the conceptual model used in this investigation.

4 Results

4.1 Descriptive and preliminary analysis

The vast majority of students use AI tools for educational purposes ($N = 515$; 97%). The predominant AI tool utilized by students, often in combination with other AI-powered applications, is ChatGPT ($N = 510$; 96%). Further analysis revealed that students most frequently use only ChatGPT ($N = 226$; 42.6%), followed by a combination of ChatGPT with other tools such as ChatGPT + Gemini ($N = 62$; 11.7%) and ChatGPT + Grammarly

($N = 48$; 9.0%), along with several lesser-used combinations. A detailed description of the AI-powered tools is presented in Table 1.

Since we used Google Forms for data collection, and all survey fields were mandatory, there were no missing data. Some outliers were identified using the Mahalanobis distance (D^2), but they remained within the acceptable range and showed no evidence of systematic error. Thus, we could not find any "demonstrable proof [that] indicates that they are truly aberrant and not representative of any observations in the population" ([98], p. 91). For this reason, we did not exclude any cases from the data set. Similarly, data entry errors and other third-party influences were unlikely because we relied on an automated survey tool.

All variables showed skewness and kurtosis values within the widely accepted thresholds (skewness: – 3 to + 3, kurtosis: – 10 to + 10). The observed values ranged from – 0.620 to 0.302 for skewness and – 0.719–0.334 for kurtosis, suggesting that the distributions of these variables were approximately normal (Table 3). The mean values of the variables under study ranged from 3.18 to 5.30, while the standard deviations varied between 1.11 and 1.36. As shown in Table 3, the participants recorded the lowest scores in AI technical understanding ($M = 3.18$; $SD = 1.36$), indicating a relative deficiency in their familiarity with the technical aspects of AI technology. The score on AI technical comprehension indicates a need to enhance participants' knowledge and expertise in these technical aspects. In contrast, the participants achieved the highest score in AI ethics ($M = 5.30$; $SD = 1.11$), which shows their relatively strong consideration of ethics when using AI tools. Students attained a moderate score in self-regulated learning ($M = 4.29$; $SD = 1.18$) and a moderate-to-high score in AI critical appraisal ($M = 5.04$; $SD = 1.20$), which implies that they engage in critical evaluations of AI use in their learning processes. The overall mean score of 4.96, with a standard deviation of 1.18, indicates moderate-to-high engagement with AI technologies for their studies. The use of AI technologies often addresses diverse issues, as evidenced by their moderate-to-high score ($M = 5.03$; $SD = 1.26$) on the AI problem-solving scale.

All relationships among the examined constructs are significant and positive (each $p < 0.001$), as shown by the Pearson correlation test (Table 3). The strongest correlation, $r = 0.64$, 95% CI [0.59, 0.69], was found between AI critical appraisal and AI practical application, indicating that participants critically assess and identify appropriate

Table 3 Descriptive findings, correlations, and normality distribution

No	Variables	Mean	SD	Skewness	Kurtosis	1	2	3	4	5	6
1	AITU	3.18	1.36	0.302	− 0.719	1	0.42** [0.35, 0.49]	0.47** [0.4, 0.53]	0.19** [0.11, 0.27]	0.33** [0.25, 0.4]	0.28** [0.19, 0.35]
2	AICA	5.04	1.20	− 0.475	0.029		1	0.64** [0.59, 0.69]	0.42** [0.35, 0.49]	0.30** [0.22, 0.38]	0.16** [0.076, 0.24]
3	AIPA	4.96	1.18	− 0.308	− 0.201			1	0.38** [0.31, 0.45]	0.52** [0.46, 0.58]	0.23** [0.15, 0.31]
4	AIETH	5.30	1.11	− 0.538	0.338				1	0.21** [0.13, 0.29]	0.29** [0.21, 0.37]
5	AIPS	5.03	1.26	− 0.620	0.324					1	0.21** [0.12, 0.29]
6	SRL	4.29	1.18	− 0.315	− 0.295						1

**. Correlation is significant at the 0.01 level (2-tailed); *. Correlation is significant at the 0.05 level (2-tailed) contexts for utilizing AI technologies in their learning endeavors. The second strongest correlation, moderate in nature, r = 0.52, 95% CI [0.46, 0.58], was observed between AI practical application and AI problem-solving, suggesting that students are very receptive to using AI technologies to address various problems they encounter. Moderate and significant correlations were revealed between AI technical understanding and AI practical application, r = 0.47, 95% CI [0.4, 0.53], implying that the use of AI tools increases as participants enhance their technical comprehension of these technologies. Interestingly, a small, yet significant, relationship was found between self-regulated learning and all other measured variables, with values ranging from 0.160 to 0.289. Detailed information regarding the correlations among all measured variables is presented in Table 3.

4.2 Measurement model evaluation

The multivariate normality of the gathered data was assessed using Mardia's test. The results indicated a significant multivariate skewness $b_{1,p} = 2.77, z = 245.28, p < 0.001$, as well as a significant multivariate kurtosis $b_{2,p} = 52.65, z = 5.47, p < 0.001$. These findings suggest that the assumption of multivariate normality was violated. Due to violation of multivariate normality, robust maximum likelihood (ML) estimation was employed, using bootstrap confidence intervals.

We conducted a confirmatory factor analysis (CFA) to evaluate the measurement model. Based on each item's standardized estimate (SE), shown in Table 4, the CFA results show that each item had acceptable loadings and, thus, significantly contributed to explaining its corresponding construct. However, several standardized loadings were below the recommended threshold of 0.70, specifically: AITU14 (0.670), AICA1 (0.624), AICA2 (0.658), AICA10 (0.690), AIPA5 (0.605), AIPA6 (0.695), AIETH1 (0.577), AIPS6 (0.575), and AIPS7 (0.604). The indicator reliability (loading^2) values for these items ranged between 0.33 and 0.48, meaning that approximately 33–48% of the variance in these indicators is explained by their respective latent constructs, and suggesting moderate contribution to their respective latent variables. Although below the ideal recommended threshold of standardized loadings of 0.70, these items were retained due to their theoretical relevance, average variance extracted (AVE > 0.50) values, and the satisfactory composite reliability (CR > 0.70) observed for all constructs [98].

RMSEA (root mean square error of approximation), TLI (Tucker-Lewis index), the χ2 value, degrees of freedom, and CFI (comparative fit index) are sufficient indicators to consider when assessing a model [93]. Carmines and McIver [99] asserted that a minimum fit function (χ2) and a ratio of χ2 to its degrees of freedom (2/df) with a value of less than 3.0 are indicative of a good fit. With a score of χ2 = 1823.005 and χ2/df = 2.122, the measurement model employed in this research satisfied the criteria mentioned above. An RMSEA of 0.03 to 0.08 with 95% confidence is deemed satisfactory by Hair et al. [93]. Thus, this assessment model's output produced adequate scores with RMSEA = 0.045, 90% CI [0.043, 0.048], and PCLOSE = 0.997 as well. The measurement model's TLI = 0.937 and CFI = 0.943 were both higher than 0.90, suggesting a satisfactory fit [100]. An SRMR (standardized root mean residual) score of less than 0.09 indicates a well-fitting model [93], and the model's test results, which came in at 0.0568, meet this criterion. The indicators listed above demonstrate that the measurement model used in this investigation provided a good fit to the data.

Table 4 The outcomes from the measuring model

Variables	Items	USE	SE	*t*-Value	P
	AITU1	0.972	0.743	15.639	***
	AITU2	0.976	0.762	15.986	***
	AITU3	0.978	0.758	15.891	***
	AITU4	0.975	0.736	15.416	***
	AITU5	1.012	0.795	15.468	***
	AITU6	1.115	0.771	16.142	***
AI Technical Understanding (AITU)	AITU7	1.149	0.815	16.933	***
	AITU8	1.039	0.752	15.804	***
	AITU9	1.211	0.851	17.532	***
	AITU10	1.057	0.743	15.649	***
	AITU11	1.072	0.771	16.155	***
	AITU12	1.136	0.826	18.222	***
	AITU13	1.078	0.763	15.978	***
	AITU14	1.000	0.670		
	AICA1	1.091	0.624	13.458	***
	AICA2	1.136	0.658	14.132	***
	AICA3	1.196	0.737	15.716	***
	AICA4	1.171	0.791	16.810	***
AI Critical Appraisal (AICA)	AICA5	1.123	0.760	16.213	***
	AICA6	1.248	0.769	16.396	***
	AICA7	1.211	0.828	17.533	***
	AICA8	1.221	0.816	17.265	***
	AICA9	1.309	0.809	17.124	***
	AICA10	1.000	0.690		
	AIPA1	1.000	0.750		
	AIPA2	1.043	0.796	20.913	***
AI Practical Application (AIPA)	AIPA3	0.897	0.748	16.233	***
	AIPA4	1.059	0.782	17.256	***
	AIPA5	0.637	0.605	13.291	***
	AIPA6	0.841	0.695	15.459	***
	AIETH1	1.000	0.577		
AI Ethics (AIETH)	AIETH2	1.656	0.793	12.297	***
	AIETH3	1.701	0.830	12.337	***
	AIPS1	1.000	0.854		
	AIPS2	1.110	0.903	32.976	***
	AIPS3	1.051	0.921	29.048	***
AI problem solving (AIPS)	AIPS4	1.028	0.896	27.924	***
	AIPS5	0.853	0.742	20.022	***
	AIPS6	0.691	0.575	14.350	***
	AIPS7	0.833	0.604	15.290	***
	SRL1	0.922	0.691	12.730	***
Self-regulated learning (SRL)	SRL2	0.937	0.731	13.118	***
	SRL3	0.972	0.774	14.682	***
	SRL4	1.000	0.757		

USE unstandardized estimates; *SE* standardized estimates; *CR* composite reliability; AVE = average variance extracted; *** = < 0.01

To assess multicollinearity, we computed variance inflation factor (VIF) values. As per established guidelines [98], VIF values below 5 indicate no serious multicollinearity issues. In our analysis, all VIF scores ranged from 1.10 to 2.24, with none exceeding the threshold of 5, confirming the absence of multicollinearity concerns (Table 5). Convergent validity for each construct was assessed using AVE and CR. In this study, all AVE values (0.536–0.635) exceeded the recommended threshold of 0.50, and all CR values

Table 5 Validity analysis (Convergent and discriminant)

Construct	CR	AVE	MSV	MaxR(H)	VIF	AIPS	AITU	AICA	AIPA	AIETH	SRL
AIPS	0.922	0.635	0.343	0.950	1.18–1.40	**0.797**					
AITU	0.953	0.592	0.339	0.955	1.34–1.39	0.370	**0.769**				
AICA	0.928	0.564	0.460	0.934	1.76–1.88	0.359	0.425	**0.751**			
AIPA	0.873	0.536	0.460	0.881	1.75–2.24	0.586	0.582	0.678	**0.732**		
AIETH	0.782	0.550	0.229	0.815	1.31–1.33	0.250	0.222	0.479	0.433	**0.742**	
SRL	0.828	0.546	0.102	0.830	1.10–1.16	0.112	0.241	0.164	0.179	0.320	**0.739**

CR Composite Reliability; *AVE* Average Variance Extracted; *MSV* Maximum Shared Variance; *VIF* Variance Inflation Factor. Benchmark criteria: CR > 0.70 indicates adequate internal consistency; AVE > 0.50 indicates convergent validity; discriminant validity is achieved when MSV < AVE [126]. VIF < 5.0 indicates the absence of multicollinearity [98]. All constructs meet the recommended thresholds, confirming satisfactory reliability and validity

Table 6 Heterotrait-Monotrait (HTMT) Ratios for Discriminant Validity

Construct	AITU	AICA	AIPA	AIETH	AIPS
AI technical understanding (AITU)	–				
AI critical appraisal (AICA)	0.370	–			
AI practical application (AIPA)	0.550	0.710	–		
AI ethics (AIETH)	0.230	0.500	0.480	–	
AI problem solving (AIPS)	0.390	0.330	0.720	0.260	–
Self-regulated learning (SRL)	0.250	0.160	0.190	0.335	0.120

Discriminant validity requires HTMT of < 0.85 (strict) or < 0.90 (lenient) [101]

(0.782–0.953) surpassed the suggested threshold of 0.70 [98] (Table 5). These results affirm that all constructs meet the criteria for convergent validity (AVE > 0.50 and demonstrate adequate internal consistency (CR > 0.70. To evaluate discriminant validity, the squared correlations between constructs were compared with the AVE values; in each case, the AVE values exceeded the squared interconstruct correlations (Table 5), confirming discriminant validity (Fornell–Larcker, 1981). Additionally, discriminant validity was assessed using HTMT (Heterotrait-Monotrait) values, which showed that all construct pairs are below the strict threshold of 0.85, further confirming discriminant validity (Table 6). This supports the Fornell–Larcker (1981) discriminant validity results by ensuring that constructs are distinct [101]. In conclusion, the results of the reliability and validity analyses (Tables 5 and 6) indicate that all constructs had satisfactory internal consistency (CR > 0.70) and convergent validity (AVE > 0.50). At the same time, discriminant validity was also demonstrated (MSV < AVE and HTMT of < 0.85).

Beyond numerical adequacy presented above, the findings indicate that the three dimensions of AI literacy, namely technical understanding, critical appraisal, and practical application, are empirically distinct, yet conceptually interconnected. This aligns with the theoretical premise that AI literacy comprises multiple complementary skills that collectively enable meaningful engagement with AI technologies. While AI literacy is theorized as a higher-order construct, the empirical model in this study considers the three dimensions as first-order constructs to ensure that each dimension independently satisfies reliability and validity criteria before evaluating their higher-order structure. Therefore, the results affirm both the empirical independence and the theoretical coherence of the three dimensions, reinforcing AI literacy as a multidimensional concept.

4.3 Structural model and hypothesis testing

Model fit indices of the structural model showed acceptable fit based on established benchmarks [98, 102], with χ^2/df = 2.122, TLI = 0.937, CFI = 0.943, RMSEA = 0.045 (90%

CI [0.043, 0.048]), PCLOSE = 0.997, and SRMR = 0.0568. The CFI and TLI values exceed the conventional cutoff of 0.90, and the RMSEA is below the recommended threshold of 0.06, which is consistent with the acceptable model fit. The 90% confidence interval around the RMSEA suggests a precise estimate, with the lower bound near zero and the upper bound well below the 0.08 threshold, confirming reasonable approximation error. Considering the $p < 0.05$ level for significance, five out of twelve hypotheses (Table 7) were supported (H2, H4, H7, H9, and H10), whereas seven were refuted (H1, H3, H5, H6, H8, H11, and H12).

The findings of the structural model demonstrated that AI technical understanding significantly predicted self-regulated learning ($\beta = 0.229$, $p = 0.002$) (H2), but not AI ethics (H1) ($\beta = -0.034$, $p = 0.265$) and AI problem-solving (H3) ($\beta = 0.048$, $p = 0.362$). Meanwhile, AI critical appraisal (H4) significantly predicted AI ethics ($\beta = 0.247$, $p < 0.001$), but its relationships with self-regulated learning (H5) ($\beta = -0.056$, $p = 0.607$) and AI problem-solving (H6) ($\beta = -0.012$, $p = 0.240$) were not significant. AI practical application significantly affected AI ethics (H7) ($\beta = 0.129$, $p = 0.012$) and AI problem-solving (H9) ($\beta = 0.604$, $p < 0.001$), but its relationship with self-regulated learning (H8) was not significant ($\beta = -0.060$, $p = 0.605$). Additionally, there was no significant relationship between AI ethics and AI problem-solving (H11) ($\beta = 0.028$, $p = 0.798$), although AI ethics significantly impacted self-regulated learning (H10) ($\beta = 0.590$, $p < 0.001$). Finally, AI problem-solving (H12) was an insignificant predictor of self-regulated learning ($\beta = 0.000$, $p = 0.992$). Table 7 displays all relationships among the measured constructs.

The study model identified three endogenous factors (Fig. 2): AI ethics, AI problem-solving, and self-regulated learning. The first variable, AI ethics, showed limited predictive strength, accounting for 25.4% of the variance ($R^2 = 0.25$) and being explained by AI technical understanding, AI practical application, and AI critical appraisal. AI problem-solving demonstrated moderate explanatory power, accounting for 34.8% of the variance

Table 7 The findings of testing hypothesized associations

Hypotheses	Predictor variables	Relationships	Criterion variables	Estimate	Bias-Corrected 95% CI Lower	Bias-Corrected 95% CI Upper	p	Label
H1	AITU	→	AIETH	−0.034	−0.100	0.025	0.265	Not Supported
H2	AITU	→	SRL	0.229	0.090	0.374	0.002	Supported
H3	AITU	→	AIPS	0.048	−0.057	0.143	0.362	Not Supported
H4	AICA	→	AIETH	0.247	0.119	0.386	***	Supported
H5	AICA	→	SRL	−0.056	−0.257	0.158	0.607	Not Supported
H6	AICA	→	AIPS	−0.102	−0.278	0.067	0.240	Not Supported
H7	AIPA	→	AIETH	0.129	0.029	0.241	0.012	Supported
H8	AIPA	→	SRL	−0.060	−0.297	0.171	0.605	Not Supported
H9	AIPA	→	AIPS	0.604	0.431	0.794	***	Supported
H10	AIETH	→	SRL	0.590	0.345	0.888	***	Supported
H11	AIETH	→	AIPS	0.028	−0.191	0.228	0.798	Not Supported
H12	AIPS	→	SRL	0.000	−0.136	0.144	0.992	Not Supported

*** = < 0.001; p < 0.05

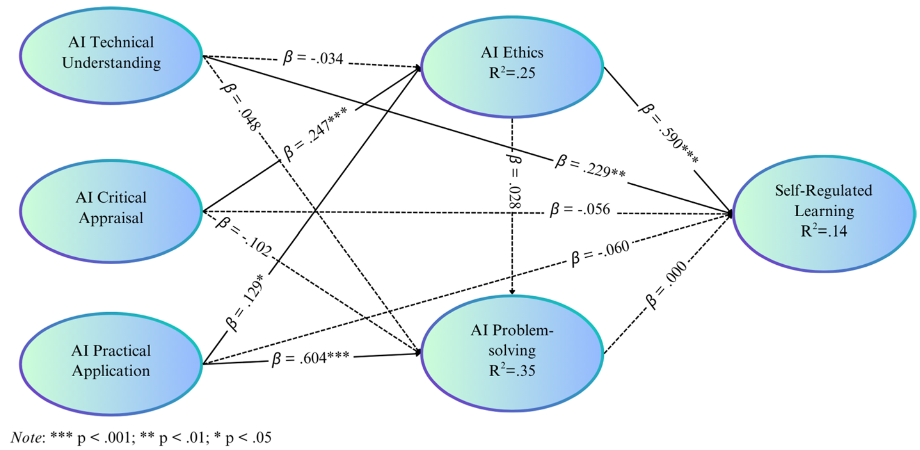

Fig. 2 The findings of the hypothesized relationships

($R^2 = 0.35$), with AI critical appraisal, AI practical application, AI technical understanding, and AI ethics as explanatory factors. Furthermore, self-regulated learning demonstrated a low predictive strength with 13.7% of the variance ($R^2 = 0.14$) explained by AI practical application, AI problem-solving, AI technical understanding, AI critical appraisal, and AI ethics. These results indicate that while the model provides meaningful insights into the relationships among the constructs, the overall explanatory power remains limited, suggesting that additional factors are likely to contribute to the prediction of these endogenous variables.

5 Discussion

This study examined the impact of students' AI literacy on their ethical issues reasoning regarding the use of AI-powered tools, their AI-assisted problem-solving abilities, and their self-regulated learning practices. It specifically evaluated how various aspects of AI literacy, such as AI technical understanding, AI critical appraisal, and practical implementation of AI, influence students' AI ethics, their experiences in using AI tools for problem-solving, and self-regulated learning. The upcoming sections discuss the findings in the context of higher education and relevant academic research.

5.1 Supported hypotheses

As shown in Table 7, the structural model revealed several statistically significant relationships. AI technical understanding was a significant predictor of students' self-regulated learning ($\beta = 0.229$, $p = 0.002$). In addition, AI critical appraisal significantly predicted AI ethics ($\beta = 0.247$, $p < 0.001$), as did AI practical application ($\beta = 0.129$, $p = 0.012$). AI practical application also exerted a significant effect on AI-supported problem-solving ($\beta = 0.604$, $p < 0.001$). Finally, AI ethics was significantly associated with self-regulated learning ($\beta = 0.590$, $p < 0.001$).

The findings revealed that students' technical understanding of AI significantly predicts their self-regulated learning (H2). This implies that students with more experience using AI technology and a deeper understanding of AI concepts, such as the functionality of algorithms, artificial neural networks, and the fundamental principles of machine learning, exhibit a greater capacity to manage, monitor, and adapt their learning experiences when utilizing AI tools. Similarly, this relationship indicates that a strong technical comprehension among students reduces their uncertainty [3–5] and the cognitive burden associated with using AI-enhanced tools. As a result, these students are better equipped with the understanding, knowledge, and experience to make informed and independent decisions in their learning processes, including setting goals, assessing outcomes, and modifying strategies as needed. A range of studies consistently support this view, showing that deeper technical understanding and feedback from AI tools foster students' confidence and autonomy in managing their learning [18, 20, 83]. Furthermore, even though many students lack formal education in AI, which also applies to our participants studying non-technical fields like economics, management, or business, the majority of them can effectively utilize AI tools, relying on hands-on experience and an intuitive understanding of how these tools operate. Having even only a basic understanding of how algorithms work, how recommendations are formed, and the limitations of models is sufficient to enhance students' ability to engage with AI feedback and improve their learning autonomy. This observation aligns with prior research showing that even a limited, yet practical understanding of AI, can meaningfully support autonomous learning, particularly when integrated into well-supported and ethically grounded educational environments [19, 103]. Self-Determination Theory [23] offers a framework for understanding how students' perceived competence and autonomy may influence their use of learning technologies, and can help interpret these findings. According to this perspective, a deeper technical understanding of AI can reflect a stronger sense of competence, while the ability to apply this knowledge independently represents an expression of autonomy in learning. Rather than implying a causal process, SDT provides a conceptual background for explaining why students who feel more capable and self-directed in using AI tend to display higher self-regulatory behaviour.

The findings indicate that both AI critical appraisal (H4) and AI practical application (H7) are significant predictors of AI ethics, underscoring two complementary aspects of students' development of ethical approaches to utilizing AI tools. These two predictors are closely linked and cannot be easily distinguished from one another. Therefore, practical application is not merely a technical skill; it also serves as a cognitive framework that fosters the ability to assess the ethical implications of AI technologies. The results suggest that the capacity of higher education students to appraise AI critically significantly predicts their ethical implications related to AI usage. Our results align with Wang et al. [47, 48], who argue that students with a greater ability to critically evaluate AI are more proficient at recognizing ethical concerns and exploring the societal consequences of AI usage. Similarly, Ferhataj et al. [104] reveal that practical experience with AI technologies enhances understanding of AI's ethical implications and significantly influences students' support for ethical governance. However, our findings are in contrast to those reported by Dobrovská et al. [105], who suggest that students are generally familiar with the practical AI application, indicating that a substantial number of students rarely or never consider ethical aspects in their use of AI. Several studies have indicated that attitudes toward ethical usage and practical application of AI differ among university student population, with notable gender and cultural variations. For instance, Australian and Chinese students differ in their perceptions of academic integrity [106], while female students tend to prioritize legal compliance and data security more than their male counterparts [69]. However, our hypotheses did not address gender and cultural differences in the relationship with AI critical appraisal, practical application, and ethics. From the SDT perspective [24, 25], this relationship can also be interpreted as an instance of value internalization, where students' critical engagement with AI and their responsible application of such tools reflect self-endorsed, autonomous forms of regulation. In this view, competence and autonomy are not causal determinants but conceptual dimensions that help interpret how students integrate ethical reasoning into their learning practices.

Our findings indicate that the practical application of AI has a significant impact on AI- supported problem-solving (H9), suggesting that students proficient in AI use are more likely to employ it for problem-solving in their studies. This means that students are more inclined to utilize AI technology to effectively address real problems in performing their academic tasks. Our results align with a growing body of research demonstrating how integrating AI into education can enhance students' problem-solving skills. In line with previous research [77, 107–109], our study showed that integrating AI into problem-based learning environments enhances students' creative and interdisciplinary problem-solving abilities.

The relationship between AI ethics and self-regulated learning represents an emerging area of research interest. A recent paper by Tang and Su [72] discusses whether incorporating ethical aspects into AI education enhances students' autonomy and regulation of their learning processes by increasing their awareness of the ethical implications of AI models in the classroom. Our findings confirm the hypothesis that AI ethics is a significant predictor of self-regulated learning (H10), illustrating a positive relationship between AI ethical approaches and students' ability to adapt their learning behaviors. This suggests that students who consider the ethical dimensions of AI technology exhibit higher levels of reflexivity and value-oriented reasoning, which are foundational cognitive skills for self-regulated learning. Furthermore, ethical reasoning about AI necessitates critical thinking and the ability to evaluate complex situations, both of which are essential capabilities for self-regulation when planning learning, identifying strategies, or seeking feedback. This association also resonates with the interpretive logic of SDT [24], which emphasizes that learning behavior grounded in internalized values is more likely to be autonomously regulated. Within this framework, ethical awareness may be viewed as an interpretive indicator of moral autonomy rather than a direct predictor of self-regulation—students' reflective engagement with ethical dimensions of AI illustrates how internal motivation can manifest in self-directed learning behavior.

5.2 Unsupported hypotheses

As presented in Table 7, several hypothesized structural paths were not statistically significant. Specifically, AI technical understanding did not significantly predict AI ethics ($\beta = -0.034$, $p = 0.265$) or AI problem-solving ($\beta = 0.048$, $p = 0.362$). Likewise, AI critical appraisal was not significantly associated with self-regulated learning ($\beta = -0.056$, $p = 0.607$) or AI problem-solving ($\beta = -0.102$, $p = 0.240$). AI practical application also did not demonstrate a significant effect on self-regulated learning ($\beta = -0.060$, $p = 0.605$). Finally, neither AI ethics significantly predicted AI problem-solving ($\beta = 0.028$, $p = 0.798$) nor did AI problem-solving significantly predict self-regulated learning ($\beta = 0.000$, $p = 0.992$).

Our findings reveal that AI technical understanding does not significantly predict AI ethics (H1), suggesting that technical expertise alone is insufficient to ensure students' ethical use of AI tools. This result is also reflected in the descriptive statistics, which show M = 3.18 for AI Technical Understanding and M = 5.30 for AI Ethics. Such a pattern indicates that students tend to perceive themselves as ethically aware even when their technical comprehension of AI remains limited. As several studies emphasize, ethical awareness tends to stem less from technical expertise and more from students' introspective and value-based understanding of technology [21, 22, 47, 48, 110]. Therefore, students may not easily connect technical concepts with ethical reasoning if educators do not make that connection explicit [111]. Consequently, they may overlook or minimize ethical problems as secondary. Furthermore, it is important to note that since our sample primarily consisted of students from non-technical fields, their understanding of AI may have been limited or merely theoretical, which in turn constrained their ability to make significant ethical assessments. This underscores the need to incorporate AI ethics into educational curricula, particularly through interdisciplinary approaches that bridge the gap between technical understanding and ethical reflection [26, 71].

In contrast to predictions, there was no statistically significant impact of AI technical understanding (H3), AI critical appraisal (H6), or AI ethics (H11) on AI-supported problem-solving. These findings suggest that while conceptual knowledge of AI, AI critical reflection, and ethical awareness of AI are essential components of AI literacy, they do not directly translate into students' readiness or motivation to use AI-powered tools for solving problems in their academic tasks.

In light of the insignificant relationship between AI technical understanding and AI problem-solving, the use of AI for problem-solving primarily depends on psychological readiness rather than solely on technical knowledge [49, 112]. As Tang and He [113] suggest, the perceived impact of using AI is a strong predictor of motivation to employ AI tools in practice. Therefore, while conceptual knowledge of AI can be beneficial, students can successfully use AI to solve problems even with minimal technical expertise if they are sufficiently motivated, confident, and perceive AI as a useful tool [114]. Additionally, AI can assist students in generating solutions and structuring problems, which reduces the significance of technical skills in addressing complex tasks [115, 116].

Regarding the insignificant impact of AI critical appraisal on AI problem-solving (H6), our results are aligned with those presented in a recent study [3–5], suggesting that when students critically assess AI tools, they may feel less confident in using AI to solve problems. However, these findings diverge from prior studies that identify critical evaluation of AI technology as one of the pillars of competent AI use [1, 2, 34]. One potential explanation for our results lies in the relative weight of affective and motivational variables. Consistent evidence indicates that motivational factors such as psychological readiness, confidence, and empowerment play a more decisive role in AI-based problem-solving than cognitive reflection alone [49, 79]. However, advanced generative tools can temporarily "bridge" the need for critical judgment on the user's part, especially if the student is not sufficiently motivated or prepared to reflect on the quality of the solution [109, 115]. In such cases, the need to actively engage in cognitive processes of evaluating AI output quality, consistency, and relevance is reduced [79, 117].

Although our findings did not confirm a significant relationship between students' AI ethics and AI problem-solving (H11), existing literature suggests that ethical awareness, as one of the four pillars of AI literacy, may still play an indirect or contextual role in shaping responsible AI use [1, 2, 112]. Proponents of the hypothesis base their arguments on frameworks that perceive ethical awareness as part of the broader concept of psychological readiness and responsible use of AI technology. For example, Kong et al. [78] state that effective problem-solving with AI tools depends on technical proficiency and the ability to consider the social impacts and ethical consequences. Meanwhile, there are convincing arguments that support our results. Above all, ethical reflection has a regulatory or framing function in decision-making [118]. Ethical awareness may encourage restraint or caution in the use of AI solutions, particularly if they raise ethical concerns. However, such an attitude may not result in greater effectiveness or creativity in problem-solving. Additionally, these variables may not be significantly correlated, especially if students do not encounter ethical dilemmas in their everyday use of AI for routine tasks.

We hypothesized that the three variables, namely AI critical appraisal (H5), AI practical application (H8), and AI problem-solving (H12), significantly predict students' self-regulated learning. However, the empirical results did not support these hypotheses, revealing an insignificant relationship between AI literacy and autonomous learning behavior.

Although previous research highlights that AI-powered tools use improves metacognition and critical reflection [16, 60, 76], these benefits do not automatically translate into self-regulated learning outcomes (H5). As the literature suggests, passive knowledge without reflective or goal-directed application may not trigger the behavioral dimensions of generative AI [20]. According to Chang and Sun [119], while AI functions as a metacognitive "mind tool" that fosters autonomous critical thinking and adaptable learning roles, its impact depends on whether students actively engage in the cyclical application of self-regulated learning phases. Moreover, recent research [120] reveals a crucial distinction: self-regulated learning is significantly affected by whether the learning agency stays human-centered or shifts to an AI-centered approach. In this way, students can evaluate AI tools critically while still depending on them in a manner that limit their autonomy and thoughtful decision-making, which prevents self-regulated learning cycles from being activated.

Similarly, regarding the relationship between AI critical appraisal and AI practical application (H8), students' practical application of AI does not necessarily predict their ability to regulate their learning. While previous studies highlight that tools like ChatGPT provide personalized feedback and support student autonomy [18, 47, 48, 84, 119], our findings suggest that knowledge and understanding of AI technology in external contexts (e.g., AI recognition in language applications or intelligent assistants) may not enhance internalized learning strategies. Practical knowledge of AI tools alone (e.g., "I know where it is used") is insufficient to support self-regulated learning unless students actively utilize these tools to manage their cognitive and motivational states during the learning process.

Although generative AI has been praised for supporting students in solving complex problems and fostering interdisciplinary thinking [62, 64, 76, 80], our findings indicate that the use of AI tools to address problems is not a significant predictor of self-regulated learning (H12). One possible explanation is that this dimension reflects motivational intention rather than specific behavior. Additionally, existing literature highlights that overreliance on AI tools like ChatGPT may hinder independent problem-solving and cognitive development if students become passive recipients of AI-generated content

[38, 121, 122]. For instance, Fan et al. [17] introduced the concept of metacognitive laziness, describing how learners' dependence on AI support can enhance short-term performance while undermining metacognitive engagement and self-regulation. Similarly, Chen et al. [81, 82] found that students interacting with ChatGPT exhibit less reflective help-seeking behavior and skipped key phases of feedback evaluation compared to those guided by human experts, suggesting that AI-mediated assistance may disrupt the natural cycle of metacognitive regulation. This means that students employ AI without adequately regulating their own planning and learning processes, or independently selecting their next strategies [117, 123]. However, generative AI, when used as a formative-iterative tool that supports ongoing feedback and reflection, has the potential to enhance students' autonomy and self-regulated learning more effectively [81, 82].

These results might indicate the existence of contextual or motivational factors that were not specifically modeled, even though a number of the examined relationships lacked statistical support. The logic of Self-Determination Theory does not suggest a direct causal mechanism; rather, it suggests that students' perceived autonomy and competence may impact their ability to apply AI literacy through psychological preparedness, confidence, or perceived utility of AI tools. According to this interpretation, the non-significant paths might indicate that learning behavior is only impacted by AI literacy when these motivational dispositions are activated. In order to better understand how students' motivational orientations influence the relationship between AI literacy, problem-solving, and self-regulated learning, future research could expand on the current framework by examining indirect or boundary mechanisms.

Overall, these results suggest that the motivational dimensions described by Self-Determination Theory can serve as interpretive background for understanding the complex interplay between students' cognitive, ethical, and self-regulatory engagement with AI tools. The findings imply that the dimensions of AI literacy—technical, critical, and practical—represent behavioral expressions of perceived competence and autonomy. However, these dispositions must be consciously activated through reflective and metacognitive engagement to manifest in self-regulated learning.

6 Conclusion

6.1 Summary of the results

Our study found that aspects of AI literacy have significant effects on students' autonomous learning practices. Specifically, an understanding of AI technology and AI ethics emerge as major predictors of self-regulated learning. Thus, technical knowledge and value-based reflection might be considered crucial prerequisites for autonomy in AI-enhanced learning environments, although prior studies have not sufficiently addressed this critical aspect of learning. However, the model explains only 13.7% of the variance in self-regulated learning, which provides an important insight. It suggests that AI literacy components, while relevant, are not the primary drivers of self-regulated learning in this student population. Rather, as indicated throughout the discussion, factors such as psychological readiness, intrinsic motivation, and students' broader metacognitive and affective dispositions may play a more decisive role in activating self-regulatory behaviors. This finding reinforces the interpretive perspective adopted in this study, emphasizing that AI literacy contributes to autonomous learning only when accompanied by psychological readiness and motivational engagement.

Empirical data also confirmed that a critical assessment of AI, along with its recognition, identification, and basic understanding, plays a significant role in shaping ethical approaches related to the use of AI technologies. The practical application of AI tools serves as a cognitive framework, helping students understand the social implications of using AI-powered tools. Similarly, identifying and applying AI technologies in daily life and learning significantly influences students' willingness and ability to leverage AI for solving real-world problems.

Our research findings also revealed insignificant relationships among the constructs examined. Thus, technical understanding of AI tools did not significantly influence AI ethics, indicating that merely having technical knowledge does not automatically lead to ethical considerations while using AI technologies. Likewise, AI problem-solving was not significantly affected by AI technical understanding, AI critical appraisal, or AI ethics. Additionally, AI critical appraisal, AI practical application, and AI problem-solving did not significantly predict self-regulated learning, suggesting that not all components of AI literacy and specific aspects of AI tools use translate equally into autonomous learning behaviors. These findings imply that general awareness or the intention to use AI-powered tools alone is inadequate to activate the cognitive, metacognitive, and motivational dimensions necessary for self-regulated learning.

Our findings indicated that the distinct components of AI literacy differ in their capacity to foster self-regulated learning. These differences likely depend on their underlying psychological orientation—specifically, the degree of cognitive engagement and intrinsic motivation they elicit. AI technical understanding and AI ethics appear to stimulate higher levels of self-motivation, autonomy, and metacognitive awareness, thereby supporting students' reflective and self-directed learning. In contrast, dimensions such as practical application or problem-solving reflect more procedural or externally guided engagement, which may involve lower psychological activation, and, thus, fail to trigger autonomous learning behaviors. Without active reflection and motivational readiness, these aspects may remain at the level of intention rather than translate into genuine self-regulatory practice.

6.2 Study contributions and practical implications

The results of this study may enhance the existing literature on AI literacy by offering new insights into the aspects of knowledge and engagement with AI-driven technology that most effectively support students' problem-solving, ethical use of AI, and self-regulation in learning.

For teaching practice, our findings indicate that teaching AI should not be limited to technical knowledge alone, but should be aligned with broader educational goals, such as students' abilities to plan their learning, assess their progress, problem-solving skills, and adapt their strategies, i.e., self-regulated learning. In non-technical fields, such as economics and business, students frequently utilize AI tools. However, they do not always know how to incorporate these tools into their learning processes in a way that enables them to learn independently and effectively and to employ AI ethically. Therefore, they need support in using these technologies strategically and responsibly, for example, to plan their studies, seek feedback, or evaluate their progress. For teachers, this means that it is insufficient to teach students merely how to use AI; they must also demonstrate how it can support autonomous learning, pursue their own goals, and avoid complete dependence on technology.

From an institutional policy perspective, educators and policymakers should implement interdisciplinary approaches that effectively link AI literacy to broader pedagogical objectives, including metacognition, reflection, and responsible engagement with digital technologies and AI. Particularly in non-technical fields like economics, business, or management, focused support is essential to help students engage with AI functionally, strategically, and ethically in their learning processes. Policymakers in higher education should endorse the development of cross-disciplinary AI literacy programs. They should also ensure that teacher training incorporates pedagogical approaches to the use of AI-powered tools, and establish institutional strategies that encourage responsible and strategic AI technology use across all fields of study, not just in STEM areas.

In terms of learner engagement, the study highlights that enhancing AI literacy involves more than just understanding how to utilize generative AI tools. It involves understanding when, why, and how to utilize AI-powered tools in ways that enhance, rather than replace, their own thinking, problem-solving, learning, and ethical judgment. Students should be encouraged to engage with AI actively and reflectively, using it as a means to strengthen self-awareness, critical reflection, and strategic learning. Fostering self-awareness, critical reflection, and effective learning strategies when engaging with AI technologies is crucial for achieving long-term academic success, including enhancing digital and AI literacy and competencies in the era of AI technology.

6.3 Limitations and suggestions for further research

It is important to highlight several limitations of our study. Firstly, the research was conducted at a single university and relied on convenience sampling, which may introduce potential selection bias and limit the generalizability of the findings to other academic contexts [88]. The institution's culture and the structure of study programs can differ, and influence how students perceive and utilize AI technologies in the learning process. Secondly, the use of an online questionnaire as the data collection method entails certain challenges. Some participants may have responded in ways they believed to be socially acceptable rather than reflecting their true attitudes or behaviors [124]. This limitation is particularly relevant for the high mean values observed in AI ethics and self-regulated learning, which may partially reflect socially desirable self-perceptions rather than actual ethical reasoning or autonomous learning behaviors. Anonymity and voluntary participation were ensured, but there is always a risk concerning the accuracy of the answers in this type of data collection. Different individual interpretations of the questions posed could also contribute to this issue. Finally, the study employed a cross-sectional design, which did not permit tracking how these variables changed over time, a limitation that a longitudinal approach could address. As students gain more experience, their digital and AI skills improve, along with the technological complexity of AI-powered tools.

Furthermore, it is worth noting that the findings are based on students' declarative statements, rather than experimentally observed data. Future research could use behavioral observation, experimental design, or longitudinal tracking to check how well self-perceived AI literacy translates into problem-solving and actual autonomous learning practices. In addition to longitudinal validation, mediation-focused analyses could provide deeper insights into the indirect mechanisms through which AI literacy affects problem-solving and self-regulated learning, for instance, via motivational or cognitive engagement factors. To complement the self-reported design, future research could adopt a performance-based instrument for assessing AI literacy, such as the recently developed Generative AI Literacy Assessment Test (GLAT) by Jin et al. [125].

Moreover, cross-cultural or cross-institutional replications would further strengthen the theoretical robustness of the findings, as cultural norms and institutional support structures may influence how students perceive, use, and integrate AI technologies into their learning processes. Future research may focus on collecting data from various universities to compare how institutional culture and curricula influence perceptions and the use of AI technologies in learning. Given that technologies are continuously evolving and students are acquiring new digital and AI literacy and competencies over time, longitudinal research is required to track the growth and effects of AI literacy on problem-solving strategies and self-regulated learning. Finally, our study did not include an intra-group analysis to identify variations among students' groups, such as by gender or seniority. Therefore, future research should examine differences within student populations and analyze how these variations affect AI literacy and its impact on problem-solving skills and self-regulated learning strategies.

Appendix

Research Instrument (with Slovak-translated Version).

Item	AI Technical Understanding
AITU1	I can describe how machine learning models are trained, validated, and tested *Viem popísať, ako sú modely strojového učenia (machine learning) školené, overované a testované*
AITU2	I can explain how deep learning relates to machine learning *Viem vysvetliť, do akej miery hlboké učenie (deep learning) súvisí so strojovým učením*
AITU3	I can explain how rule-based systems differ from machine leaning systems *Viem vysvetliť, ako sa systémy založené na pravidlách (rule-based systems) líšia od systémov strojového učenia (machine learning)*
AITU4	I can explain how AI applications make decisions *Viem vysvetliť, ako aplikácie AI robia svoje rozhodnutia*
AITU5	I can explain how 'reinforcement learning' works on a basic level (in the context of machine learning). (*Viem vysvetliť, ako „posilňované učenie " (reinforcement learning) funguje na základnej úrovni (v kontexte strojového učenia)*)
AITU6	I can explain the difference between general (or strong) and narrow (or weak) artificial intelligence *Viem vysvetliť rozdiel medzi všeobecnou (general) a úzkou (narrow) AI*
AITU7	I can explain how sensors are used by computers to collect data that can be used for AI purposes *Viem vysvetliť, ako sú počítačové senzory využívané na zber dát, ktoré môžu byť využité na účely AI*
AITU8	I can explain what the term 'artificial neural network' means *Viem vysvetliť, čo znamená pojem „umelá neurónová sieť " ('artificial neural network')*
AITU9	I can explain how machine learning works at a general level *Viem vysvetliť, ako strojové učenie funguje na základnej úrovni*
AITU10	I can explain the difference between "supervised learning" and "unsupervised learning" (in the context of machine learning) *Viem vysvetliť rozdiel medzi učením s učiteľom (supervised learning) a učením bez učiteľa (unsupervised learning) (v kontexte strojového učenia)*
AITU11	I can describe the concept of explainable AI *Viem popísať koncept vysvetliteľnej AI*
AITU12	I can describe how some artificial intelligence systems can act in their environment and react to their environment *Viem opísať, ako sa niektoré systémy AI dokážu správať vo svojom prostredí a reagovať na svoje prostredie*
AITU13	I can describe the concept of big data *Viem popísať koncept big data*

Item	AI Technical Understanding
AITU14	I can evaluate whether media representations of AI (e.g., in movies or video games) go beyond the current capabilities of AI technologies *Viem posúdiť, či mediálne zobrazenia AI (napr. vo filmoch alebo videohrách) presahujú súčasné možnosti AI technológií*
Item	AI Critical Appraisal
AICA1	I can explain why data privacy must be considered when developing and using artificial intelligence applications *Viem vysvetliť, prečo súkromie údajov musí byť brané do úvahy počas vývoja a využívania aplikácií AI*
AICA2	I can explain why data security must be considered when developing and using artificial intelligence applications *Viem vysvetliť, prečo ochrana údajov musí byť braná do úvahy počas vývoja a využívania aplikácií AI*
AICA3	I can identify ethical issues surrounding artificial intelligence *Viem identifikovať problémy súvisiace s etikou ohľadom AI*
AICA4	I can describe risks that may arise when using artificial intelligence systems *Viem opísať riziká, ktoré by mohli vzniknúť pri využívaní systémov AI*
AICA5	I can name weaknesses of artificial intelligence *Viem pomenovať slabé stránky AI*
AICA6	I can describe potential legal problems that may arise when using artificial intelligence *Viem popísať potenciálne právne problémy, ktoré by mohli vzniknúť pri využívaní systémov AI*
AICA7	I can critically reflect on the potential impact of artificial intelligence on individuals and society *Viem kriticky uvažovať nad potenciálnym dopadom AI na jednotlivcov a spoločnosť*
AICA8	I can describe why humans play an important role in the development of artificial intelligence systems *Viem popísať, prečo ľudia zohrávajú dôležitú úlohu v rozvoji systémov AI*
AICA9	I can explain why data plays an important role in the development and application of artificial intelligence *Som schopný vysvetliť, prečo údaje zohrávajú dôležitú úlohu v rozvoji systémov AI*
AICA10	I can describe what artificial intelligence is *Viem vysvetliť, čo je umelá inteligencia*
Item	AI Practical Application
AIPA1	I can name examples of technical applications that are supported by artificial intelligence *Viem uviesť príklady technických aplikácií, ktoré sú podporované AI*
AIPA2	I can tell if the technologies I use are supported by artificial intelligence *Viem povedať, či technológie, ktoré využívam, sú podporované AI*
AIPA3	I can assess if a problem in my field can and should be solved with artificial intelligence methods *Viem posúdiť, či problémy v mojom odbore by mohli byť riešené za pomoci metód AI*
AIPA4	I can name applications in which AI-assisted natural language processing/understanding is used *Viem vymenovať aplikácie, ktorých účelom je spracovanie a porozumenie prirodzenému jazyku s pomocou AI*
AIPA5	I can explain why AI has recently become increasingly important *Viem vysvetliť, prečo sa AI v poslednom čase stáva čím viac dôležitejšou*
AIPA6	I can critically evaluate the implications of artificial intelligence applications in at least one subject area *Viem kriticky ohodnotiť dôsledky aplikácií AI aspoň v jednej tematickej oblasti*
	AI Ethics
AIETH1	*I can weigh the consequences of using AI for society* *Viem zvážiť dôsledky využitia AI pre spoločnosť*
AIETH2	*I can incorporate ethical considerations when deciding whether to use data provided by an AI* *Pri rozhodovaní sa, či použiť údaje poskytované AI, viem zvážiť etické hľadisko*
AIETH3	*I can analyze AI-based applications for their ethical implications* *Som schopný analyzovať aplikácie založené na AI z hľadiska ich etických následkov*
Item	AI Problem-solving
AIPS1	*I am good at solving problems with AI* *Som dobrý/á v riešení problémov pomocou AI*
AIPS2	*I think of myself as someone who can solve problems with AI* *Považujem sám seba za niekoho, kto dokáže riešiť problémy pomocou AI*
AIPS3	*I have the knowledge and skills to solve problems with AI* *Mám vedomosti a zručnosti na riešenie problémov pomocou AI*

Item	AI Technical Understanding
AIPS4	*I have confidence in my ability to solve problems with AI* *Verím vo svoje schopnosti riešiť problémy pomocou AI*
AIPS5	*Using AI to solve problems will help me achieve my goals* *Používanie AI na riešenie problémov mi pomáha dosiahovať moje ciele*
AIPS6	*I want to be good at solving problems with AI* *Chcem byť dobrý v riešení problémov pomocou AI*
AIPS7	*Using AI to solve problems is important to me* *Používanie AI na riešenie problémov je pre mňa dôležité*
Item	Self-Regulated Learning
SRL1	*I always reflect on what I have learned and how I have grown during a learning process* *Vždy sa zamýšľam nad tým, čo som sa naučil a ako som rástol počas procesu učenia sa*
SRL2	*When learning does not go well, I reflect repeatedly on my learning targets and strategies to see if any adjustments need to be made* *Ak učenie nejde podľa očakávania, opakovane sa zamýšľam nad svojimi cieľmi a stratégiami učenia, aby som zistil, či je potrebné vykonať nejaké úpravy*
SRL3	*I always deduce conclusions about effective learning strategies* *Vždy vyvodzujem závery ohľadom efektívnych stratégií učenia*
SRL4	*I regularly review my learning outcomes and analyze my learning problems* *Pravidelné kontrolujem výsledky učenia a analyzujem problémy spojené s učením*

Author contributions

Senad Bećirović conceived the idea, designed the study, prepared the questionnaire, wrote the methodology, handled software, performed data analysis, wrote the results, and reviewed and edited the entire manuscript. Michael Augustin prepared the questionnaire, collected data, wrote the abstract, discussion, and conclusion, and reviewed the introduction. Boris Mattoš prepared the questionnaire and wrote the introduction. Jan Dančo collected data and wrote the literature review. All authors read and approved the final manuscript.

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Data availability

Data available from the corresponding author upon reasonable request due to data protection restrictions.

Declarations

Ethics approval

This study did not involve experiments with humans or the use of human tissue samples. Ethical approval for the study was granted by The Ethics Committee of the Bratislava University of Economics and Business (EKEUBA-RRP09103-03-V04-00523/4/2024) on October 2, 2024. The study adhered to the Declaration of Helsinki and relevant national laws to protect participants' rights and well-being. All steps complied with ethical standards for research involving human data. The online survey ensured participant confidentiality and anonymity.

Consent to participate

Informed consent was obtained from all individual participants involved in the study. It was obtained in two stages. First, participants received an information sheet explaining the study's goals, methods, rights, and data protection measures. They were told participation was voluntary and they could withdraw at any time without penalty. No personal identifiers were collected, and responses were securely stored. Data were anonymized before analysis, with access restricted to authorized researchers. The online survey was distributed with approval from the appropriate university officials.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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