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Artificial Intelligence Literacy Structure and the Factors Influencing Student Attitudes and Readiness in Central Europe Universities

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ABSTRACT This study examines the structure of artificial intelligence (AI) literacy and factors influencing students' attitudes, readiness, and perceived relevance of AI in higher education at Central European universities. The research, based on data from 1,195 students enrolled in various study programs between 2022 and 2024, examines how variables such as gender, academic discipline, and year of study influence perceptions related to AI. A validated questionnaire targeting constructs including satisfaction, readiness, and relevance of AI was used. Non-parametric statistical methods were used to identify significant differences between groups, including Kruskal-Wallis and Mann-Whitney tests with Dunn-Bonferroni post hoc analysis. The findings reveal consistent differences across genders and disciplines, with males and IT students demonstrating significantly higher readiness and satisfaction with AI. Furthermore, satisfaction levels fluctuated over time, peaking in 2023 – likely influenced by the widespread adoption of tools like ChatGPT. Correlation analysis further highlighted the subtle interrelationships between constructs across different subgroups. The study underscores the importance of tailored AI education strategies and calls for targeted interventions to ensure equitable engagement with AI across diverse student populations.

INDEX TERMS Artificial intelligence, AI literacy, AI relevance, Technology adoption, Higher education

I. INTRODUCTION

Artificial intelligence has quickly become a transformative force across sectors, reshaping industries, labor markets, and the future of jobs [1], [2]. AI technologies personalize learning, improve teaching methods, and streamline administrative processes in education. The role of AI goes beyond technological innovation; it is critical to preparing students for a future dominated by data-driven decision-making and automation. As AI evolves, students must understand these technologies and be equipped to engage with, develop, and critically evaluate AI applications [3], [4].

The arrival of ChatGPT, a sophisticated language model developed by OpenAI, marked a breakthrough in the development and perception of AI among experts and across society [5]. Its ability to conduct conversations nearly indistinguishable from human-like, produce creative text, and perform a wide range of tasks has garnered significant public attention and brought AI into the mainstream of discussion and attention.

Before ChatGPT, AI was primarily used in specialized areas such as medical diagnostics, financial analysis, or self-driving cars. While these applications demonstrated the enormous potential of AI, the details often remained inaccessible to the general public. The complex nature of

AI algorithms and the specialized knowledge required to interact with them posed a challenging barrier to understanding by the public [6].

With ChatGPT's user-friendly interface, conversational style, and subsequent solutions such as Bard, Claude, Jasper, etc., these tools broke down barriers and made AI accessible to a broad audience [7]. Presenting helpful ideas and functional answers to everyday tasks helped create a more positive perception of AI technologies.

The growing popularity of AI has thus gained and is likely to increase its significant economic impact in the long term [8]. Investment in AI startups and research has increased dramatically, creating new jobs and business opportunities. Industries such as healthcare, finance, and manufacturing are increasingly adopting AI solutions to improve efficiency, reduce costs, and gain competitive advantage.

However, the rise of AI has also raised many questions about the future of work, privacy, and ethics [9], [10]. As AI systems become more capable, concerns are growing about their potential to displace human workers and exacerbate existing inequalities between regions and within society. The collection and use of personal data by AI-powered systems raises concerns about privacy and the potential for oversight of the use of the collected data. These tasks will be handled by professionals in positions still being created. These professionals, likely current university students, are preparing for careers not only in IT but also as managers, teachers, translators, and other professionals. This article aims to map their readiness and attitudes towards artificial intelligence and, in particular, to examine how selected factors related to current perceptions of AI and students' career orientation are interconnected.

Research questions are defined as follows:

- RQ1: To what extent does the year of study impact perceived satisfaction with learning AI?
- RQ2: Is there a relationship between gender and satisfaction with learning AI?
- RQ3: Is there a relationship between the study program and satisfaction with learning AI?
- RQ4: How does the satisfaction level associated with learning AI change between 2022 and 2024?
- RQ5: How does AI readiness differ between men and women?
- RQ6: Is there a relationship between the study program and AI readiness?
- RQ7: How does AI relevance differ between men and women?

II. RELATED WORK

The rise of AI has sparked a wave of research on how individuals, especially students, prepare for an AI-powered world. Several studies have focused on the development of AI literacy, attitudes toward AI, the role of education in preparing students for AI, and the socio-economic implications of AI for future career prospects. These studies contribute to understanding the importance of student readiness for the AI age, focusing on critical constructs such as AI literacy, career motivation, social implications, and AI anxiety.

A. AI LITERACY FRAMEWORKS

According to a survey [11], AI literacy can be understood at three basic levels:

- **Knowing and understanding AI** aims to equip students with the fundamental concepts, skills, knowledge, and attitudes related to AI, regardless of their prior experience. It is considered an essential foundation for AI literacy. Beyond being merely end-users of AI applications, students should understand the underlying technologies that power these systems. This perspective is consistent with previous research [12], [13] that highlights the importance of understanding the fundamental techniques and principles of AI across domains so that students use AI tools and have an overview of how they work and evolve.
- **AI application** emphasizes teaching students how to apply AI concepts and tools in various contexts [14], [15]. Students must understand how AI applications impact everyday life and know the ethical issues surrounding AI technologies. AI education at this level is based on computational thinking, emphasizing developing logical reasoning, algorithmic problem solving, and using knowledge bases. Students learn to use AI for semantic processing, unstructured data manipulation, and practical decision-making, fostering more profound engagement with AI-based solutions.
- **Evaluate and create AI** – in addition to understanding and using AI concepts and practices, AI literacy can extend to other competencies, such as critically evaluating AI technologies and effectively communicating and collaborating with AI systems. Several studies have described how students have improved their AI-driven science and technology knowledge, which they then apply in inquiry-based learning to solve practical problems [16], [17]. By engaging in AI evaluation and creation, students could derive, connect, manipulate, and categorize AI concepts innovatively.

Findings highlight that basic AI knowledge and skills significantly increase career motivation and interest [18], [19], [20]. Studies [21], [22], [23] suggest that introducing AI literacy early in education fosters a more inclusive understanding of the role of AI in society. They advocate integrating AI curricula into school systems to better prepare students for careers increasingly relying on AI.

Beyond ethical considerations and responsible use of AI, AI literacy encompasses a broader set of competencies that enable individuals to critically assess AI technologies and

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effectively communicate and collaborate with AI systems [21]. Tuomi extends this concept by introducing „critical AI literacy," which encompasses not only technical knowledge but also the ability to critically evaluate the social, ethical, and economic impacts of AI [24], [25].

The UNESCO AI Competency Framework for Students [26] is built on these experiences and competencies, aiming to help educators integrate AI, outlining individual competencies defined as levels of progress (understand, apply, create) across four dimensions specifying the core elements of AI competencies that students need to build and continuously develop to become responsible and active users of the AI:

- **Human-centered thinking** focuses on values, beliefs, and critical thinking related to the purpose of AI, ethical reasoning, and human interaction. Emphasizes social responsibility and the pursuit of inclusive and just AI systems.
- **Artificial intelligence ethics** covers ethical decision-making, understanding of legal regulations, and social awareness. Students learn to evaluate the impact of AI at the local and global levels while considering evolving laws, principles, and controversies.
- **AI techniques and applications** provide a technical foundation in AI, including data processing, programming, algorithmic thinking, and integrating ethical and social considerations into their practical development.
- **AI system design** focuses on engineering and design thinking, which includes problem-solving, system architecture, and model optimization. Prepares students for advanced AI development, emphasizing the principles of „ethics by design".

In recent years, researchers have developed modifications and alternative versions of the UNESCO framework to better align AI literacy with the skills and competencies of specific target groups. The focus has been on adapting AI literacy for younger learners and ensuring its integration at lower levels of education. This shift not only recognizes the growing role of AI in everyday life but also actively prepares students to engage with AI from an early age, thereby promoting a more inclusive and fundamental understanding of AI in all aspects of society.

One such modification is the K-12 AI Competency Framework [27], which defines AI competence as „The confidence and ability of an individual to clearly explain how AI technologies work and impact society, to use them ethically and responsibly, and to communicate and collaborate with them in any setting effectively. Individuals should also be confident and able to self-reflect on their understanding of AI to learn continuously.".

This framework introduces five key dimensions that define AI competence in the following aspects:

- technology – confidence, and ability to clearly explain how AI technologies work
- impact – confidence and ability to articulate the effects of AI on society
- ethics – confidence and ability to use AI responsibly and ethically
- collaboration – confidence and ability to effectively communicate and work with AI in any environment
- self-reflection – confidence and ability to assess one's understanding of AI for continuous learning. Individuals with a strong self-reflective mindset are more likely to reevaluate their knowledge and identify areas for improvement.

The multidisciplinary and holistic ED-AI Lit framework [28] proposes six components for effective AI literacy training: knowledge, assessment, collaboration, contextualization, autonomy, and ethics. The framework emphasizes that AI literacy goes beyond factual knowledge to support reflection on the interconnectedness of AI in everyday life, the functioning of AI systems, critical evaluation of their implications, and fostering collaborative relationships with AI.

Yim focuses on conceptualizing AI literacy by integrating existing ones into an inclusive AI literacy framework for young learners, defining the following constructs [29]:

- **AI ethics** covers responsible AI development, human impact, data privacy, and bias mitigation. It emphasizes the sociocultural implications of AI, justice, and ethical governance.
- **Computational thinking** develops problem-solving, coding, and algorithmic skills essential to understanding AI. It supports practical applications of AI at K-12 and advanced concepts at higher levels.
- **Digital literacy** is a prerequisite for developing foundational AI literacy – ensuring students can engage with AI technologies by understanding how AI perceives, processes, and makes decisions.
- **Data literacy** covers the fundamentals of machine learning, data collection, cleaning, and visualization.
- **Interdisciplinary and transdisciplinary knowledge** extends AI literacy beyond computer science, including engineering, ethics, social sciences, and real-world problem-solving to support a holistic perspective on AI.
- **AI thinking** is a cognitive approach that combines human and AI intelligence. It includes cognitive, creative, and analytical thinking emphasizing social, ethical, and environmental aspects. Its strengthening creates prerequisites for students to become not only AI users but also future contributors to AI.

These frameworks provide structured guidance for developing AI literacy and ensure that individuals – particularly students – acquire the technical, ethical, and cognitive skills needed to engage with AI responsibly. They

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aim to adapt AI education to different age groups and educational contexts, make AI accessible, foster critical thinking, and prepare future generations to navigate and contribute to an AI-powered world.

B. STUDENTS' ATTITUDES TOWARD AI

Understanding students' attitudes toward AI is crucial for assessing their readiness to adopt AI tools in academic and professional contexts. Recent studies have examined students' perceptions of AI, their level of trust, ethical concerns, and willingness to integrate AI into their education and future careers. These studies usually focus on specific areas of AI deployment or application.

A study [30] investigated the factors influencing students' behavior and attitudes toward using AI in higher education. While perceived risks negatively influenced the attitudes, factors such as performance expectancy and facilitating conditions strongly affected attitudes and behavioral intentions to use AI in education. Interestingly, perceived effort was not a significant factor in shaping attitudes towards AI. These results suggest that students are aware of the potential of AI to enhance performance, especially when given adequate support, despite some concerns about its risks.

The study [31] found that social science students have a generally positive view of AI, particularly emphasizing its emotional dimension. Their willingness to use AI in the future was strongly associated with positive emotional and cognitive attitudes, with overall feelings of security about technology playing a significant role.

Several surveys of medical students have revealed a strong interest in AI, although they also point to a significant lack of education on the topic within their curriculum. Many students report that they do not fully understand the basic computational principles of AI or its limitations, evoking the conclusion that AI is currently underrepresented in the medical curriculum. Most students expressed support for incorporating AI education into their studies, with the vision that such additions could better prepare them for future challenges in AI-driven medical advances [32], [33], [34].

In a study of medical students' attitudes toward AI and medical chatbots, participants showed strong support for using AI in administrative tasks and health data research. However, concerns have been raised about data protection and the potential for increased monitoring in the workplace. The results suggest that while medical students are open to integrating AI into their field, they remain wary of privacy issues and the ethical implications of AI technologies [35].

A survey of 399 students in Hong Kong [36] showed a generally positive attitude towards ChatGPT in higher education. Students appreciated its ability to provide personalized learning support, help with writing and brainstorming, and enhance research opportunities. However, significant concerns have been raised regarding accuracy, privacy, ethical implications, and potential impact on personal growth and societal values. The study highlighted the importance of carefully integrating AI technologies into educational environments to ensure they effectively enhance the learning experience.

A survey of 5,894 students from Swedish universities [37] revealed significant differences in attitudes towards AI chatbots based on gender, field of study, and academic level. More than a third of students reported regular use of AI chatbots such as ChatGPT, but many expressed concerns about their future implications. Engineering students showed more frequent positive attitudes, while humanities students, and especially medicine students, expressed more concern about the accuracy of the generated results.

A case study on using AI in academic writing among Indonesian students showed a generally positive acceptance of AI tools such as grammar checkers and plagiarism detectors. Students recognized that these tools help improve their writing skills, increase self-efficacy, and promote academic integrity. However, some have expressed concern that an over-reliance on AI could stifle creativity and critical thinking [38].

The mentioned research results show that even if students' attitudes toward AI are generally positive, they are influenced by factors such as academic background, gender, and knowledge of AI tools. These findings illustrate a complex but promising situation regarding student attitudes toward AI in educational settings. Although many students express enthusiasm for the potential of AI tools to improve their learning experience (performance, emotional engagement), they also perceive risks related to privacy, data protection, and ethical implications of AI technology.

C. RESEARCH HYPOTHESES

The existing research findings suggest that while student attitudes toward AI are generally positive, they are shaped by factors such as academic background, gender, and familiarity with AI tools. Students recognize AI's potential to enhance learning performance and engagement but also express concerns about privacy, data security, and ethical implications.

To further investigate these relationships, this study formulates the following research hypotheses:

The study considers the following research hypotheses:

- H1: Years of study are associated with greater perceived satisfaction in learning AI.
- H2: Men tend to experience greater satisfaction in learning AI than women.
- H3: Study programs significantly impact satisfaction levels in learning AI.
- H4: Between 2022 and 2024, the level of satisfaction associated with learning AI evolved significantly.
- H5: Men tend to demonstrate higher levels of AI readiness than women.
- H6: IT students demonstrate higher levels of AI readiness than other study programs.
- H7: Men tend to demonstrate higher levels of AI relevance than women.

III. RESEARCH METHODOLOGY

A. RESEARCH FRAMEWORK

To systematically analyze student attitudes toward AI, this study follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology [39]. CRISP-DM provides a structured approach for data-driven research, ensuring logical progression from problem definition to data analysis and interpretation.

- Business understanding – understanding the problem and its context in connection with the collected data, selecting specific measure tools, and setting requirements and procedures for analyzing data.
- Data understanding and preparation – describing the data acquisition and preparation process.
- Data analysis – implementing specific analytical steps to obtain answers to RQs.
- Understanding results – interpreting findings, identifying key patterns, and determining how they answer the research questions.
- Applying research results – exploring the practical implications of the results, their relevance to AI acceptance, and potential areas for further research.

B. BUSINESS UNDERSTANDING

The rapid advancement of artificial intelligence is reshaping various industries and highlights the need for students to develop AI literacy and readiness.

While the complexity and continuous evolution of AI may inspire some students, it may intimidate others [40]. Educational programs must, therefore, focus on strengthening students' readiness, confidence, and motivation to engage with AI and ensure that they can effectively navigate AI-driven environments in both academic and professional settings.

To assess students' attitudes toward AI, this study uses a validated questionnaire designed to assess key constructs related to AI literacy, which captures the following constructs [41]. While the entire framework includes multiple dimensions, for this research, we focus on three key constructs:

- AI learning satisfaction measures students' overall satisfaction with learning AI, including enjoyment, sense of achievement, and perceived value.
- AI relevance evaluates students' perception of AI's importance, its impact on their personal and professional lives, and its integration into everyday contexts.
- AI readiness assesses how prepared and confident students feel about using AI, their willingness to engage with AI tools and their perception of AI's potential benefits.

Respondents were invited to participate in the research through versions of the questionnaire created in the LMS Moodle and Google Forms environment. In the case of SK, CZ, and PL, the versions of the questionnaire were translated into the languages of the individual countries with the aim of better understanding and the possibility of involving non-IT departments as well, where there is an insufficient command of English in specific age categories and study programs.

The data collection process was conducted anonymously, with respondents informed that their participation and the results would be used exclusively for scientific purposes.

C. DATA UNDERSTANDING AND PREPARATION

A total of 1195 participants took part in the study, including:

- 827 IT-related students
- 36 STEM and IT teachers
- 185 teachers from other disciplines
- 28 language specialists
- 52 management and marketing students
- 67 students from other fields

The sample comprised 402 women and 793 men, ensuring diverse representation across disciplines and educational backgrounds. Respondents gave their consent to the processing of anonymized data under the *UKF Ethics Committee Approval* for this research.

In addition to providing basic demographic information (gender, country, age, and study program), participants responded to items corresponding to the constructs described above using a 5-point Likert scale (ranging from 1 to 5). If participants could not respond, a value of 0 was used, which was excluded from subsequent data analysis.

The first section of the questionnaire focused on sociological metrics, covering questions about: Grade (year of study), Age, Gender, University, Study program, How many hours of AI-related courses have you taken (from 0 to many, not per week, summary in your study).

The year of data collection probably influenced the responses, as the questionnaire was available from 2022 to 2024 – a period marked by rapid advancements in AI and the widespread adoption of large language models (LLMs) and AI chatbots. Therefore, we also keep this information in the data.

The frequency tables of responses to each question on the sociological metric are visualized in the following graphs and tables.

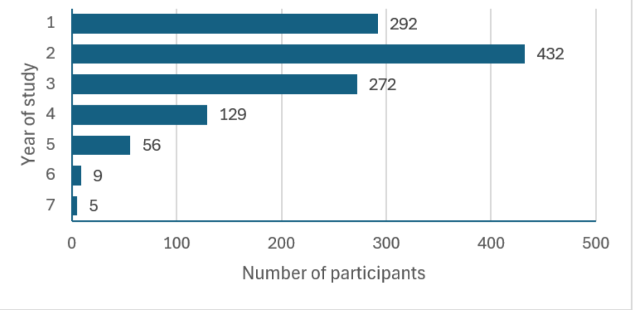

FIGURE 1. Frequency of responses for Grade.

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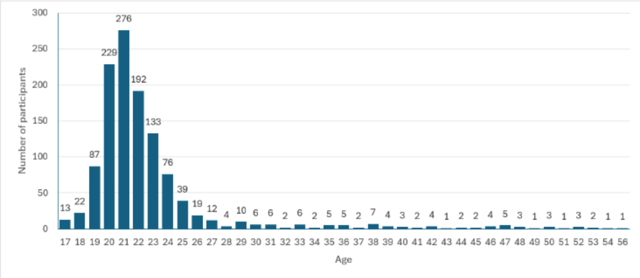

FIGURE 2. **Frequency of responses for Age.**

TABLE 1
FREQUENCY TABLE OF RESPONSES FOR GENDER

	Number	Cumulative Number	Percent	Cumulative Percent
male	793	793	66.36	66.36
female	402	1195	33.64	100
Missing	0	1195	0	100

TABLE 2
FREQUENCY TABLE OF RESPONSES FOR UNIVERSITY

	Number	Cumulative Number	Percent	Cumulative Percent
SK	682	682	57.07	57.07
CZ	106	788	8.87	65.94
PL	295	1083	24.69	90.63
ID	65	1148	5.44	96.07
TR	6	1154	0.50	96.57
LT	36	1190	3.01	99.58
FR	3	1193	0.25	99.83
UA	2	1195	0.17	100
Missing	0	1195	0	100

TABLE 3
FREQUENCY TABLE OF RESPONSES FOR THE STUDY PROGRAM

	Numb er	Cumulative Number	Percent	Cumulative Percent
IT	827	827	69.21	69.21
education	185	1012	15.48	84.69
IT education	22	1034	1.84	86.53
STEM education	14	1048	1.17	87.70
other	67	1115	5.61	93.31
language	28	1143	2.34	95.65
management	52	1195	4.35	100
Missing	0	1195	0	100

For the question „How many hours of AI-related courses have you taken (from 0 to many, not per week, summary in your study)?" a wide variety of values were indicated, with the smallest value 0 and the largest value 1,000. Therefore, we do not show a frequency table for this question, which does not add much to the data evaluation.

TABLE 4
FREQUENCY TABLE OF RESPONSES FOR YEAR

	Number	Cumulative Number	Percent	Cumulative Percent
2022	532	532	44.52	44.52
2023	110	642	9.21	53.72
2024	553	1195	46.28	100
Missing	0	1195	0	100

As shown in Figures 1 and 2 and Tables 1-4, the data set consists of 1,195 students with no missing data. Most students (83.35%) are in their first three years of study, while the sixth and seventh years have the fewest participants, totaling just over 1%.

The sample predominantly comprises young adults of college age, as shown by the concentration of ages between 20 and 24. The presence of older individuals in smaller numbers might indicate a mix of traditional and non-traditional students or participants in a specific educational or professional context. The most common ages are between 20 and 22, accounting for the majority (58.33%) of the respondents. Specifically, age 21 has the highest frequency, representing 23.1% of the total sample. Older respondents (25 and over) comprise only 14% of the sample, indicating a mix of traditional and non-traditional students.

The sample is dominated by males, with 793 males (66.36%), almost double the number of female respondents.

The sample is geographically concentrated in Central and Eastern Europe, especially Slovakia and Poland. The largest group of respondents is from Slovakia (SK), with 682 students (57.07%), followed by Poland (PL), with 295 students (24.69%) and the Czech Republic (CZ) with 106 students (8.87%). Other countries, such as Indonesia (ID), with 65 respondents (5.44%), and Lithuania (LT) with 36 respondents (3.01%), contribute smaller shares. Turkey (TR), France (FR), and Ukraine (UA) have minimal representation, accounting for only 0.92% of the total sample.

Regarding study programs, most respondents (69.21%) are enrolled in IT-related fields. The second most represented category is educational programs, with 185 students (15.48%). Other fields, such as IT education (1.84%) and STEM education (1.17%), have only a small number of participants.

Most respondents (61.51%) reported taking 0 hours of AI-related courses, indicating that many participants have not completed formal AI coursework. A small number of respondents have taken between 1 and 10 hours of courses, with 65 individuals reporting 1 hour and a gradual decrease in the number of respondents for each subsequent hour up to 10 hours (28 respondents). Only 37 respondents have taken 100 hours of courses, representing 3.10% of the total.

Most respondents provided their data in 2022, with 532 individuals representing 44.52%. In 2023, the participation significantly decreased, with only 110 respondents accounting for 9.21% of the total. In 2024, responses were substantially increased, with 553 respondents constituting 46.28% of the total.

All this information will be used in the following analysis.

D. DATA ANALYSIS

This section covers the analytical approach to gain insight into student attitudes towards AI. The analysis focuses on key constructs – satisfaction with AI learning, readiness for AI, and relevance of AI – and examines how demographic and educational factors influence these perceptions.

1) AI LEARNING SATISFACTION

The analysis begins by examining respondents' perceived satisfaction with AI learning. The following questions were designed to assess this aspect:

- S1: Learning AI makes me feel very satisfied.
- S2: Successfully completing the AI course made me feel good.
- S3: I think learning AI is very interesting.
- S4: I am satisfied with what I have learned from the AI course.
- S5: I feel rewarded for learning AI.

Respondents answered questions on a five-point scale:

- 5 - strongly agree
- 4 - agree
- 3 - neither agree nor disagree
- 2 - disagree
- 1 - strongly disagree
- 0 - not applicable

The box plot of responses to the questions in Figure 3 shows no significant differences among individual responses. Question S3, „I find learning AI to be very interesting.“, received a slightly higher rating than the others.

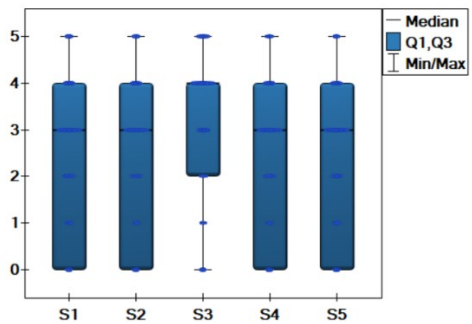

FIGURE 3. The box plot of responses for questions S1-S5.

To address the first research question, „**To what extent does year of study affect perceived satisfaction with learning AI?**“ the collected data were divided into seven independent samples, each representing a different year of study. Given that the data are measured on an ordinal scale, the Kruskal-Wallis test was used to assess whether the mean satisfaction scores across these groups were significantly different.

The null hypothesis (H_0) assumed that there were no statistically significant differences in the median responses to satisfaction questions S1–S5 across the different years of the study. The test was conducted separately for each question to determine whether the groups had differences in satisfaction.

Table 5 presents the test statistics (H values) and the corresponding p-values, indicating whether the observed differences were statistically significant.

TABLE 5
RESULTS FOR THE KRUSKAL–WALLIS TEST AND QUESTIONS S1-S5, GROUPS DEFINED BY YEAR OF STUDY

	H statistic	p-value
S1	48.23	0.000001**
S2	73.33	0.000001**
S3	26.23	0.002*
S4	63.71	0.000001**
S5	26.58	0.0001**

Since the Kruskal-Wallis test confirmed significant differences in satisfaction across years of study (we can reject the null hypothesis), a post-hoc Dunn-Bonferroni test was performed to determine which specific years of study differed from each other. This test adjusts for multiple comparisons, ensuring statistically reliable results. The findings are presented in Table 6.

TABLE 6
THE P-VALUE OF THE POST-HOC DUNN BONFERRONI TEST FOR QUESTIONS S1-S5 CONCERNING YEAR OF STUDY

S1	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1		1	0.187	0.001**	0.002**	1	1
2	1		0.009*	0.001**	0.000**	1	1
3	0.187	0.009*		0.734	0.402	1	0.831
4	0.001**	0.000**	0.734		1	1	0.237
5	0.002**	0.000**	0.402	1		1	0.134
6	1	1	1	1	1		1
7	1	1	0.831	0.237	0.134	1	
S2	1	2	3	4	5	6	7
1		1	0.000**	0.000**	0.000**	1	1
2	1		0.000**	0.000**	0.000**	1	1
3	0.000**	0.000**		1	1	0.574	1
4	0.000**	0.000**	1		1	0.285	1
5	0.000**	0.000**	1	1		0.124	1
6	1	1	0.574	0.285	0.124		1
7	1	1	1	1	1	1	
S3	1	2	3	4	5	6	7
1		0.734	1	1	0.041*	1	1
2	0.734		0.103	0.054	0.000**	1	1
3	1	0.103		1	0.153	1	1
4	1	0.054	1		1	1	1
5	0.041*	0.000**	0.153	1		1	1
6	1	1	1	1	1		1
7	1	1	1	1	1	1	
S4	1	2	3	4	5	6	7
1		1	0.000**	0.000**	0.002**	1	1
2	1		0.000**	0.000**	0.001**	1	1
3	0.000**	0.000**		1	1	0.676	1
4	0.000**	0.000**	1		1	0.475	1
5	0.002**	0.001**	1	1		0.297	1
6	1	1	0.677	0.476	0.297		1
7	1	1	1	1	1	1	

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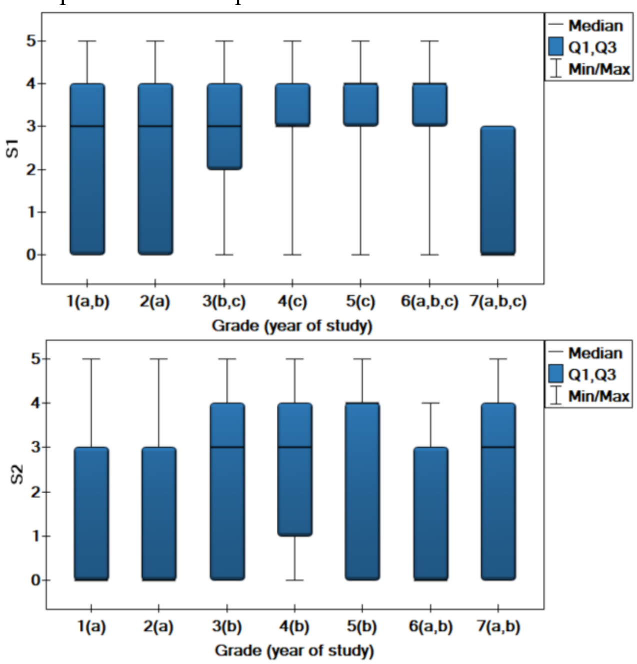
S5	1	2	3	4	5	6	7
1		1	0.291	0.392	0.948	1	1
2	1		0.001**	0.009*	0.112	1	1
3	0.291	0.001**		1	1	1	1
4	0.392	0.009*	1		1	1	1
5	0.948	0.112	1	1		1	1
6	1	1	1	1	1		1
7	1	1	1	1	1	1	

The analysis identified different homogeneous groups of responses depending on the question, indicating differences in satisfaction levels over the years of study.

- For S1, the homogeneous groups are: {1, 2, 6, 7}, {1, 3, 6, 7}, {3, 4, 5, 6, 7}.
- For S2, the homogeneous groups are: {1, 2, 6, 7}, {3, 4, 5, 6, 7}.
- For S3, the homogeneous groups are: {1, 2, 3, 4, 6, 7}, {3, 4, 5, 6, 7}.
- For S4, the homogeneous groups are: {1, 2, 6, 7}, {3, 4, 5, 6, 7}.
- For S5, the homogeneous groups are: {1, 2, 5, 6, 7}, {1, 3, 4, 5, 6, 7}.

These findings present the difference between some questions in the few introductory and later years of study. However, satisfaction with AI learning tends to decrease slightly in the higher years of study rather than increase. This trend is presented in Figure 4, which illustrates the box plots of responses for each question.



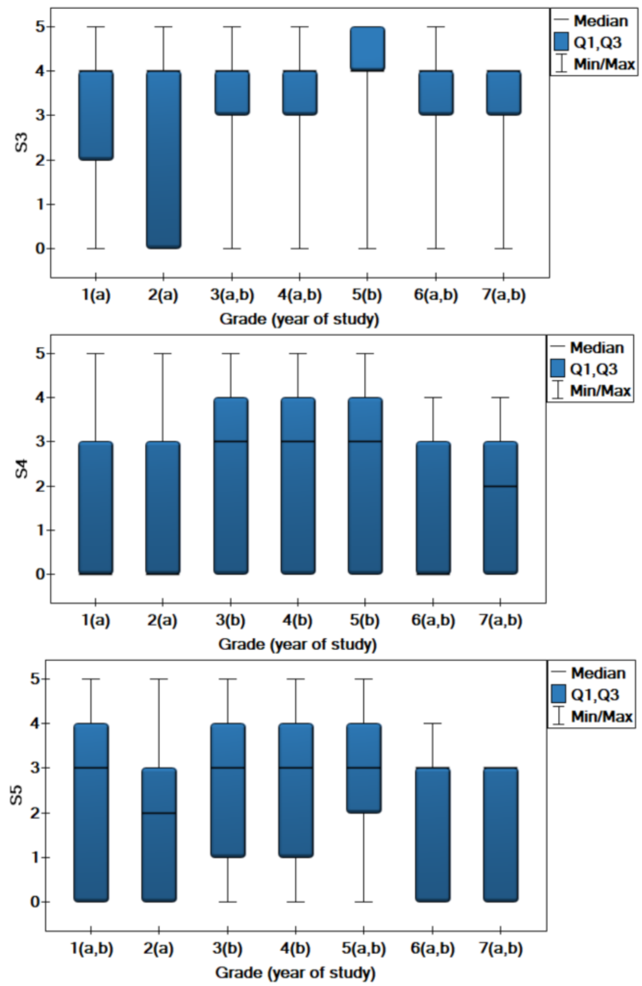


FIGURE 4. The box plots responses to questions S1-S5 concerning the year of study.

In conclusion, these findings support the hypothesis that years of study are associated with differences in perceived satisfaction with AI learning.

To determine **whether satisfaction levels differ significantly between genders**, the data set was divided into two independent samples: 402 women and 793 men. Since the dependent variable is measured on an ordinal scale, the Mann-Whitney test was used to test the null hypothesis (H_0) – that there are no significant differences in satisfaction levels between men and women. The test results, including test statistics and p-values, are presented in Table 7.

TABLE 7
RESULTS FOR THE MANN-WHITNEY TEST AND QUESTIONS S1-S5, GROUPS DEFINED BY GENDER

	Z statistic	p-value
S1	3.20	0.0014**
S2	4.32	0.0001**
S3	3.58	0.0003**
S4	4.69	0.0001**
S5	3.52	0.0004**

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The results indicate a significant difference in satisfaction levels between men and women in all aspects tested. As shown in Figure 5, the box plots clearly show that men report higher satisfaction with AI learning than women.

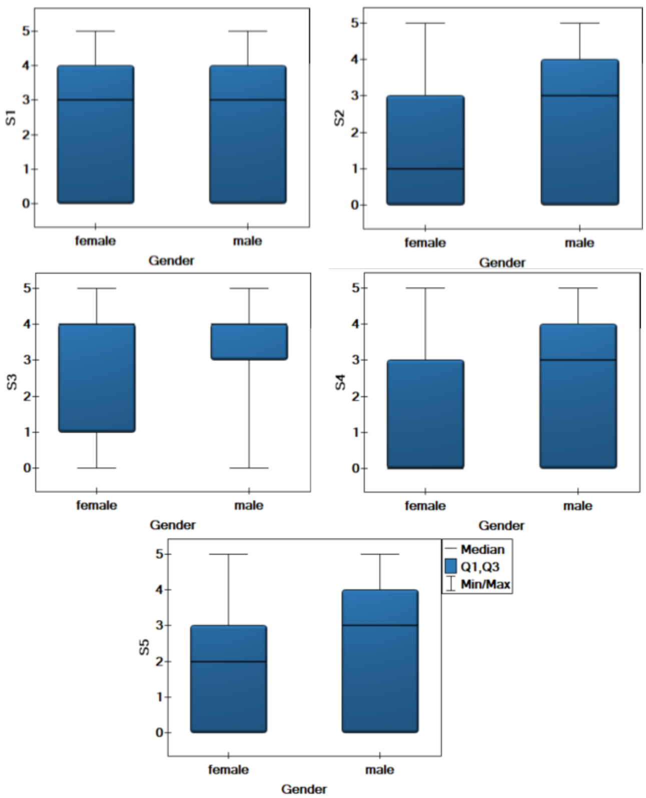


FIGURE 5. The box plots responses to questions S1-S5 concerning gender.

These findings support hypothesis H2, which states that men feel more satisfied with AI learning than women.

In the following analysis stage, we examine **whether the study program influences perceived satisfaction with AI learning**. It is hypothesized that students enrolled in IT-focused programs may demonstrate higher satisfaction, as AI-related topics are more likely to align with their academic interests and hobbies.

The dataset was divided into seven independent groups based on study programs to test this hypothesis: IT, education, IT education, STEM education, language, management, and others. Since the dependent variable is ordinal, the Kruskal–Wallis test was applied to determine whether statistically significant differences exist in satisfaction levels across these groups. The test results, including test statistics and p-values, are presented in Table 8.

TABLE 8
RESULTS FOR THE KRUSKAL–WALLIS TEST AND QUESTIONS S1-S5, GROUPS DEFINED BY THE STUDY PROGRAM

	H statistic	p-value
S1	31.40	0.0001**
S2	58.77	0.0001**
S3	27.76	0.0001**
S4	55.61	0.0001**
S5	48.41	0.0001**

The results indicate a significant difference in the level of satisfaction with AI learning between at least two study program groups (questions S1–S5). Post-hoc tests were conducted to determine which specific groups differed. The results of these pairwise comparisons are presented in Table 9.

TABLE 9
THE P-VALUE OF THE POST-HOC TEST FOR QUESTIONS S1-S5 CONCERNING THE STUDY PROGRAM

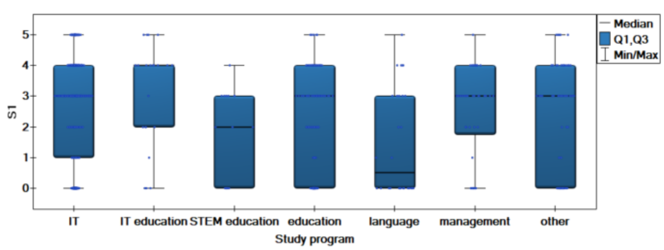
S1	IT	educ ation	IT edu	STE M	other	lang.	man ag.
IT		0.011	1	0.430	1	0.016	1
educati on	0.011		0.439	1	1	1	1
IT edu	1	0.439		0.243	1	0.040	1
STEM edu	0.430	1	0.243		1	1	1
other	1	1	1	1		0.841	1
languag es	0.016	1	0.040	1	0.841		1
manage ment	1	1	1	1	1	1	
S2	**IT**	**educ ation**	**IT edu**	**STE M**	**other**	**lang.**	**man ag.**
IT		0.000 **	1	0.570	0.002 **	0.001 **	0.360
educati on	0.000 **		1	1	1	1	1
IT educati on	1	1		1	0.765	0.110	1
STEM educati on	0.570	1	1		1	1	1
other	0.002 **	1	0.765	1		1	1
languag e	0.001 **	1	0.110	1	1		1
manage ment	0.360	1	1	1	1	1	
S3	**IT**	**educ ation**	**IT edu**	**STE M**	**other**	**lang.**	**man ag.**
IT		0.002 **	1	0.247	1	1	1
educati on	0.002 **		0.182	1	1	1	1
IT educati on	1	0.182		0.107	1	1	0.968
STEM educati on	0.247	1	0.107		1	1	1
other	1	1	1	1		1	1

S1	IT	education	IT edu	STEM	other	lang.	manag.
language	1	1	1	1	1		1
management	1	1	0.968	1	1	1	

S4	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.000 **	1	0.443	0.004 **	0.001 **	0.378
education	0.000 **		0.908	1	1	0.981	1
IT education	1	0.908		0.768	0.425	0.054	1
STEM education	0.443	1	0.768		1	1	1
other	0.004 **	1	0.425	1		1	1
language	0.001 **	0.981	0.054	1	1		1
management	0.378	1	1	1	1	1	

S5	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.006 *	1	0.440	0.124	0.001 **	0.129
education	0.006 *		0.137	1	1	0.308	1
IT education	1	0.137		0.127	0.141	0.002 **	0.113
STEM education	0.440	1	0.127		1	1	1
other	0.124	1	0.141	1		1	1
language	0.001 **	0.308	0.002 **	1	1		1
management	0.129	1	0.113	1	1	1	

The most frequently significant differences in satisfaction levels are observed between IT and educational students and between IT and language students. Box plots present these differences, confirming that IT students are significantly more satisfied with AI learning than other groups (Figure 6).



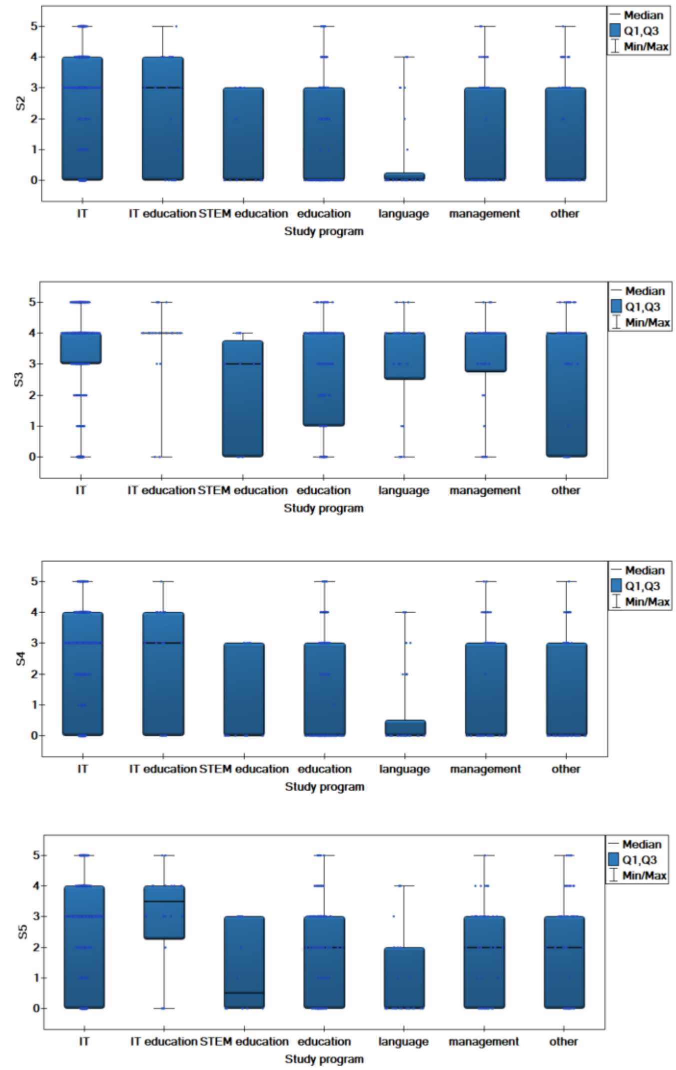


FIGURE 6. The box plots responses to questions S1-S5 concerning the study program.

It can be stated that IT, IT in education, and management students indeed feel higher satisfaction from learning AI. The hypothesis was therefore confirmed H3: The study program significantly impacts the level of satisfaction in learning AI.

We further analyze **whether satisfaction with AI learning has changed significantly over the years 2022, 2023, and 2024**. For this purpose, three independent samples were created, each representing responses from a different year. The Kruskal-Wallis test was used to determine whether there were statistically significant differences in satisfaction levels between these years. The test results, including test statistics and p-values, are presented in Table 10.

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TABLE 10
RESULTS FOR THE KRUSKAL–WALLIS TEST AND QUESTIONS S1-S5, GROUPS DEFINED BY YEARS 2022, 2023, 2024

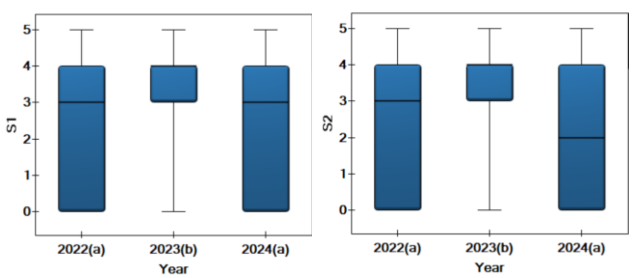
	H statistic	p-value
S1	22.19	0.0001**
S2	65.11	0.0001**
S3	7.53	0.023*
S4	63.08	0.0001**
S5	53.65	0.0001**

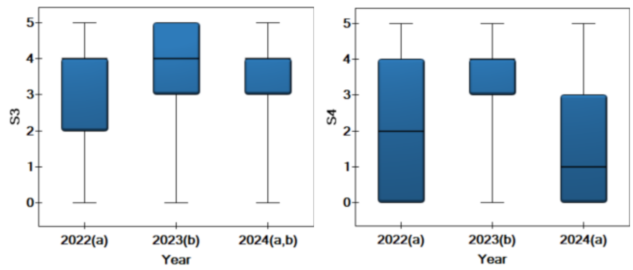
The results indicate that the year of responses significantly affects satisfaction with AI learning. To identify which specific years differ, a post-hoc Dunn-Bonferroni test was conducted, with the results presented in Table 11.

TABLE 11
THE P-VALUE OF THE POST-HOC DUNN BONFERRONI TEST FOR QUESTIONS S1-S5 CONCERNING YEARS OF RESPONSES

S1	**2022**	**2023**	**2024**
2022		0.000**	0.239
2023	0.000**		0.001**
2024	0.239	0.000**	
S2	2022	2023	2024
2022		0.000**	0.620
2023	0.000**		0.000**
2024	0.620	0.000**	
S3	2022	2023	2024
2022		0.018*	1
2023	0.018*		0.064
2024	1	0.064	
S4	2022	2023	2024
2022		0.000**	0.516
2023	0.000**		0.000**
2024	0.516	0.000**	
S5	2022	2023	2024
2022		0.000**	1
2023	0.000**		0.000**
2024	1	0.000**	

The analysis reveals statistically significant differences in satisfaction levels between 2022 and 2023 and 2023 and 2024, suggesting that 2023 was a year of notable variation. The trend of these changes is visually represented in Figure 7.





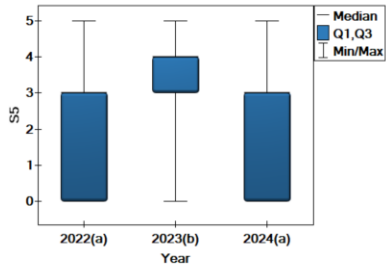


FIGURE 7. The box plots of responses for questions S1-S5 concerning the year of responses.

The results indicate that satisfaction with AI learning increased in 2023, while in 2022 and 2024, it remained at a similar level. This trend may be linked to the launch of ChatGPT by OpenAI in November 2022, based on the GPT-3.5 model, followed by the release of an improved GPT-4 version in March 2023. The availability and advancements in AI tools during this period may have contributed to the higher satisfaction levels observed in 2023.

Thus, hypothesis H4, "Between 2022 and 2024, the level of satisfaction associated with learning AI evolved significantly." is confirmed.

2) AI READINESS

The next phase of the analysis examines AI readiness, evaluating students' confidence in using AI tools and their perception of AI's impact on daily life and personal development. The following questions were designed to assess this construct:

- RE1: AI technology can help people in their daily lives.
- RE2: The AI tool is becoming more and more convenient to use.
- RE3: I like to use advanced AI technology.
- RE4: The technology can help me adjust things to my needs.
- RE5: The new AI technology will stimulate my thinking.
- RE6: I am confident that AI technology will do things following my instructions.

A box plot of responses to the AI readiness questions is shown in Figure 8. The data suggests that respondents generally perceive AI technology as beneficial in everyday life and acknowledge that it increases over time.

However, when considering AI's ability to simulate thought and reliably follow instructions, there is more significant

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uncertainty and hesitation among respondents. The following analysis explores potential factors influencing this perception to identify key drivers of trust and skepticism in AI readiness.

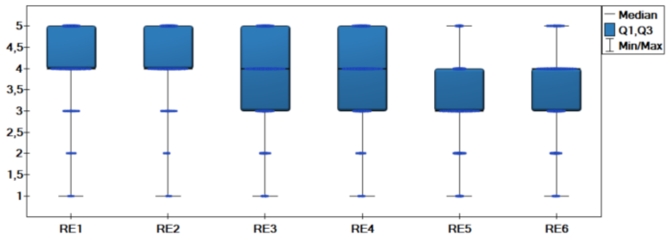

FIGURE 8. The box plot of responses for questions RE1-RE6.

The data set was divided into two independent samples to determine whether AI readiness levels differ significantly between genders. The Mann-Whitney test was used to test the null hypothesis (H_0) that there are no significant differences in AI readiness levels between men and women. The results, including test statistics and p-values, are presented in Table 12.

TABLE 12
MANN-WHITNEY TEST RESULTS FOR RESPONSES TO QUESTIONS RE1-RE6, GROUPED BY GENDER

	Z statistic	p-value
RE1	9.94	0.0001**
RE2	7.81	0.0001**
RE3	8.26	0.0001**
RE4	5.48	0.0001**
RE5	4.93	0.0001**
RE6	6.34	0.0001**

The results indicate that the readiness levels for AI differ significantly between men and women across all dimensions. As shown in Figure 9, the box plots illustrate that women generally report lower readiness levels for AI than men.

However, when asked whether AI can help people and whether AI is becoming more convenient, the gap in responses between men and women is narrower, although still statistically significant, as confirmed by the test results.

The findings indicate that while both men and women acknowledge the practical benefits of AI, there is an apparent disparity in overall AI readiness and acceptance levels. The results suggest a need for targeted strategies to address gender-specific attitudes and concerns, fostering greater AI readiness across diverse populations.

Thus, hypothesis H5, "Men tend to demonstrate higher levels of AI readiness compared to women." is confirmed.

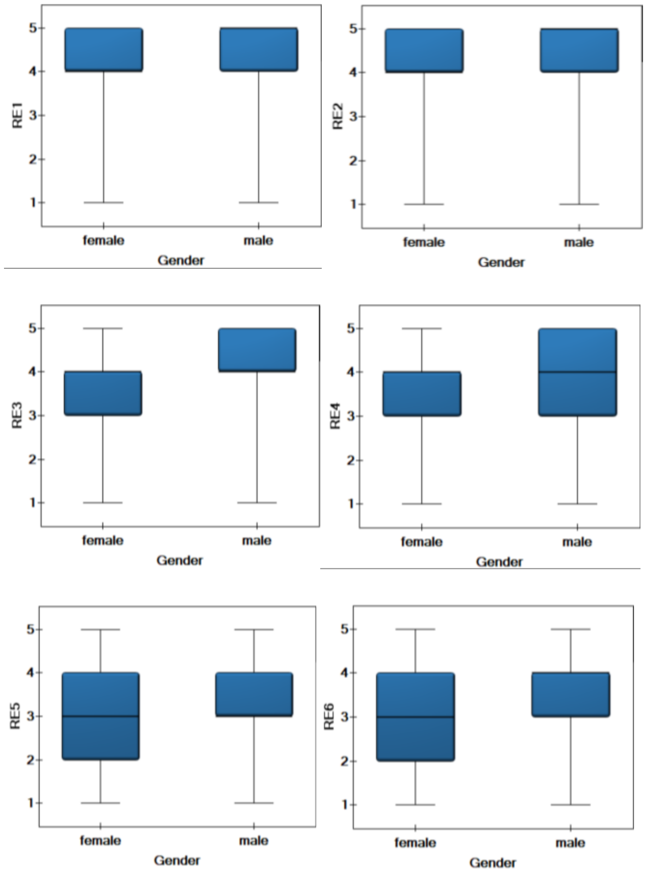

FIGURE 9. The box plots responses to questions RE1-RE6 concerning gender.

We next examine **whether the study program influences AI readiness**. To investigate, the data set was divided into seven independent groups, each representing a different study program. The Kruskal-Wallis test was used to determine whether these groups had statistically significant differences in AI readiness. The results, including test statistics and p-values, are presented in Table 13.

TABLE 13
RESULTS FOR THE KRUSKAL–WALLIS TEST AND QUESTIONS RE1-RE6, GROUPS DEFINED BY THE STUDY PROGRAM

	H statistic	p-value
RE1	127.97	0.0001**
RE2	56.69	0.0001**
RE3	96.33	0.0001**
RE4	59.12	0.0001**
RE5	36.58	0.0001**
RE6	36.40	0.0001**

The test results confirm that the study program significantly influences readiness for AI. Post-hoc tests were conducted to determine which specific groups differed. The results of these pairwise comparisons are presented in Table 14.

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TABLE 14
THE P-VALUE OF THE POST-HOC TEST FOR QUESTIONS RE1-RE6 CONCERNING THE STUDY PROGRAM

RE1	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.001 **	0.194	0.004 **	0.002 **	0.011 *	0.514
education	0.001 **		1	1	1	1	0.319
IT edu	0.194	1		1	1	1	1
STEM edu	0.004 **	1	1		1	1	0.461
other	0.002 **	1	1	1		1	1
languages	0.011 *	1	1	1	1		1
manag.	0.514	0.319	1	0.461	1	1	

RE2	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.001 **	1	1	1	0.070	1
education	0.001 **		1	1	0.829	1	0.566
IT edu	1	1		1	1	1	1
STEM edu	1	1	1		1	1	1
other	1	0.829	1	1		1	1
languages	0.070	1	1	1	1		1
manag.	1	0.566	1	1	1	1	

RE3	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.001 **	1	0.005 *	0.004 **	0.001 **	0.528
education	0.001 **		1	1	1	1	1
IT edu	1	1		0.320	1	0.521	1
STEM edu	0.005 *	1	0.320		1	1	0.537
other	0.004 **	1	1	1		1	1
languages	0.001 **	1	0.521	1	1		0.835
manag.	0.528	1	1	0.537	1	0.835	

RE4	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.001 **	1	0.065	0.131	0.046 *	0.630
education	0.001 **		1	1	1	1	1
IT edu	1	1		1	1	1	1
STEM edu	0.065	1	1		1	1	1
other	0.131	1	1	1		1	1
languages	0.046 *	1	1	1	1		1
manag.	0.630	1	1	1	1	1	

RE5	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.001 **	1	0.483	1	0.025 *	1
education	0.001 **		0.263	1	1	1	1
IT edu	1	0.263		0.324	1	0.069	1
STEM edu	0.483	1	0.324		1	1	1
other	1	1	1	1		1	1
languages	0.025 *	1	0.069	1	1		0.874
manag.	1	1	1	1	1	0.874	

RE6	IT	education	IT edu	STEM	other	lang.	manag.
IT		0.004 **	1	0.078	1	0.008 *	1
IT	0.004 **		1	1	1	1	1
education	1	1		0.261	1	0.174	1
IT edu	0.078	1	0.261		1	1	0.607
STEM edu	1	1	1	1		0.756	1
other	0.008 *	1	0.174	1	0.756		0.374
languages	1	1	1	0.607	1	0.374	

The results indicate that IT students are the most prominent group, demonstrating significantly higher readiness levels for AI than students from other fields. This status is particularly evident in their responses to statements such as „Technology can help me customize things to my needs.“ and „New AI technology will stimulate my thinking.“.

Furthermore, IT students express stronger beliefs in the potential of AI to improve problem-solving and creativity, suggesting that their knowledge of technology has fostered a more optimistic view of the role of AI in both academic and personal growth.

Hypothesis H6, „IT students demonstrate higher levels of readiness for AI compared to students in other study programs.“, is therefore confirmed.

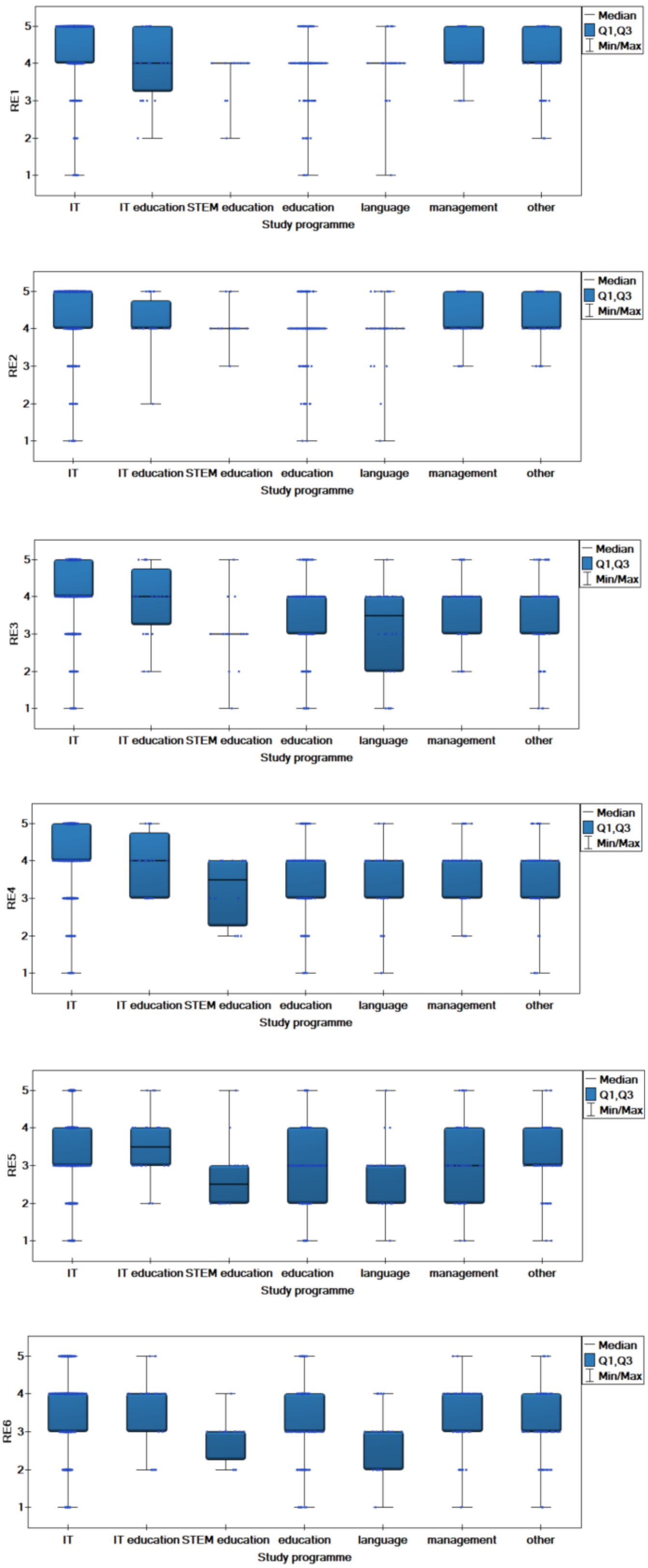

FIGURE 10. The box plots responses to questions RE1-RE6 concerning the study program.

It was also verified that the year of study and the year of response had no significant effect on the change in AI readiness among respondents.

3) AI RELEVANCE

Now, we turn to the analysis of the relevance of AI. The questions on this topic were as follows:

- R1: I know that AI technology will change the world.
- R2: Learning AI-related knowledge is very useful to me.
- R3: I should learn the basics of AI.
- R4: I know what my future has to do with AI.
- R5: The content of the AI course is related to my interests.
- R6: I can connect AI with everyday life outside the classroom.

The box plot of responses to questions about the relevance of AI is shown in Figure 11. The results indicate that respondents generally acknowledge the broader importance of AI (R1) and see value in learning about it (R2). However, there is more significant uncertainty or lower enthusiasm regarding personal relevance (R4, R5) and its connection to everyday life (R6). This result may indicate a gap in AI education where students struggle to connect AI concepts with practical, real-world applications.

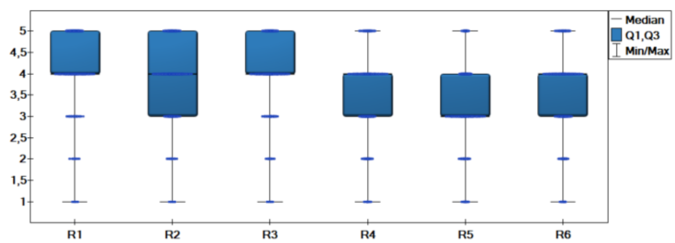

FIGURE 11. The box plots of responses for questions R1-R6.

We analyzed the relationship between responses to questions R1-R6 and factors such as the year of response, study program, and year of study. These factors had minimal impact on the responses overall. However, there were statistically significant differences in responses to R1-R6 between IT and education students.

On the other hand, it was observed that the AI relevance level is significantly different in the populations of respondents of different genders.

The Mann-Whitney test was used to verify the null hypothesis that no significant differences in relevance AI levels exist for men and women. The results obtained, test statistics, and the p-value are given in Table 15.

As can be seen, all questions demonstrate statistically significant gender differences in responses, with the most remarkable differences in questions R1, R2, R3, R5, and R6.

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TABLE 15
MANN-WHITNEY TEST RESULTS FOR RESPONSES TO QUESTIONS R1-R6, GROUPED BY GENDER

	Z statistic	p-value
R1	9.34	0.0001**
R2	6.84	0.0001**
R3	6.45	0.0001**
R4	2.67	0.008*
R5	5.89	0.0001**
R6	4.34	0.0001**

These results suggest that gender may influence attitudes toward AI's impact, relevance, and personal interest with varying intensity.

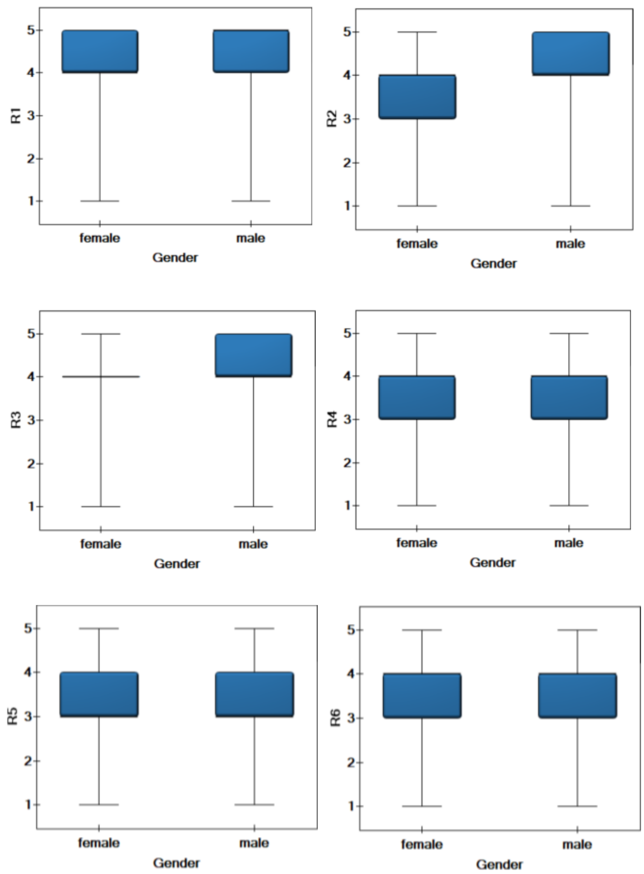

FIGURE 12. The box plot of responses for questions R1-R6 concerning gender.

Figure 12 shows the box plots in a group of men and women. The boxplot analysis reveals that women generally perceive AI as less relevant than men across multiple aspects, which supports hypothesis H7, which states that men tend to demonstrate higher levels of AI relevance than women.

This result is evidenced by lower median responses from women on questions related to AI's usefulness, impact on future careers, and connection to everyday life.

These differences suggest that women may feel less engaged with or interested in AI topics, potentially indicating a gender gap in perceived relevance and enthusiasm toward AI. Addressing this gap could be important in designing more inclusive AI education strategies.

4) CORRELATION ANALYSIS

The following analytical approach to examine the relationships between AI satisfaction, AI readiness, and AI relevance was applied:

First, for each respondent, an average score was computed separately for each group of questions:

- AI Satisfaction: S1–S5, denoted as AVG S
- AI Readiness: RE1–RE6, denoted as AVG RE
- AI Relevance: R1–R6, denoted as AVG R

Next, Spearman's rank correlation was used to assess the relationships between the newly created variables. The results are summarized in Table 16, with the correlations visualized graphically in Figure 13.

TABLE 16
SPEARMAN'S RATING CORRELATIONS BETWEEN THE QUESTION GROUPS AVG S, AVG RE, AND AVG R. MARKED CORRELATION COEFFICIENTS ARE SIGNIFICANT WITH P <0.05

	AVG S	AVG RE	AVG R
AVG S	1	0.224	0.291
AVG RE	0.224	1	0.643
AVG R	0.291	0.643	1

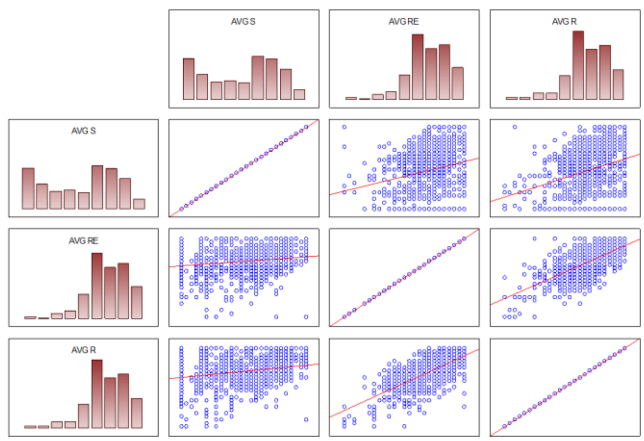

FIGURE 13. The correlations between the groups of questions AVG S, AVG RE, and AVG R visualized graphically.

The results indicate that satisfaction with AI has a weak but positive correlation with both AI readiness (0.224) and AI relevance (0.291), suggesting that individuals who perceive AI as more relevant or feel better prepared to use it tend to report slightly higher satisfaction levels. However, other factors likely contribute to overall satisfaction. A stronger relationship emerges between AI readiness and AI relevance (0.643), suggesting that those who feel better prepared to adopt AI also tend to recognize its relevance in different contexts.

This finding demonstrates the close link between knowledge equipment for working with AI and recognition of its importance in different contexts and underscores readiness

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as a key factor in shaping how individuals perceive the value and importance of AI.

Since the above studies noted a wide variation in results between IT students and students outside the IT field, similar analyses were calculated with a breakdown of these groups.

Next, Spearman's rank correlation only for IT students is summarized in Table 17, with the correlations visualized graphically in Figure 14.

TABLE 17
SPEARMAN'S RATING CORRELATIONS BETWEEN THE QUESTION GROUPS AVG S, AVG RE, AND AVG R FOR IT STUDENTS. MARKED CORRELATION COEFFICIENTS ARE SIGNIFICANT WITH P <0.05

	AVG S	AVG RE	AVG R
AVG S	1	0.150	0.261
AVG RE	0.150	1	0.610
AVG R	0.261	0.610	1

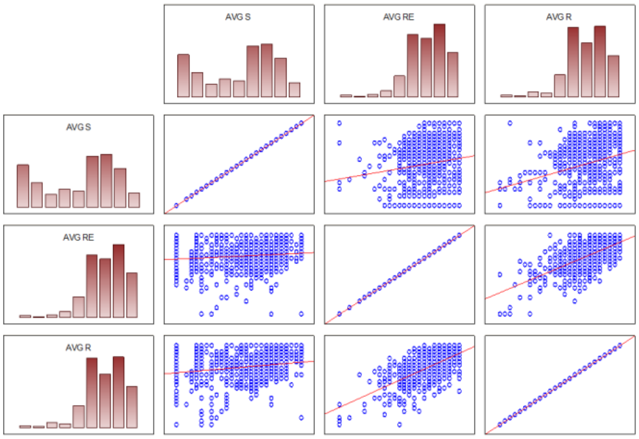

FIGURE 14. The correlations between the groups of questions AVG S, AVG RE, and AVG R visualized graphically for IT students.

The results for IT students reveal differences in the strength of the relationships between satisfaction with AI (AVG S), readiness for AI (AVG RE), and relevance for AI (AVG R), providing insight into how perceptions of AI vary within this group.

- The correlation between satisfaction with AI (AVG S) and readiness for AI (AVG RE) is weak (0.150), suggesting a minimal relationship between feeling ready for AI and overall satisfaction.
- The correlation between satisfaction with AI (AVG S) and relevance for AI (AVG R) is slightly stronger (0.261), suggesting that students who perceive AI as more relevant tend to report higher levels of satisfaction.
- The strongest relationship is between readiness for AI (AVG RE) and relevance for AI (AVG R) (0.610), indicating a significant link between readiness to adopt AI and recognition of its importance.

Figure 14 visually highlights the stronger association between readiness and relevance, while the relationships involving satisfaction remain weaker. These findings suggest that while IT students recognize the importance of AI preparation, their satisfaction with AI learning may be influenced by other factors beyond readiness and relevance.

Analogous results for non-IT students are shown in Table 18 and Figure 15.

TABLE 18
SPEARMAN'S RATING CORRELATIONS BETWEEN THE QUESTION GROUPS AVG S, AVG RE, AND AVG R FOR IT NON-STUDENTS. MARKED CORRELATION COEFFICIENTS ARE SIGNIFICANT WITH P <0.05

	AVG S	AVG RE	AVG R
AVG S	1	0.238	0.262
AVG RE	0.238	1	0.640
AVG R	0.262	0.640	1

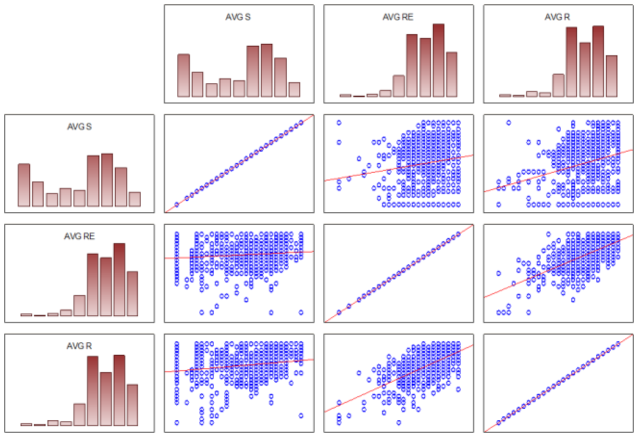

FIGURE 15. The correlations between the groups of questions AVG S, AVG RE, and AVG R visualized graphically for non-IT students.

Both IT and non-IT students show similar correlation patterns, with the strongest relationship consistently observed between AI readiness and AI relevance. However, the strength of these relationships varies slightly between the two groups.

- For non-IT students, the correlation between AI satisfaction (AVG S) and AI readiness (AVG RE) is 0.238, which is stronger than the equivalent value for IT students (0.150).
- The correlation between AI satisfaction (AVG S) and AI relevance (AVG R) is almost identical for both groups (0.262 for non-IT students versus 0.261 for IT students).
- The relationship between AI readiness (AVG RE) and AI relevance (AVG R) is high for both groups but slightly stronger for non-IT students (0.640) compared to IT students (0.610).

These results suggest that non-IT students achieved a slightly stronger link between their satisfaction with AI and their readiness to use it than IT students, although the overall link remains weak. The stronger correlation between readiness and relevance among non-IT students means that those who feel more ready to adopt AI tend to perceive it as more relevant, even more so than their IT peers.

The graphical visualizations (Figures 14 and 15) likely highlight these subtle differences in the strength of the correlation between groups, particularly for readiness and relevance.

While the general trends are consistent, non-IT students exhibit marginally stronger correlations between the studied variables, particularly in how readiness relates to satisfaction and relevance. This result may reflect differing perspectives or levels of experience with AI between the two groups, with IT students perhaps relying on other factors beyond readiness and relevance to shaping their satisfaction.

We also analyzed the correlation for the division concerning gender, as this was another critical factor that significantly impacted the relationships discussed in previous sections. Spearman's rank correlations for males are summarized in Table 19, with the correlations visualized graphically in Figure 16.

TABLE 19
SPEARMAN'S RATING CORRELATIONS BETWEEN THE QUESTION GROUPS AVG S, AVG RE, AND AVG R FOR MALES. MARKED CORRELATION COEFFICIENTS ARE SIGNIFICANT WITH P <0.05

	AVG S	AVG RE	AVG R
AVG S	1	0.618	0.254
AVG RE	0.618	1	0.139
AVG R	0.254	0.139	1

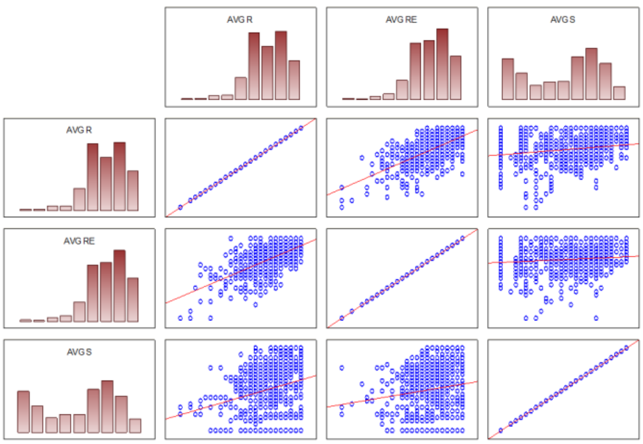

FIGURE 16. The correlations between the groups of questions AVG S, AVG RE, and AVG R visualized graphically for males.

The analysis examines the relationships between satisfaction with AI (AVG S), readiness for AI (AVG RE), and relevance of AI (AVG R) among male respondents.

- The correlation between satisfaction with AI (AVG S) and readiness for AI (AVG RE) is strong (0.618), significantly higher than in previous analyses for other groups. This correlation suggests that men who feel more prepared for AI also report higher satisfaction levels.
- The relationship between satisfaction with AI (AVG S) and relevance of AI (AVG R) is weaker (0.254) but still positive, suggesting that while the perception of AI as relevant contributes to satisfaction, the association is not as strong as with readiness.
- In contrast to other groups, the correlation between readiness for AI (AVG RE) and relevance of AI (AVG R) is very weak (0.139). This contrasts with the stronger correlations observed in previous analyses, suggesting that readiness and relevance are not strongly linked for male respondents.

These findings suggest that men’s satisfaction with AI learning is directly influenced by their level of readiness for AI rather than their perception of AI relevance. The weak association between readiness and relevance may indicate different perceptions or experiences with AI compared to broader or mixed-gender samples.

Overall, the results for female respondents emphasize the importance of readiness in driving satisfaction with AI, a trend that is more pronounced than in other groups.

TABLE 20
SPEARMAN'S RATING CORRELATIONS BETWEEN THE QUESTION GROUPS AVG S, AVG RE, AND AVG R FOR FEMALES. MARKED CORRELATION COEFFICIENTS ARE SIGNIFICANT WITH P <0.05

	AVG S	AVG RE	AVG R
AVG S	1	0.625	0.300
AVG RE	0.625	1	0.302
AVG R	0.300	0.302	1

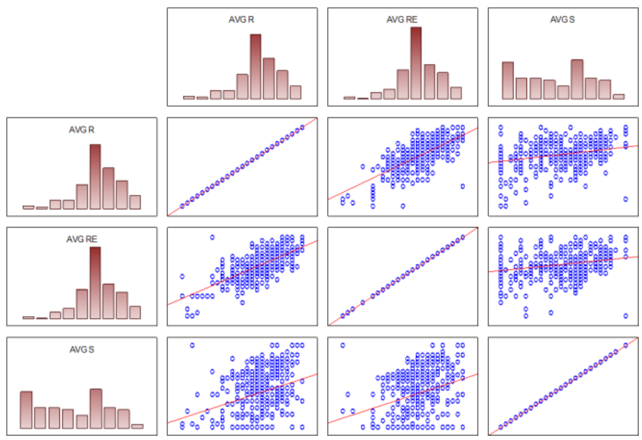

FIGURE 17. The correlations between the groups of questions AVG S, AVG RE, and AVG R visualized graphically for females.

Spearman's rank correlations for males are summarized in Table 20, with the correlations visualized graphically in Figure 17.

- The correlation between satisfaction with AI (AVG S) and readiness for AI (AVG RE) is strong (0.625) for women, closely matching the value observed for men (0.618). The results suggest that individuals who feel more prepared for AI report significantly higher satisfaction levels for both genders.

- However, the correlation between satisfaction with AI (AVG S) and the relevance of AI (AVG R) is slightly higher for women (0.300) compared to men (0.254). This suggests that the perceived relevance of AI plays a slightly more significant role in shaping satisfaction among women than men.
- A key difference emerges in the relationship between readiness for AI (AVG RE) and the relevance of AI (AVG R). For women, this correlation is moderate (0.302), while for men, it is very weak (0.139). This result means that women who feel more prepared for AI are more likely to perceive it as relevant, suggesting a stronger connection between the two constructs than their male counterparts.

Overall, the results highlight notable gender-based differences. For females, readiness and relevance are more closely linked, and relevance plays a slightly more significant role in influencing satisfaction. These findings suggest that females may view readiness and relevance as more interconnected factors, while males may weigh readiness more heavily in determining satisfaction.

IV. DISCUSSION AND CONCLUSION

The analysis revealed several significant differences in students' perceptions and attitudes towards AI, shaped by gender, field of study, and year of study.

While some groups, such as IT and male students, show higher levels of confidence and engagement, others, particularly non-IT students and female respondents, show lower levels of readiness and satisfaction with AI.

Furthermore, the evolution of satisfaction levels over time, particularly the increase in 2023, suggests that external factors, such as the widespread adoption of AI tools, may influence students' attitudes.

The analysis provides a more detailed view of the proposed hypotheses and a deeper understanding of how individual parts of AI literacy develop across different student populations.

1) YEARS OF STUDY & SATISFACTION IN AI LEARNING

The study looked at how students in different years of study rated their satisfaction with learning AI to test hypothesis H1. The results confirmed a statistically significant difference, but the post-hoc tests showed mixed results. Some questions suggested higher satisfaction in earlier years of study, while others showed a slight decrease in later years.

Therefore, the study's conclusion regarding hypothesis H1 is nuanced: **While years of study are associated with differences in perceived satisfaction in learning AI, these differences do not indicate a clear pattern of increased satisfaction with more years of study.**

This view is supported by previous research, confirming that students tend to show a high interest in AI in the early stages of their studies, but this interest may decline. One explanation is that the quality of AI-related information and services is strongly correlated with user satisfaction [42], and as AI use becomes more routine or more complex topics are introduced, perceived quality may decrease. According to Panagoulias [43], individuals report greater satisfaction with AI when it meets their needs and offers practical value. Furthermore, interest and motivation are critical drivers of AI literacy, as they encourage students to explore and engage with AI technologies [19], which seems to explain the positive correlation between satisfying user needs and developing AI literacy [44].

While initial enthusiasm is typical, the observed decline in satisfaction in later years highlights the potential challenge of maintaining student engagement. This is a key finding because it challenges the assumption that longer exposure to AI in education naturally leads to greater satisfaction. Instead, the relationship between AI experiences and satisfaction appears to be more nuanced and likely shaped by factors beyond the scope of this study – such as course content, instructional approaches, or students' evolving career aspirations and interests during their studies.

2) MEN TEND HIGHER SATISFACTION THAN WOMEN

To test hypothesis H2, the research compared satisfaction levels between male and female students. The results of the test identified a statistically significant difference in satisfaction levels. Figure 5 visually confirmed that men consistently reported higher satisfaction with learning AI than women.

Therefore, the study **supports the statement that men experience greater satisfaction in learning AI than women**.

This finding is consistent with other findings observed in the study, where men also demonstrated higher readiness levels for AI and were more likely to perceive AI as relevant to their future careers. These patterns are consistent with previous research – for example, [45] confirms that men generally show greater readiness and satisfaction with AI than women, while studies [46] and [47] suggest that men tend to have more trust in AI.

The results support broader observations that gender significantly influences the intention to adopt new technologies, especially when technology is perceived as a broad and evolving concept [48], [49]. They may indicate the need for initiatives to increase women's engagement in AI and ensure equal opportunities to develop confidence and interest in the field.

Although this study does not explicitly examine the underlying reasons for the gender gap in satisfaction, the results point to a potential difference in engagement and experience. This difference highlights the need for further research and targeted educational strategies to promote equal enthusiasm, motivation, and satisfaction with AI learning among male and female students.

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3) IMPACT OF STUDY PROGRAM ON SATISFACTION

To test hypothesis H3, the study investigated how satisfaction with AI learning varied across different study programs. Seven distinct study programs were considered: IT, education, IT education, STEM education, languages, management, and others. The results confirmed a statistically significant difference in satisfaction levels based on the study program, meaning that students in some study programs reported significantly different levels of satisfaction with AI learning than students in other programs.

To test hypothesis H3, the study examined whether satisfaction with AI learning varies across study programs. Seven different fields were considered: IT, education, IT education, STEM education, languages, management, and others. The analysis revealed a statistically significant difference in satisfaction levels between these groups, confirming that students from different study programs experience AI learning differently.

Post-hoc tests were conducted to determine which specific study programs differed significantly in terms of satisfaction with AI learning. The results showed that the most significant differences occurred between:

- IT students and education students
- IT students and language students

These findings were further supported by box plot visualizations (Figure 6), which clearly illustrated that IT students consistently reported the highest levels of satisfaction with AI learning.

In addition, IT education and management program students reported relatively high satisfaction levels, although not as pronounced as their IT counterparts. This observation suggests that familiarity with technology or a stronger alignment of specialization with AI topics may positively influence student satisfaction with AI learning.

Therefore, the study strongly **supports the statement that the study program has a significant impact on satisfaction levels in learning AI**. This finding suggests that students in fields more closely related to AI, such as IT, are likely to experience greater satisfaction with AI learning, potentially due to increased relevance, familiarity with concepts, or career aspirations aligned with AI.

While many existing studies examine satisfaction with AI deployments in educational settings [50], [51], [52], relatively few have specifically focused on the link between satisfaction with AI instruction and a student's academic discipline [53]. This limited attention may result from AI not being widely integrated into most academic curricula, especially outside IT-focused programs. However, as AI becomes an increasingly important element across disciplines, this area of research is expected to expand. Research suggests that students from different academic disciplines approach learning through distinct cognitive frameworks and mindsets shaped by the norms and methods of their fields of study [54]. For example, students in engineering or IT majors generally find the computational and logical components of AI more accessible, which may lead to greater satisfaction with learning AI. On the other hand, students in non-technical majors may have more difficulty because the content may be less aligned with their prior knowledge or experience.

Studies also show that disciplinary background impacts students' general technological skills [55], [56], which may influence their initial experience and confidence in working with AI. Those who enter AI-related courses with more developed digital competencies are more likely to feel comfortable, confident, and satisfied with the learning process [57], highlighting the importance of digital readiness in shaping the overall AI learning experience.

Although results from direct comparisons of satisfaction with learning about AI across degree programs are still limited, the evidence strongly suggests that students' academic background influences their engagement, confidence, and ability to learn independently with AI tools.

These elements are closely related to satisfaction – students from majors with greater conceptual overlap with AI may experience smoother learning curves and higher satisfaction. In contrast, students from less technically oriented programs may need additional support and tailored teaching strategies to achieve similar satisfaction and engagement levels.

4) THE LEVEL OF SATISFACTION BETWEEN 2022-2024

To test hypothesis H4, we examined data collected over three years (2022, 2023, and 2024) to assess whether there were significant differences in satisfaction levels across these years. The finding implies that satisfaction levels were not static over time, and tests revealed statistically significant differences in satisfaction levels between the following years:

- 2022 and 2023
- 2023 and 2024

Visual analysis of the data using box plots (Figure 7) helped to clarify the trend: **satisfaction levels increased significantly in 2023 but then returned to levels similar to those observed in 2022 by 2024**.

It can be speculated that this fluctuation in satisfaction may be related to the release and improvement of ChatGPT [58], [59], [60]:

- Based on the GPT-3.5 model, the initial version was launched in November 2022.
- A more advanced version, powered by the GPT-4 model, became available in March 2023.

The significant leap in capabilities between these versions may have increased student satisfaction in 2023, as students encountered a more robust and accessible tool for interacting with AI. ChatGPT's improved performance and visibility likely made AI feel more engaging, practical, and relevant, improving students' perceptions of their AI learning experiences.

However, by 2024, this initial enthusiasm may have waned as such tools became more normalized and integrated into everyday academic life. The return to baseline satisfaction levels suggests that while technological innovation can generate increased interest, this effect may be temporary unless supported by continued novelty or deeper pedagogical integration.

The study confirms that AI learning satisfaction increased significantly between 2022 and 2024, particularly between 2022-2023 and 2023-2024. The fluctuation, likely influenced by advances in AI technology such as ChatGPT, underscores the dynamic and context-dependent nature of AI learning experiences and highlights how student perceptions shape curriculum and broader technological shifts.

5) MEN TEND TO HAVE HIGHER AI READINESS LEVELS

To test hypothesis H5, responses to six questions (RE1–RE6) related to AI readiness were analyzed to determine whether there were significant differences between male and female students. The results revealed a statistically significant difference across all six questions, indicating that **males and females consistently differ in their perceptions of AI readiness**. This finding provides strong evidence of a gender gap in AI readiness within the current sample, with male respondents consistently reporting higher levels of confidence and readiness in using AI tools than their female counterparts.

Visual analysis using box plots (Figure 9) reinforces this conclusion and illustrates that across all measured dimensions of AI readiness, men report higher scores than women. This result is consistent with other patterns observed in the study, such as men reporting greater satisfaction with learning AI and having stronger perceptions of the importance of AI for their future careers.

These observations are also supported by previous research – for example, studies [41], [61], and [62] similarly found that male students reported higher levels of confidence, perceived relevance, and readiness for AI-related tasks.

However, not all studies support this pattern universally. For example, [63] found that in the context of medical education, females showed slightly better readiness for AI, although the difference was not statistically significant. Similarly, [64] reported that female students had more positive attitudes towards AI in the context of second language learning, a field characterized by complex cognitive and personalized learning demands.

These conflicting findings suggest that while a general gender gap in AI readiness exists, it cannot be universally applied across academic disciplines or contexts. The observed differences may stem from multiple factors, including prior exposure to technology, curriculum and educational experience variations, and societal influences and gender stereotypes related to technology. Further research is needed to examine the underlying causes of these disparities and to design inclusive strategies that promote equal AI readiness among students of all genders.

6) IT STUDENTS DEMONSTRATE HIGHER AI READINESS

To test hypothesis H6, the study examined whether levels of AI readiness differed across academic disciplines. Responses were compared across seven study program categories: IT, education, IT education, STEM education, languages, management, and others. The statistical analysis results confirmed a **significant difference in AI readiness levels based on the study program, suggesting that students' academic background plays a role in how prepared they are to use AI technologies**.

Further insight was gained through post-hoc testing, which revealed a clear and consistent pattern: IT students showed significantly higher levels of AI readiness than students from all other program categories, likely reflecting their greater familiarity with digital technologies and computational thinking. This difference was particularly evident in questions assessing perceptions of AI's ability to support personalization and its potential to stimulate cognitive engagement (Figure 10).

This finding is consistent with an overall trend observed throughout the study: students in fields more closely related to AI consistently demonstrate greater engagement, confidence, and comfort with AI technologies. The higher readiness levels among IT students can be attributed to several key factors, including increased exposure to AI concepts and tools across their curriculum, better knowledge of practical AI applications and career trajectories directly influenced by AI advances.

These results are consistent with existing research showing that IT students are typically more receptive to new technologies [65], [66]. While IT is not always considered a separate technology base within broader AI education frameworks, and specific AI competency tools are often developed with alternative disciplinary foundations in mind [67], [68], the knowledge and technical orientation inherent in IT programs contribute to higher levels of student readiness for AI [69].

7) MEN TEND TO HAVE A HIGHER AI RELEVANCE LEVEL

To test hypothesis H7, the study examined whether there were significant gender differences in how students perceived the relevance of AI. Responses to six questions (R1–R6) were analyzed, each addressing a specific aspect of AI relevance. The results revealed statistically significant differences between male and female respondents across all six questions, strongly suggesting that **gender influences individuals' perceptions of the importance and relevance of AI to their personal and professional lives**.

The findings support the hypothesis that males perceive AI as more relevant than females. This observation is consistent with broader trends observed across this study, in which male respondents consistently reported higher levels of satisfaction, readiness, and relevance of AI.

This pattern is not unexpected, as it reinforces previously observed gender-based differences discussed earlier in the study. They included men's greater confidence in using AI tools and their stronger belief in the value of AI for future careers, all of which contribute to higher overall perceptions of AI's relevance. Overall, the results clearly show how gender shapes attitudes toward AI and underscore the importance of targeted strategies to promote more balanced engagement among diverse student groups.

8) CORRELATION ANALYSIS RESULTS

Analyzing Spearman correlations across different groups – namely, IT vs. non-IT students and male vs. female respondents – offers valuable insights into how different populations perceive satisfaction, readiness, and relevance of AI. Across all groups, AI readiness consistently plays a central role, directly influencing satisfaction or through a strong association with relevance. However, the strength and nature of these relationships vary significantly by group.

- For IT and non-IT students, the correlation between readiness and relevance of AI is strong, suggesting that students who feel more prepared to use AI tend to view it as more important.
- However, gender differences present a more complex picture. For male respondents, readiness correlates more strongly with satisfaction, while the link between readiness and relevance is relatively weak. In contrast, readiness and relevance are more balanced among female respondents, and satisfaction is more loosely tied to perceived relevance.

These patterns suggest that the path to engagement with AI differs by gender and academic background. Such findings highlight the need for tailored educational strategies that reflect the specific experiences and perceptions of different groups of learners. For example:

- Improving AI readiness may be particularly effective for male students, while strategies that enhance relevance and readiness may yield better outcomes for female students.
- Non-IT students may benefit from increased exposure to real-world AI applications, which will help them connect abstract concepts with practical value.
- Meanwhile, for IT students, improving satisfaction may require addressing factors beyond content knowledge - such as teaching methods, engagement strategies, or course design.

This study examined how various factors - including gender, academic discipline, and year of study - influence students' satisfaction with AI learning, readiness to use AI, and perceptions of its relevance. The results confirm that AI readiness is a central construct influencing satisfaction and relevance, although the strength of these relationships varies across demographic groups. IT students and male respondents consistently reported higher levels of satisfaction, readiness, and perceived relevance, while non-IT students and female respondents expressed more cautious attitudes with lower levels of trust and personal connection to AI tools.

Year-over-year analysis revealed a notable peak in satisfaction in 2023, likely driven by the public release and adoption of ChatGPT and similar tools. However, this enthusiasm appears to have stabilized in 2024, suggesting that novelty plays a role in shaping students' engagement with AI, but long-term satisfaction may depend on other factors such as instructional design, perceived usefulness, and relevance to the field of study.

Gender differences were evident across all constructs. Men consistently reported higher readiness and satisfaction, while women showed a more balanced relationship between AI readiness and relevance. These findings reflect existing research while highlighting the importance of context – particularly discipline-specific experiences and societal factors influencing engagement with technology. Similarly, IT students' significantly higher readiness level underscores the importance of prior experience and digital competence in fostering confidence in AI technologies.

This study highlights the need for more inclusive and adaptive approaches to AI education. Future efforts should focus on reducing gender and disciplinary gaps by providing tailored support, scaffolding, and real-world examples that make AI more accessible to all students. In addition, more research is needed to explore the underlying causes of these gaps, mainly qualitative studies that examine student motivation, perceptions of AI ethics, and learning environments. As AI continues to shape the future of education and work, equitably promoting AI literacy across diverse student populations will be critical to ensuring readiness and engagement on a broader scale.

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