frontiers in Education

TYPE Original Research
PUBLISHED 06 March 2026
DOI 10.3389/feduc.2026.1717886

OPEN ACCESS

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RECEIVED 02 October 2025
REVISED 11 January 2026
ACCEPTED 18 February 2026
PUBLISHED 06 March 2026

CITATION
Yotov K, Gaftandzhieva S, Hadzhikolev E, Hadzhikoleva S and Gorgorova M (2026) AI in education through the learners' eyes: practical experience, perceptions, and challenges.
Front. Educ. 11:1717886.
doi: 10.3389/feduc.2026.1717886

AI in education through the learners' eyes: practical experience, perceptions, and challenges

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Introduction: In order to remain competitive, higher education institutions strive to enhance the student experience by integrating modern technologies for both educational and administrative purposes. This paper presents the results of a study exploring students' attitudes toward the use of artificial intelligence (AI) in higher education.
Methods: The data was collected through a survey conducted among 138 students, who responded to 50 questions regarding their level of awareness, practical experience, perceived benefits of using AI tools, potential issues and challenges, as well as ideas and suggestions for more effective use of AI technologies. The analysis was conducted using both traditional statistical techniques and contemporary machine learning methods.
Results: Findings show that students who understand AI capabilities are more confident and proactive in using it for learning purposes. Those who utilize AI believe it enhances their academic performance and recommend its use to their peers.
Discussion: Overall, students support the innovative use of AI and believe it will improve the educational process. According to them, the main risks associated with AI use include academic misconduct and the loss of critical thinking skills. The findings can serve as a starting point and foundation for future, more extensive studies exploring the attitudes of students from various academic disciplines and institutions.

KEYWORDS
AI in higher education, AI literacy, educational innovation, stem education, student perceptions, survey

1 Introduction

In today's era of increasing study abroad opportunities and intense competition for fewer students, higher education institutions (HEIs) face challenges in attracting more students, retaining them, and improving their success rates. This requires HEI management to seek and implement strategies that enrich student experiences regarding high-quality pedagogical delivery and effective administrative support and increase student motivation. To address these challenges, HEIs and faculty staff are increasingly exploring the possibilities of integrating modern technologies and their benefits for HEIs. The emergence of sophisticated Artificial Intelligence (AI) tools that can synthesize content and perform complex cognitive operations represents an opportunity for transformation in educational paradigms (Elmessiry and

Elmessiry, 2024). Researchers highlight AI's potential to personalize learning paths, tailor educational content and delivery to individual student needs and learning styles, and promote enhanced engagement and knowledge acquisition (Balaquiao, 2024). Furthermore, AI can increase student engagement and accessibility by using AI-driven platforms to create interactive learning environments and expand access to educational resources for diverse student groups (Balaquiao, 2024). Implementing data-driven achievement monitoring and outcome optimization through AI tools allows for tracking student progress, identifying areas for improvement, and refining pedagogical strategies to maximize learning outcomes (Gaftandzhieva et al., 2022). On the other hand, AI offers the potential to automate pedagogical and administrative processes, streamlining routine tasks such as assessment, scheduling, and student support, freeing faculty and administrators to focus on higher-level strategic initiatives (Harry, 2023). Effective implementation of AI in HEIs requires rigorous research and evaluation to ensure ethical considerations, pedagogical efficacy, and the preservation of human-centered educational principles.

The paper explores students' awareness of the possibilities of using AI tools, practical experience of using intelligent tools in education, benefits, potential problems and challenges when using AI in the educational process, ideas and suggestions for using AI tools to improve training and administrative services so that HEIs better meet the needs and preferences of students.

2 Literature review

The rapid integration of AI into people's daily lives has stimulated its use for educational purposes. In recent years, numerous studies across various countries have explored the attitudes of both educators and learners toward the use of AI in education. These studies cover a wide range of aspects – from the opportunities and benefits AI offers for the learning process to concerns related to academic integrity, critical thinking, and the ethical use of technology. The findings from such research can inform decision-making processes aimed at creating a better learning environment in which AI is used appropriately and ethically.

Contemporary empirical studies conducted across diverse national and institutional contexts report predominantly positive student attitudes toward the use of AI in higher education. Students perceive AI tools as beneficial for enhancing learning effectiveness, providing personalized academic support, improving access to educational resources, and increasing motivation and engagement in the learning process (Balogh, 2024; Idroes et al., 2023; Gheție et al., 2025; Katsantonis and Katsantonis, 2024; Khodeir et al., 2024). AI applications are most commonly used for information search and processing, self-study, clarification of learning content, and support for academic tasks, with chatbots being among the most widely used tools (Dobrovská et al., 2024; Grájeda et al., 2023; Ruiz-Rojas et al., 2024; Aydemir and Seferoğlu, 2024). At the same time, the review of the academic literature reveals that learners also express a range of concerns regarding the use of AI. These include disruptions in teacher–student communication, loss of human interaction, and distortion of traditional pedagogical models (Herawati et al., 2024; Balogh, 2024); the erosion of critical thinking skills (Idroes et al., 2023; Saúde et al., 2024; Darwin et al., 2024); excessive dependence on technology (Dobrovská et al., 2024; Al Zaidy, 2024); and covert usage driven by fear of misuse, potential punishment, and pressure to achieve high grades (Shalevska and Kostadinovska-Stojchevska, 2024; Nguyen and Goto, 2024). The moral discomfort associated with the unregulated use of AI by students for completing academic tasks has led to the emergence of the phenomenon known as "AI guilt." In Chan (2024), a study is presented that identifies three core dimensions of AI guilt: feelings of laziness and inauthenticity, fear of judgment, and concerns related to self-perception and identity.

Educators also address numerous risks associated with the improper and unregulated use of AI tools by students. Uncontrolled use of AI by learners raises concerns among instructors about dishonest behaviors and academic misconduct, which may hinder students' academic development (Mohammadkarimi, 2023; Islam et al., 2024). Another significant topic of discussion is plagiarism – intentional or unintentional – which can result from the use of AI tools (Kotsis, 2024; Nguyen, 2023). Students who feel incapable of completing their assignments effectively often turn to AI, believing they lack the necessary skills. This further undermines their confidence and critical thinking abilities, reinforcing their dependence on technology (Chavez et al., 2024; Hur, 2025).

Several studies indicate that, despite students' frequently reported familiarity with AI concepts and tools, their understanding often remains superficial, revealing a discrepancy between perceived competence and actual AI literacy (Jereb and Urh, 2024; Brown et al., 2024). This gap highlights the need for structured guidance, ethical frameworks, and targeted training initiatives.

Studies examining the relationship between students' attitudes, competence, and actual use of AI indicate that cognitive factors – such as understanding the capabilities and limitations of AI – play a more substantial role in predicting awareness and usage than affective or behavioral attitudes alone (Otermans et al., 2025). Students' AI literacy and self-efficacy have been identified as significant predictors of their attitudes toward AI (Asio and Gadia, 2024). Practical, hands-on interaction with AI tools has been shown to strengthen students' confidence, academic performance, and perceived learning effectiveness, while simultaneously increasing their willingness to recommend AI tools to peers (Balogh, 2024; Bation and Pudan, 2024). In some cases, positive attitudes toward AI have also been associated with improved academic outcomes, although the authors emphasize the need for further validation using objective performance indicators.

Comparative studies further reveal systematic differences between students' and instructors' perceptions of AI use in education. While students generally demonstrate greater openness and readiness to adopt AI tools, instructors value AI's role in facilitating teaching, increasing efficiency, and promoting student engagement, but more frequently emphasize ethical risks, academic dishonesty, and potential negative impacts on teaching quality and learning outcomes (Robinos et al., 2024; Buyakova et al., 2024; Stoyanova et al., 2025). These differences point to a misalignment of expectations and underscore the importance of institutional dialogue, shared guidelines, and professional development initiatives to support instructors in adapting to AI-enhanced learning environments.

Another issue explored by numerous researchers concerns the social and psychological effects resulting from the shift in

Abbreviations: HEI, Higher Education Institution; AI, Artificial Intelligence; ANN, Artificial Neural Network; SVM, Support Vector Machine; KNN, K-Nearest Neighbors; RMSE, Root Mean Square Error; MSE, Mean Square Error; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; R2, R-squared or Coefficient of Determination.

learners' interaction – from teachers to AI. This shift hinders the development of essential learner competencies, including challenges to the growth of ethical and communication skills (Lima et al., 2024), collaboration skills (Idroes et al., 2023), and poses risks of alienation and a reduction in the depth of social interactions within the educational process (Vorontsov and Vorontsova, 2024). Replacing direct communication with AI may negatively affect students' motivation, critical thinking, and engagement, potentially fostering passivity (Plattner et al., 2024). In some cases, it has an adverse impact on the social adaptability of children and adolescents, particularly in the absence of family support (Lai et al., 2023). While AI can enhance student engagement and self-confidence, it can also contribute to stress, anxiety, social isolation, and moral dilemmas related to privacy and fairness (Kundu and Bej, 2024). Furthermore, it may encourage superficial understanding of educational content, as students tend to accept information without deep evaluation – negatively affecting their academic development (Kharis and Indriyani, 2024).

The reviewed literature points to a growing consensus that the effective integration of AI in higher education requires more than the mere availability of technology. Higher education institutions are not yet fully prepared for the widespread adoption of AI due to the lack of regulatory frameworks, methodological grounding, and instructional support (Petruneva et al., 2024). Many authors emphasize the need for institutional policies, ethical and legal regulations, transparent data governance mechanisms, and continuous training for both students and academic staff. While most existing studies focus primarily on the use of AI within the learning process, relatively limited attention has been paid to students' attitudes toward AI-supported administrative services, activity tracking, success prediction, and automated student support – gaps that the present study seeks to address.

Systematized information on the reviewed literature sources and their findings is presented in Appendix A.

The conducted literature review shows that over the past two years, there has been a significant increase in research dedicated to the use of AI in education. Numerous studies have been carried out across different countries and educational contexts, involving various target groups, examining the impact of AI on the learning process, learners' and instructors' perceptions, as well as the ethical and pedagogical dimensions of its application. These studies provide a valuable foundation for understanding the current state and global trends stemming from the potential for AI integration in education.

However, the rapid pace of technological development and the specific characteristics of educational systems underscore the need for new research that reflects the current state of awareness and attitudes among students and educators.

The present study aims to explore comprehensively:

1 Students' level of awareness regarding AI and its capabilities;
2 Students' practical experience with the use of AI tools in the educational process;
3 Students' opinions on the benefits and limitations of AI technologies in education;
4 The problems and challenges they face in using AI, including ethical dilemmas and academic dishonesty; and
5 Students' ideas and suggestions for more effective and meaningful use of AI in education.

This research is motivated by the need to develop educational strategies and policies that are aligned with the needs, expectations, and real-life experiences of students and instructors within the context of the digital transformation of education.

3 Materials and methods

This section presents the research questions, details about the study design – including its objectives, data collection methods, measurement instruments, participants, data analysis techniques, and other relevant aspects.

3.1 Study design

The study is organized as a cross-sectional, quantitative survey aimed at analyzing students' attitudes, experiences, and perceptions regarding the use of artificial intelligence in education. Data were collected at a single point in time using a standardized questionnaire and analyzed using classical statistical methods and machine learning models. The quantitative research design was chosen in view of the study's objectives, which include measuring clearly defined latent constructs and examining the relationships between them using numerical indices and formalized analytical models. This approach allows for an objective assessment of the level of awareness, practical use of AI tools, perceived benefits and risks, and attitudes toward their innovative application in the educational process. The design used is consistent with the applied data processing and analysis methods, including the calculation of aggregate index values, correlation analysis, and the application of artificial neural networks. In this way, methodological consistency is ensured between the data collection process, analytical techniques, and formulated conclusions, while the study retains its quantitative nature and analytical rigor.

3.2 Research questions

The development of AI in recent years has opened up many opportunities to innovate education, including easier access to new learning technologies, personalized curricula, automated feedback, and innovative tools for learners' self-study. Despite these potential benefits, the effectiveness of AI integration in education largely depends on how well students understand both the opportunities and the risks associated with this technology. Confirming this relationship would imply that educational institutions investing in awareness-raising initiatives – such as training sessions, seminars, and best practice sharing – can expect higher levels of student engagement and more effective use of AI in the learning process. Based on this, the following research question is proposed:

> *RQ1:* Is students' level of awareness regarding the use of AI in education positively correlated with their confidence and actual use of AI tools?

Learners' awareness of AI capabilities is a prerequisite for its use. What significantly influences the development of confidence and the enhancement of skills in the context of modern education is real, hands-on experience. The hypothesis that the level of practical experience with AI is positively related to students' confidence, academic performance, and willingness to recommend AI tools to others deserves careful investigation. Confirming this relationship would demonstrate that practical interaction with AI – through self-study, the use of chatbots, personalized learning platforms, and other tools – not only improves learning effectiveness but also builds a strong sense of competence and initiative among students. This leads to the following research question:

> *RQ2:* Is the level of practical experience with AI in education positively related to students' confidence, academic performance, and their willingness to recommend AI tools to others?

Recognizing and acknowledging the benefits that students can gain from using AI in education is a key factor for the sustainable adoption of AI. The hypothesis that greater recognition of AI's educational benefits is positively related to students' preferences for using innovative, AI-based learning methods is central to analyzing this process. If students identify specific advantages such as personalized learning, progress tracking, instant feedback, and increased motivation, it is reasonable to assume that this positive perception will influence their choice of learning methods. Based on this, the following research question is formulated:

> *RQ3:* Is the awareness of the benefits of AI in education positively related to students' preferences for using innovative, AI-based learning methods?

Students' concerns about the potential negative consequences of using AI in education deserve special attention, as they are active participants in the learning process. These concerns may involve the perceived loss of personal contact with instructors, automated assessment without teacher oversight, fear of misusing AI resources, and more. Identifying the risks highlighted by students can support the development of balanced strategies for integrating AI into educational systems. This approach can help address the real needs and concerns of the student community. This motivates the following research question:

> *RQ4:* Do students perceive the use of AI in education as associated with a number of significant risks, including the reduction of critical thinking, ethical issues, and the potential for academic misconduct?

The younger generation views AI not only as a tool for improving efficiency but also as an opportunity for more personalized, accessible, and high-quality education. Exploring students' visions for the future integration of AI in education could provide a foundation for developing innovative educational practices driven by students' needs. Their expectations may help identify areas where AI is still underutilized or where its potential has yet to be realized. This leads to the following research question:

> *RQ5:* Do students support the potential for more meaningful and innovative use of AI in education and consider it necessary for improving the learning process?

3.3 Instrument development and validation

The data for the study were collected using a custom-designed survey questionnaire. The questionnaire was developed in several stages and is based on a clear theoretical basis derived from the systematic literature review presented in Section 2. The analysis of contemporary research devoted to the use of AI in education allowed the identification of key thematic areas that are consistently present in the empirical models used in various educational and cultural contexts. In this regard, when constructing the questionnaire cognitive, behavioral and affective aspects of students' attitudes towards AI, as well as the practical and ethical dimensions of its application, were taken into account.

Based on the literature analysis, five main latent constructs were defined, which summarize the leading dimensions of the research problem. These include:

(1) level of awareness and information about the possibilities and limitations of AI in education;
(2) practical experience and real use of AI tools in the learning process;
(3) perceived benefits of using AI technologies;
(4) perceived risks, problems and challenges associated with the use of AI;
(5) attitudes towards innovative and more effective integration of AI in education.

Each of these latent constructs was conceptually defined based on previous empirical research and adapted to the specifics of higher education and the profile of the studied student population.

The initial version of the questionnaire included 40 statements, formulated to cover the content of each of the five constructs maximally. When formulating the individual questions, a combination of clarity, unambiguousness and substantive adequacy was sought, and the statements were aligned with the use of a five-point Likert scale. The initial set of questions served as the basis for a subsequent process of expert evaluation and refinement of the instrument, which led to the final version of the questionnaire.

The validation of the content of the developed questionnaire was carried out through an expert review, the aim of which was to ensure the conceptual correctness, clarity and relevance of the included statements to the defined latent constructs. The expert evaluation process involved specialists in the field of artificial intelligence, educational technologies and pedagogy in higher education, with practical and research experience related to the application of AI in education. The experts were asked to assess each statement in terms of its clarity of formulation, substantive adequacy, unambiguity and degree of correspondence with the construct it aims to measure. In addition, it was analyzed to what extent the individual questions sufficiently cover the relevant thematic areas and whether any significant aspects were missing that could affect the instrument's completeness. As a result of the expert review, targeted corrections were made to the initial version of the questionnaire. Five of the statements were reformulated to increase their clarity and eliminate potential ambiguities that could make interpretation difficult for respondents. Additionally, 16 new statements were included, which expanded the content coverage of the individual latent constructs, especially with regard to the practical use of AI tools, perceived risks and attitudes towards their innovative application in education. The changes made contributed to improving the overall structural logic of the questionnaire, to better balancing the number of statements in the individual scales and to increasing the content validity of the instrument. In this way, the final version of the survey provides a more accurate and reliable measurement of the studied latent constructs, while maintaining its applicability and comprehensibility for the target student audience.

The final questionnaire consists of 50 questions organized into six sections.

The items in Section 1. Participant Profile aim to gather demographic information about the respondents, including gender, age, year of study (1st, 2nd, 3rd, or 4th), and academic major. The items in the remaining sections address the core indicators under investigation:

Section 2. Level of Awareness – 7 statements

Section 3. Practical Experience – 9 statements

Section 4. Perceived Benefits of Using AI Tools – 10 statements

Section 5. Potential Problems and Challenges – 9 statements

Section 6. Ideas and Suggestions for More Effective Use of AI Tools – 11 statements

A 5-point Likert scale was used to measure students' level of agreement with the statements (1 – Strongly disagree; 2 – Disagree; 3 – Neither agree nor disagree; 4 – Agree; 5 – Strongly agree). To ensure a complete dataset for quantitative analysis, all questions in the questionnaire were mandatory. Statements covered in Sections 2–6 are presented in Appendix B.

The developed questionnaire was created using Google Forms. Utilizing an online survey for conducting the study offers several advantages. Online questionnaires enable quick and easy access to a large number of respondents. Participants can complete the survey at any time and from any location, which significantly increases the likelihood of participation and the collection of more responses. Additionally, the results are collected automatically and are available immediately upon completion of the survey, saving time in the data analysis process.

Before completing the questionnaire, participants were informed about the purpose of the study, how their data would be used, and were asked to complete an informed consent section confirming their voluntary participation. Participation in the study was anonymous, which encouraged respondents to provide more open and honest answers.

Before the final distribution, an initial test was conducted with a limited number of respondents to check the comprehensibility of the wording, the logical sequence of the questions and the overall functionality of the tool. The primary goal of this stage was not a statistical evaluation, but to identify potential problems related to unclear or ambiguous statements, as well as difficulties in completing the survey. As part of this initial test, the approximate time to complete the questionnaire and the perceived respondents' workload were also assessed. The feedback showed that the survey's structure was logical and consistent, and the five-point Likert scale used was intuitive and easy for students to use. As a result of the initial test, minor edits were made to improve the linguistic clarity and refine the wording of individual statements. These adjustments do not change the conceptual structure of the questionnaire and the defined latent constructs, but minimize the risk of different interpretations and increase the reliability of the collected data. After making these adjustments, the questionnaire was finalized and used in the main empirical study.

To assess the internal consistency and reliability of the developed questionnaire, a reliability analysis was conducted using Cronbach's Alpha coefficient. This indicator is widely used in social and educational research to assess the degree to which individual statements within a scale measure the same latent construct.

The Cronbach's Alpha coefficient was calculated separately for each of the five multi-item scales corresponding to the defined latent constructs: level of awareness, practical experience, perceived benefits, perceived risks and attitudes towards innovations. The analysis was performed on the full dataset collected within the framework of the main empirical study.

When interpreting the results, generally accepted methodological criteria were used, according to which Cronbach's Alpha values $\alpha \geq 0.70$ are considered an indicator of satisfactory internal consistency, and values $\alpha \geq 0.80$ – for good reliability of the scale. These thresholds are widely accepted in the literature and provide a basis for using average index values in subsequent statistical and machine learning analysis. We calculate Cronbach's Alpha according to the formula (Cronbach, 1951) (Equation 1):

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_{total}^2}\right) \tag{1}$$

where k is the number of questions in the respective scale, σ_i^2 is the variance of each question, and σ_{total}^2 is the variance of the total score on the scale. The results are reported as follows (Suárez-Lantarón et al., 2023; Botello-Hermosa et al., 2024; Steingräber et al., 2025):

- $\alpha \geq 0.70$: acceptable internal consistency;
- $\alpha \geq 0.80$: good internal consistency;
- $\alpha \geq 0.90$: very high internal consistency, but sometimes even considered excessive and leading to doubts about repeatability, i.e., statistically, the questions are almost interchangeable (Tavakol and Dennick, 2011).

The Cronbach's Alpha values obtained for all scales indicate that the included statements demonstrate adequate internal consistency and can be combined into the corresponding indices (see Table 1).

The high consistency in the heterogeneous cognitive domain Awareness (knowledge, understanding, awareness) shows that students perceive AI awareness as a coherent concept, and not as fragmented knowledge. The lowest, but still acceptable, value of Cronbach's Alpha is observed in the Experience part. This is logical since the scale includes real behavioral practices (independent

TABLE 1 Cronbach's Alpha for individual scales.

Scale	Cronbach's α	Interpretation of the internal consistency
Awareness	0.835	Good
Experience	0.760	Acceptable
Benefits	0.837	Good
Risk	0.857	Very good
Innovation	0.786	Acceptable

work, confidence, recommendation, support from teachers), and different forms of experience do not always manifest themselves simultaneously. We believe that the low value here is not a weakness, but a reflection of real variability in behavior. Benefits also has good consistency, which means that students perceive the benefits of AI as a clearly structured and stable whole, something that, by the way, justifies the strong relationship between Benefits and Innovation, which we subsequently analyzed. The highest value of Cronbach's Alpha is in the Risk part of the questions. It shows that risks (ethics, honesty, critical thinking, security) are perceived as systematically related. In our opinion, this is a strong argument that students are aware of the complexity of risks, and do not perceive them fragmentarily. We also have stable consistency for the Innovation scale, which includes future attitudes, contains normative and visionary elements. This suggests moderate but consistent support for innovation—this conclusion is reached and described later in Section 4.5.

Ultimately, as a result of the reliability analysis, no need was found to exclude individual statements from the scales, since all included questions contribute positively to the internal consistency of the relevant measurements.

3.4 Methods of analysis

In the present study, which evaluates students' attitudes, experiences, and perceptions regarding the use of AI in education, a purely quantitative analytical approach was applied, which combines classical statistical techniques (such as histograms, boxplot diagrams, and correlation analysis) with modern machine learning methods to analyze the numerical data collected. This multilayered analytical approach allows for the objectivity of quantitative measurements to be complemented by the depth of modeling complex interrelationships in the data.

To quantitatively assess participants' responses by section, five index values were calculated (Table 2): Awareness (A), Practical Experience (P), Benefits (B), Risk (R), and Innovation (I). The indices were computed using the following formula (Equation 2):

$$\widetilde{Ind}_k = \frac{\sum_{i=1}^{n} Ind_{k,i}}{n} \tag{2}$$

where:

- k is the number of each respondent in the survey $(k = 1,2,\ldots,138)$,
- i is the sequential number of the question $(1,2,\ldots,n)$ within the respective section of the questionnaire,
- n is the number of questions in that section.

In practice, $\widetilde{Ind}_k$ represents the average value of a student's responses to all questions in a given section and can take real values from 1 to 5. The resulting index value is interpreted as follows:

- $\widetilde{Ind}_k \in (1,2]$ – Low level;
- $\widetilde{Ind}_k \in (2,3]$ – Moderate level;
- $\widetilde{Ind}_k \in (3,4]$ – Good level;
- $\widetilde{Ind}_k \in (4,5]$ – High level.

Table 2 presents the correspondence between the research questions, the sections of the survey questionnaire, the statements, and the indices used for quantitative evaluation.

A thorough analysis was conducted for all sections of the survey, with each statement matched to a corresponding criterion. To enable numerical processing and analysis, an index was calculated for each section of the questionnaire.

Histograms are a graphical tool used to display the distribution of data by grouping values into intervals. They allow for quick identification of trends, dominant values, and potential deviations or anomalies in students' responses. In the context of this study, histograms were used to visualize the distribution of the main indices (awareness, practical experience, perceived benefits, perceived risks, and innovation-related attitudes) and to detect dominant groups and patterns within the data.

Boxplot diagrams were employed to visualize the central tendency, dispersion, and potential outliers in the data. They provide an effective means for comparing the median, variability, and anomalies across different student groups (by gender, year of study, and academic program), thereby highlighting both within-group and between-group variation.

Correlation analysis (based on Pearson's correlation coefficient) was used to evaluate the strength and direction of relationships between the various indices and criteria. This analysis provides a basis for identifying hidden patterns in students' attitudes and behaviors. The results of the correlation analysis may inform the formulation of hypotheses about causal relationships, which can be tested in future, more targeted studies. To ensure the reliability of the conclusions and to avoid misleading interpretations, the statistical significance of the observed correlations was also examined.

To uncover internal structure in the data, segment objects into meaningful groups, and generate new insights applicable across different areas, cluster analysis was performed.

In addition, ANNs were applied to model nonlinear dependencies and to reveal complex patterns that are not easily detectable through classical statistical methods. ANNs provided valuable insights into the influence of factors such as awareness, gender, year of study, and academic discipline on students' confidence and actual use of AI.

To explore the structure of decision-making and identify the most important factors influencing student behavior, the performance of classification trees, Random Forests, Support Vector Machines

TABLE 2 Research questions, sections of the survey questionnaire, statements, and indices.

Research question	Survey section	Survey statements	Evaluation index
R1	S2	$A_1 - A_7$	Awareness ($\tilde{A}_k$)
R2	S3	$P_1 - P_9$	Practical Experience ($\tilde{P}_k$)
R3	S4	$B_1 - B_{10}$	Benefits ($\tilde{B}_k$)
R4	S5	$R_1 - R_9$	Risk ($\tilde{R}_k$)
R5	S6	$I_1 - I_{11}$	Innovation ($\tilde{I}_k$)

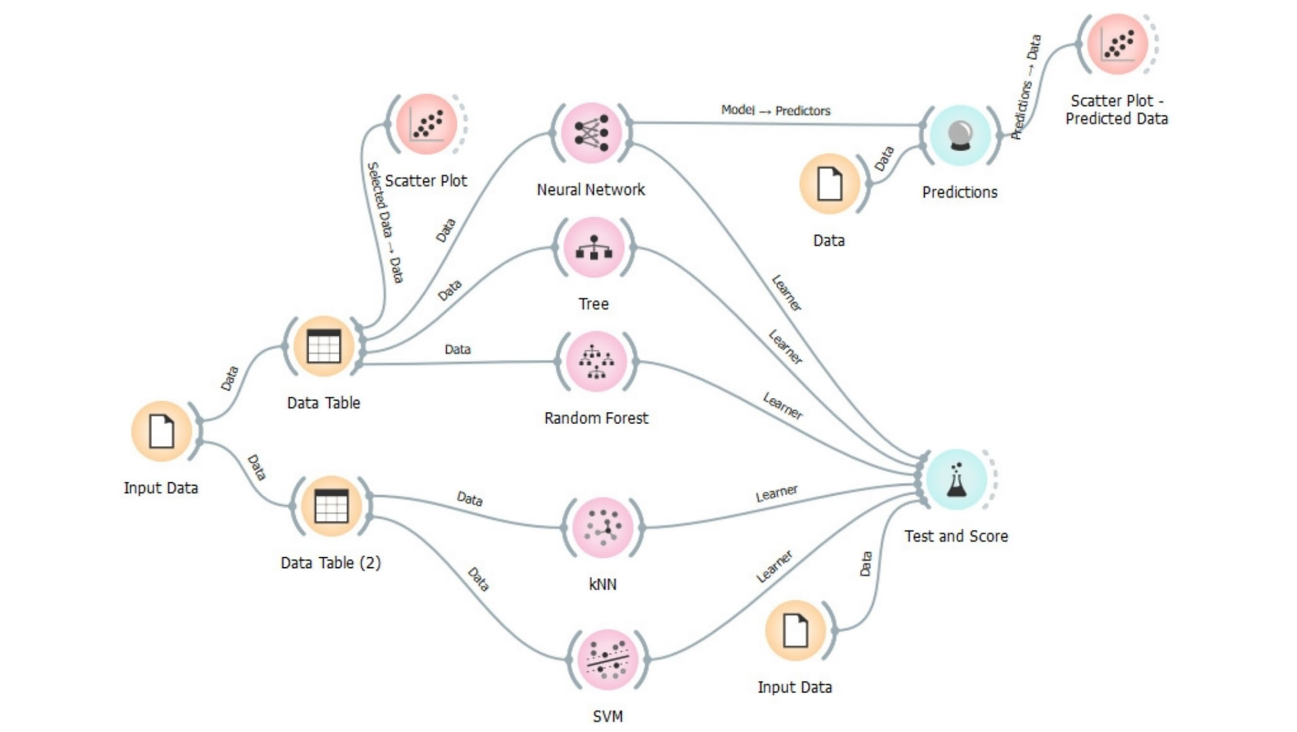

FIGURE 1
Workflow diagram in the orange data mining environment (Orange v.3.25).

(SVMs), and K-Nearest Neighbors (KNN) was tested and compared to that of ANNs.

In order to conduct a more in-depth analysis of students' responses, uncover hidden patterns, behavioral models, and socio-psychological profiles, various machine learning models were applied, including ANNs, using platforms such as MATLAB and Orange Data Mining. To track emerging trends, a system of models was developed within the Orange Data Mining environment (Figure 1).

The responses collected from the survey were preprocessed to ensure standardization. For example, when students indicated their field of study using variations such as "BIT," "bit," "Business and Information Technologies," or other similar terms, all were unified under the standardized label "BIT." This step was necessary to assist the software in treating them as one category rather than different disciplines. After preprocessing, the data were imported into the Input Data module, where the roles of the individual components were also configured.

All data processing methods were selected with the research goal in mind: to achieve a balance between the quantitative rigor of classical statistical analysis and the ability of machine learning to detect complex, nonlinear relationships. Classical statistical approaches provide transparency and straightforward interpretation of fundamental patterns, while machine learning models allow for deeper exploration of the data and identification of trends that might otherwise remain hidden.

Based on the results, concrete recommendations were formulated for the academic community – on how to foster innovative thinking, how to support students with polarized attitudes, and how to leverage personal experience as a pedagogical resource. Although the study places strong emphasis on the statistical processing of the survey data, it also addresses the psychological and social dimensions of students' perceptions – ranging from gender differences in the assessment of academic risks to the diverse motivational mechanisms behind students' openness to innovation.

3.5 Participants

Students from two faculties of Plovdiv University "Paisii Hilendarski" – the Faculty of Mathematics and Informatics and the Faculty of Physics and Technology – enrolled in bachelor's degree programs, were invited to participate in the survey. The study targeted students from these faculties for several reasons. First, they study technology-related disciplines and are therefore expected to have a deeper understanding of AI principles, algorithms, and development methods compared to students from other fields. As a result, they are likely to be more open to the adoption of new technologies. This background allows them to provide informed opinions about the potential applications and risks of AI, as well as innovative ideas for using AI in education.

All students received an email invitation to participate in the study. A total of 138 students participated in the survey, ranging in age from 18 to 39 years, including 86 men and 52 women (Table 3). All participants gave their consent for data processing, and participation in the study was anonymous. The distribution of participants across academic years was relatively even, with first-year students being the most represented (34.1%) and second-year students the least (16.7%).

4 Results

4.1 Students' level of awareness regarding the use of AI tools in education

To examine students' level of awareness regarding the possibilities of using AI, the responses to the questions in Section 2 (A_1–A_7) were analyzed, and the awareness index $\tilde{A}_k$ was calculated. The survey

TABLE 3 Participant profile.

Characteristic	Value	Number	Percentage
Gender	Male	86	62.3
	Female	52	37.7
Year of Study	1	47	34.1
	2	23	16.7
	3	29	21
	4	39	28.3

results indicate a high level of technological awareness. A large portion of students (40 students, 29%) demonstrated a very high awareness index [$\tilde{A}_k \in (4.5,5)$] (Figure 2a).

The analysis of individual criteria (Figure 2b) confirms that students are well-informed about the benefits of AI applications across different disciplines (A_1), are familiar with various software tools (A_2), and are aware of both the real benefits (A_3) and the risks associated with the misuse of AI tools (A_4). Fewer students reported participating in discussions with peers and instructors regarding the use of AI in education (A_6). This moderate engagement does not indicate a lack of interest, but rather reflects social and psychological barriers, such as insecurity or limited experience in openly discussing emerging technologies. Nevertheless, even this criterion demonstrates an impressive average awareness level of 3.54, suggesting that students' knowledge of technological advancements increasingly goes beyond the traditional classroom setting.

Of particular interest in this study is the internal interrelation among the awareness criteria (A_1–A_7). The results of the correlation matrix (Figure 2c) highlight several meaningful associations, showing that increased knowledge in one area tends to trigger awareness in another – much like a chain reaction (Equation 3):

$$(A_1 <-> A_3),(A_2 <-> A_3) \text{ и } (A_2 <-> A_5) \tag{3}$$

Pearson's correlation coefficient was used to analyze the relationships, revealing a moderate strength of positive correlations. For example, greater familiarity with different AI software tools (A_2) is associated with better awareness of their safe use in education (A_5). The correlation matrix shows that an increase in awareness in one criterion correlates with increases in others, suggesting a chain reaction of conscious knowledge acquisition. All extracted p-values (Figure 2d) are below the accepted significance level of $\alpha = 0.05$, which ensures 95% confidence in the established correlations and indicates that they reflect actual cognitive processes rather than random chance.

The analysis of the results shows that students in higher years of study feel more informed about the benefits of AI (Figure 3). The median awareness index for first-year students is lower than that of students in all other years. These results are expected, as upper-year students have had more opportunities to encounter AI in their education, whereas first-year students have accumulated less practical experience. When interpreting the boxplot diagram, it is important to consider the psychological context. The survey was conducted only three to four months after the start of the academic year, which may explain the more cautious self-assessments of awareness by first-year students, likely due to their search for security in the new academic environment. Interestingly, one first-year student reported significantly lower awareness, marked in the diagram as an outlier beyond the interquartile range (indicated with a "+" in Figure 3). As students progress in their studies, their confidence and sense of awareness tend to increase, likely leading to greater willingness to experiment, deeper understanding, and more knowledge sharing.

Male and female students exhibit similar levels of AI awareness and are distributed almost symmetrically across the clusters formed based on the awareness index (Figure 4a). There are no significant differences, distinct gender-based extremes, or dominant trends, which indicates a shared culture of technological awareness among students. This consistency in awareness is also observed when comparing responses from students in different academic programs (Figure 4b). Overall, students demonstrate comparable levels of understanding and knowledge of AI. However, slight uncertainty is noticeable among students from the programs "Business Information Technologies" and "Information and Computer Engineering", with some students giving less confident responses. This should not be viewed as a weakness but rather as an indicator of the need for support and encouragement, particularly for students who, despite being in technology-oriented programs, have not yet fully engaged with AI tools.

To uncover deeper interrelationships, the internal structure of the awareness index was analyzed by comparing factors such as gender, age, year of study, and field of study with each of the seven criteria (A_1 –A_7). A particularly interesting insight from this analysis is illustrated in Figure 5, which shows the cluster distribution of students based on their responses to criterion A_6: "I have discussed different possibilities for using AI in my education with peers and/or instructors."

The analysis of the mean values for this criterion reveals a slight gender difference: female students show a lower tendency to engage in discussions about AI with instructors and peers. From a socio-psychological perspective, this may be interpreted as a result of greater tendency toward internal reflection, a heightened sense of vulnerability when sharing ideas, or a stronger need for confidence before participating in discussions about technology. It is important to emphasize that this difference does not indicate a weakness among women, but rather reflects the natural diversity in social engagement and interpersonal communication styles typically observed between genders.

During the course of the study, multiple experiments were conducted. However, due to space limitations in the current article, it is not possible to present all of them in full detail. Therefore, only a selection is demonstrated here. The featured experiment focuses on students' confidence in using AI tools. The target variable is the students' response to the question: "I feel confident when using AI tools in my learning."

The input variables for the models included the awareness index, gender, age, and field of study. The Test and Score module was used for error evaluation, revealing that the ANN produced the lowest deviation from the actual data, with a root mean square error (RMSE) of 1.034 (Figure 6). The ANN consisted of three hidden layers with 10, 30, and 100 neurons, respectively. This architecture was determined to be optimal after experimenting with different layer and unit configurations. Through experimentation, gradient descent was identified as the most suitable training method, resulting in a 9.7% lower error compared to the Quasi-Newton method and a 10.3% lower error compared to the Adam optimizer. The transfer function used in the neuron bodies was the hyperbolic tangent, and the number of training epochs was set to 1,000.

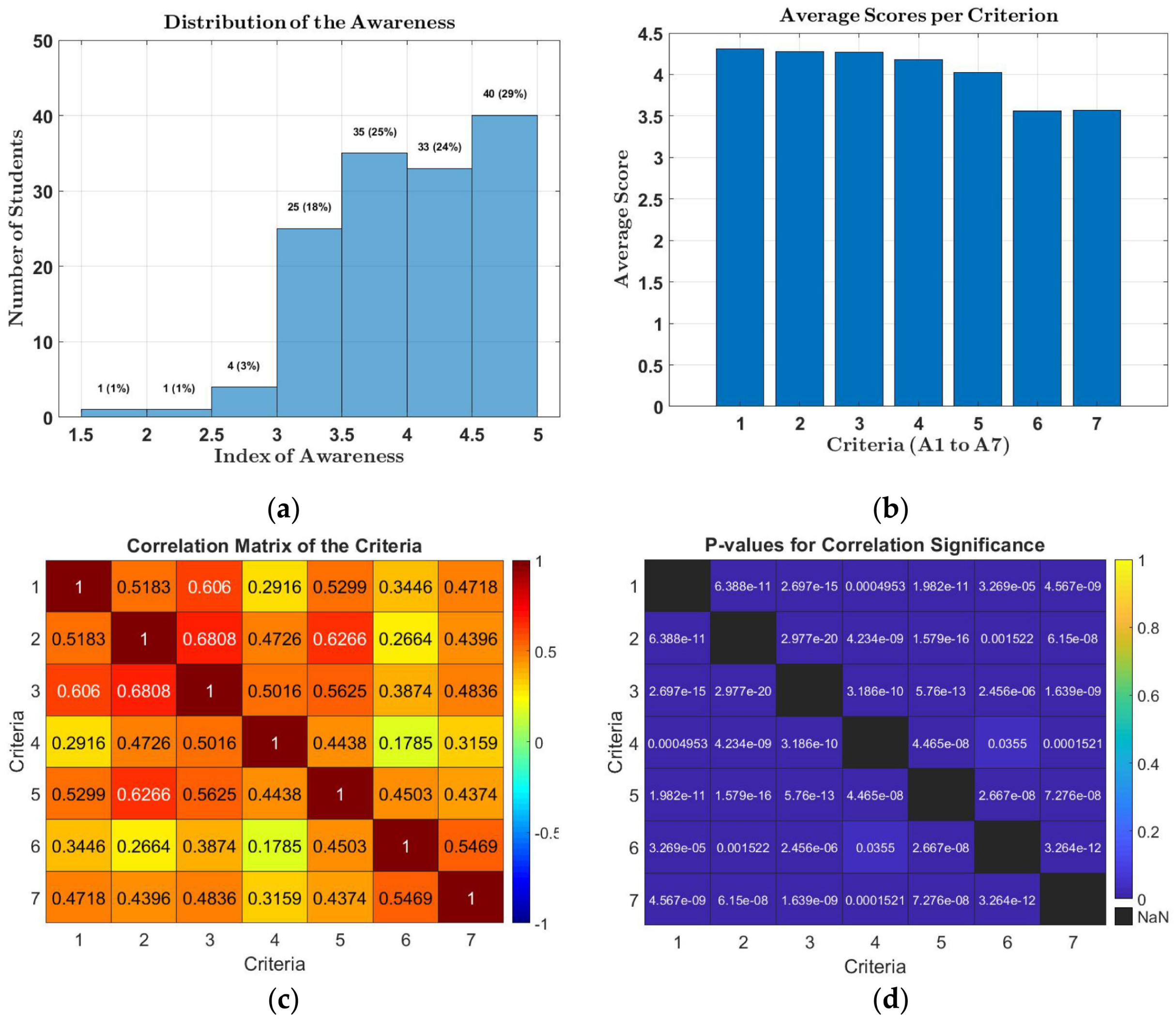

FIGURE 2
Analysis of the results for the awareness index: **(a)** histogram of the awareness index; **(b)** mean value of each criterion; **(c)** correlation matrix of the criteria; **(d)** significance of correlations between criteria (Matlab v.2018a).

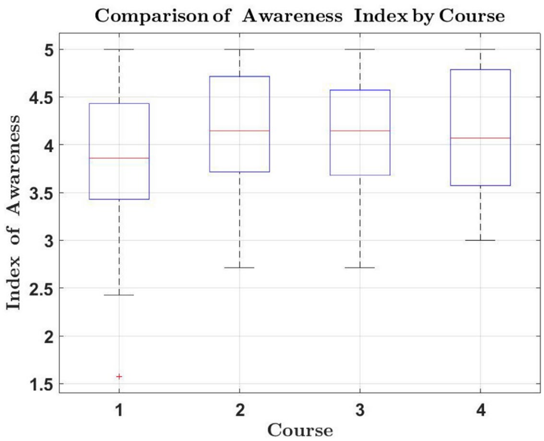

FIGURE 3
Boxplot comparing the awareness index across different years of study (Matlab v.2018a).

Figure 7 illustrates the relationship between students' confidence in using AI and the factors of gender, age, academic program, and awareness index. According to the ANN model, gender is not a determining factor for students' confidence in using AI (Figure 7a) – confidence and hesitation appear almost symmetrically across men and women. The analysis of the relationship

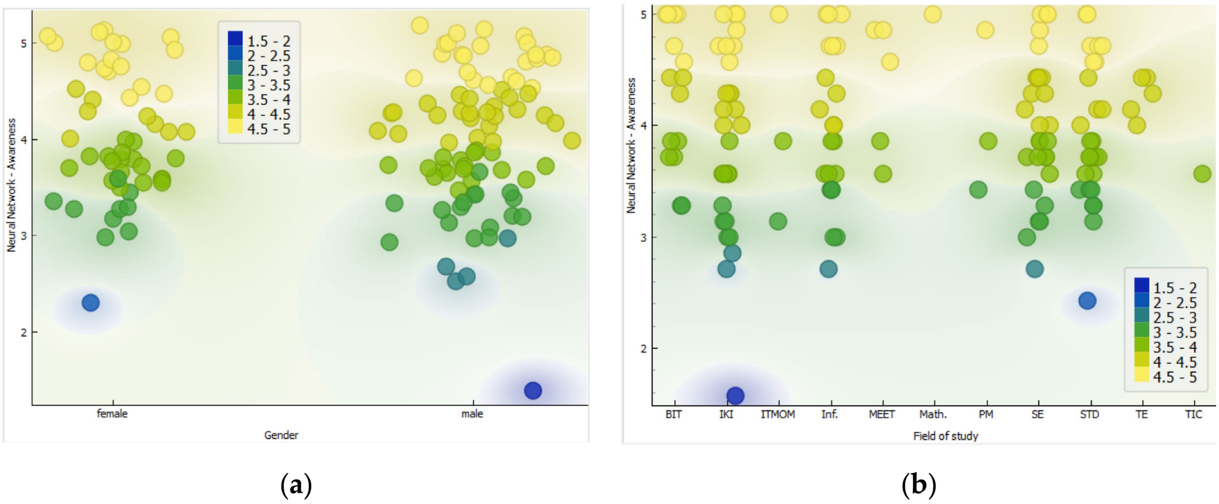

FIGURE 4
Analysis of the awareness index: **(a)** gender; **(b)** professional field (Orange v.3.25).

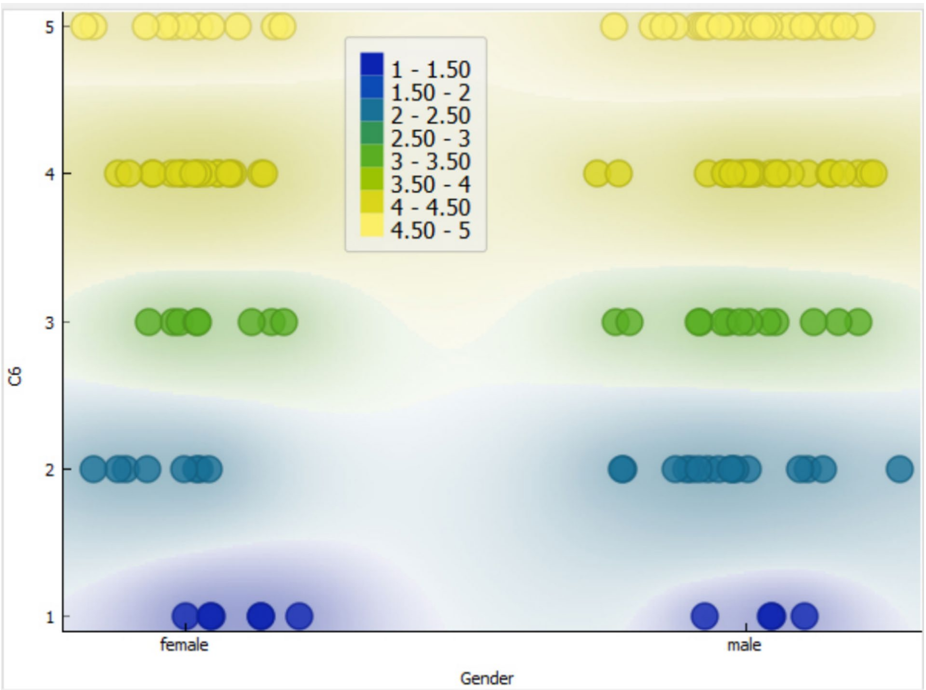

FIGURE 5
Segmentation of criterion A_6 (Orange v.3.25).

Model	MSE	RMSE	MAE	MAPE	R2
Neural Network	1.070	1.034	0.821	0.324	0.114
Tree	1.479	1.216	0.901	0.351	-0.225
Random Forest	1.345	1.160	0.909	0.346	-0.114
kNN	1.113	1.055	0.847	0.338	0.078
SVM	1.193	1.092	0.838	0.345	0.013

FIGURE 6
Training errors of the models (Orange v.3.25).

between confidence and year of study shows that some students from different academic years exhibit a degree of uncertainty. Lower levels of confidence are observed in two students from the first and second year, as well as in two female students from the fourth year (Figure 7b).

The most significant relationship is between the awareness index $\tilde{A}_k$, formed from criteria A_1–A_7, and students' confidence in using AI (Figure 7c). The graph shows that confidence is not directly related to gender or year of study, but rather to the student's level of awareness. At every level of confidence (represented on the ANN y-axis), there are students from men and women and all academic years. At the same time, the graph clearly demonstrates a

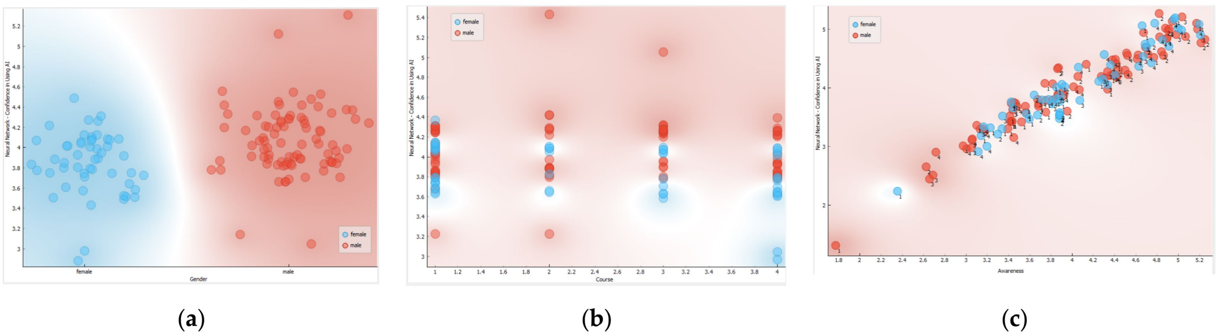

FIGURE 7
Students' confidence in using AI based on the trained ANN: **(a)** gender; **(b)** gender and year of study; **(c)** awareness index (Orange v.3.25).

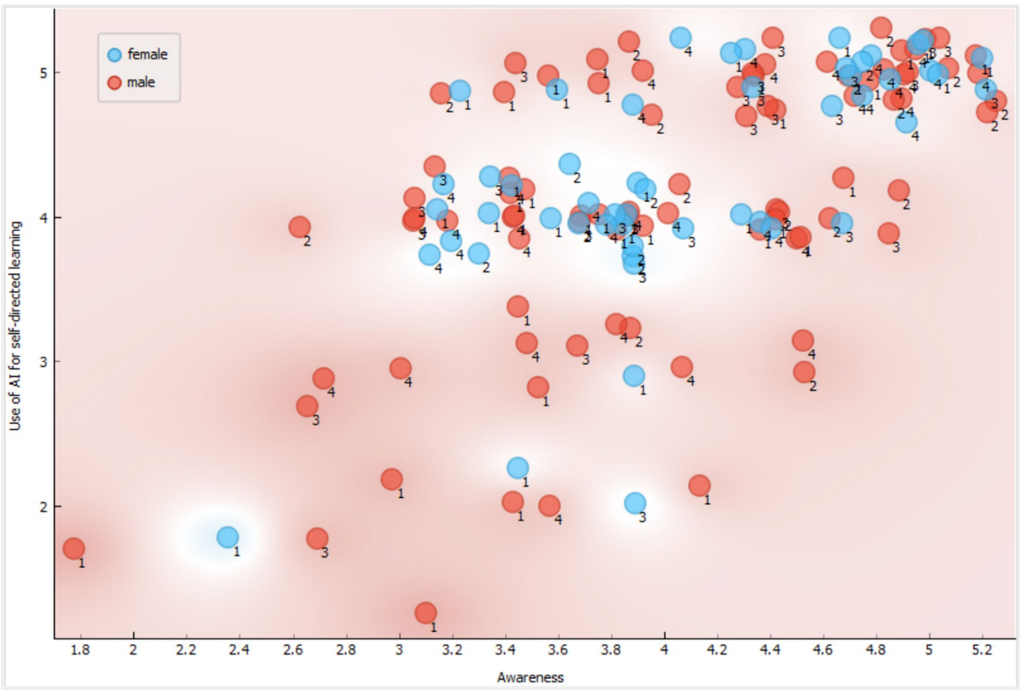

FIGURE 8
Use of AI for self-study (including coursework and homework) based on the trained ANN, according to students' awareness index (Orange v.3.25).

nearly linear correlation between increasing confidence and a higher awareness index.

Similar results are observed in the analysis of responses to the question: "I have used AI for self-study (including for coursework and homework)." Using the same input variables (gender, age, field of study, and awareness index), a strong relationship was identified between actual use of AI for academic purposes and the awareness index (Figure 8).

The graph clearly shows that across different levels of AI usage (on the y-axis), students are nearly evenly grouped by gender and year of study, indicating that neither gender nor academic year is a determining factor in whether a student has already used AI in their learning. However, the distribution along the x-axis reveals that awareness of the benefits and risks of AI use is a determining factor – as awareness increases, so does the actual usage of AI tools.

4.2 Level of practical experience with AI in education

To analyze students' practical experience with AI, the responses from Section 3 (P_1–P_9) were evaluated, and the practical experience index $\tilde{P}_k$ was calculated. The analysis reveals a moderate self-assessment by students regarding their hands-on experience with AI (Figure 9a). Most students rated their experience as fairly good (27%, 37 students) or good (38%, 53 students), while only 12% (17 students) considered their practical experience to be excellent. It was observed that 9% of students had an index below 3, indicating that they do not actively use AI. The reasons for this may vary: insufficient awareness of AI's capabilities, technical difficulties, skepticism, or a lack of interest. These findings emphasize the need for universities to continue integrating AI into the educational process by providing training, technical support, and accessible resources. In the long term, such

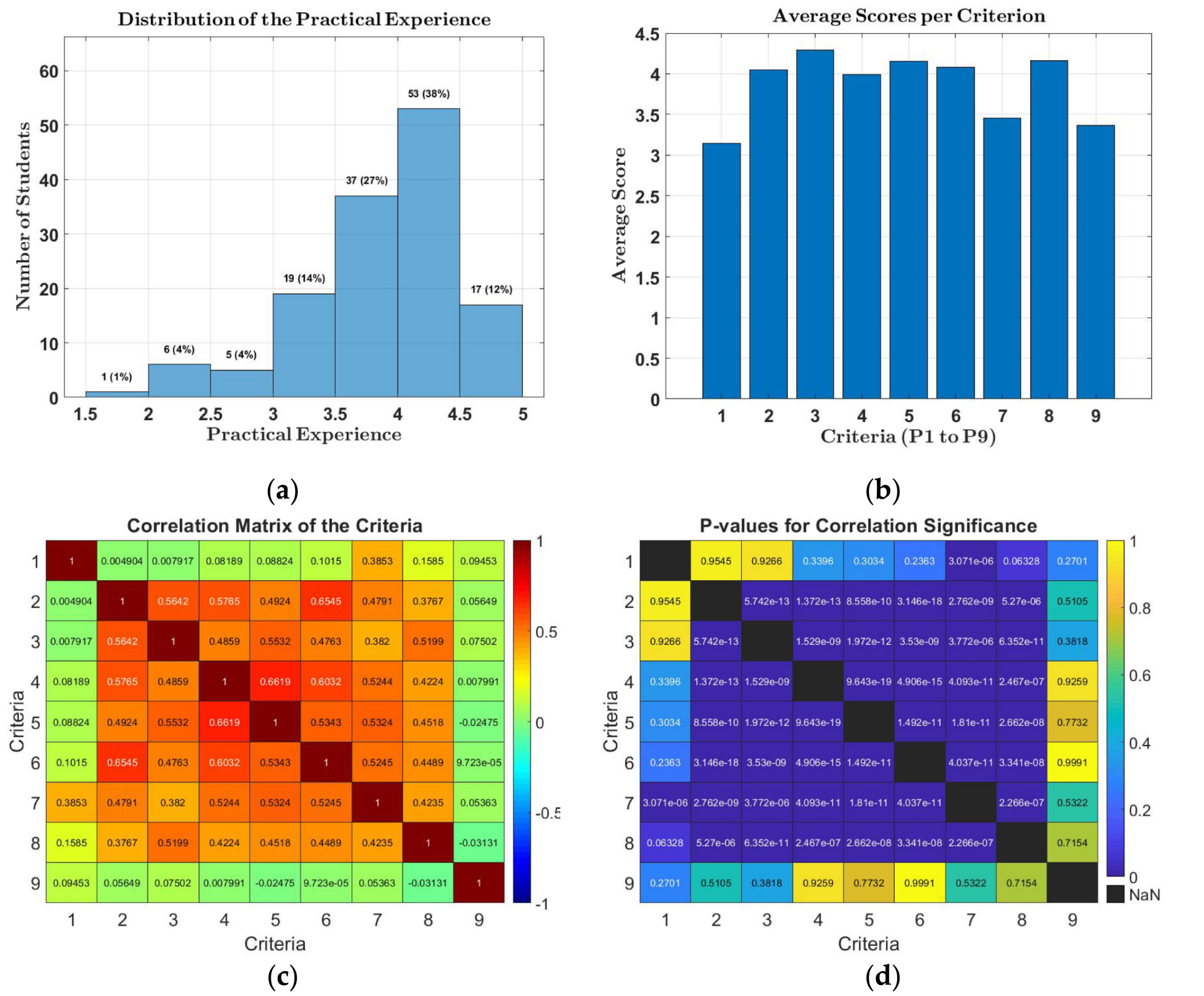

FIGURE 9
Analysis of the results for the practical experience index: **(a)** histogram of the practical experience index; **(b)** mean value of each criterion; **(c)** correlation matrix of the criteria; **(d)** significance of correlations between criteria (Matlab v.2018a).

efforts can contribute to more effective and innovative learning and ensure equal access to technology for all students.

When assessing students' levels of practical experience across the individual criteria (P_1 to P_9), their performance appears to be relatively consistent (Figure 9b). For nearly all criteria, students – as a unified group – reported having relatively high levels of practical experience, with scores around or above 4. The survey results reveal that students have the most experience using chatbots to search for information related to the learning process (P_3), which they rated 4.29 out of 5. Their enjoyment in working with AI (P_8) was also rated highly. The lowest score was given to the criterion regarding support from instructors in recommending the use of AI tools (P_1), with a score of 3.14 out of 5. This is somewhat understandable, given that many instructors prefer to assess students' individual capabilities. On the other hand, it suggests that most students engage with AI on their own initiative, which may also explain the lower score for P_7 – students are less likely to recommend AI to their peers, possibly because their use of AI is a personal, self-directed activity.

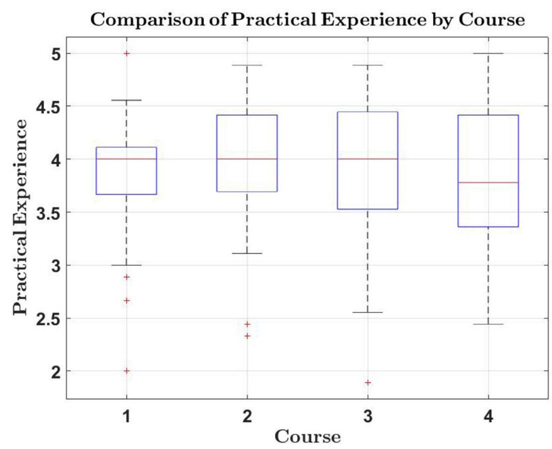

FIGURE 10
Practical experience by year of study (Matlab v.2018a).

The analysis of the relationships between different aspects of students' practical experience revealed several interesting correlations (Figure 9d). A particularly strong positive correlation was observed between P_4 (feeling confident when using AI) and P_5 (improved learning effectiveness). This suggests that students who perceive AI tools as effective are more likely to feel confident when using them. The

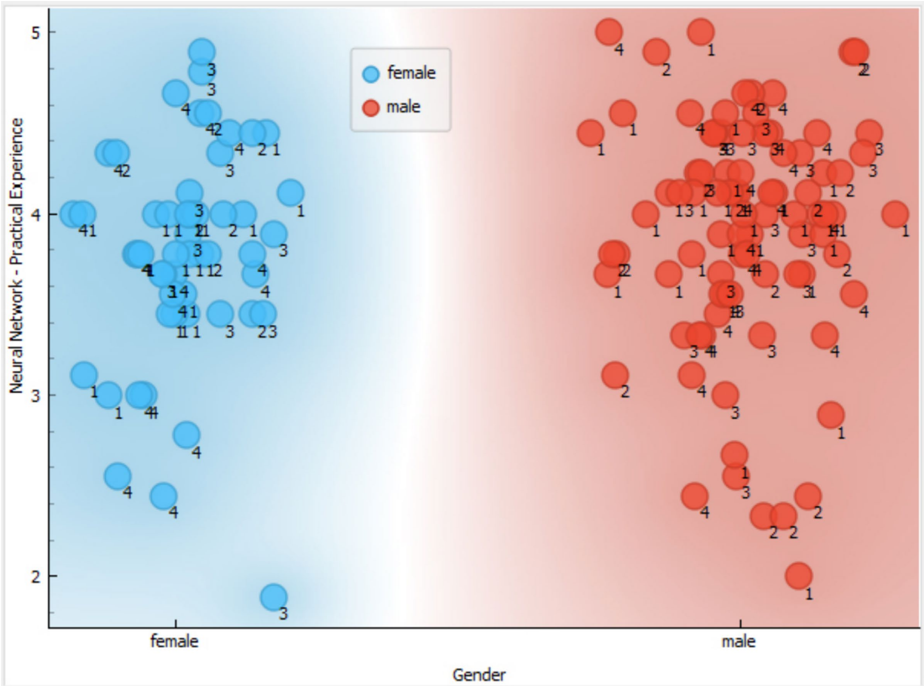

FIGURE 11
Practical experience by gender and year of study (Orange v.3.25).

relationship between P_2 (using AI for self-study) and P_6 (improved academic performance) indicates that students who use AI for independent learning often believe it contributes to better academic outcomes.

The analysis revealed notable deviations in students' self-assessments of practical experience across different years of study (Figure 10). Values outside the interquartile range, marked with a "+," indicate significantly higher or lower self-assessments compared to the average for the respective year. The highest number of outliers was observed among first-year students (4), followed by second-year (2) and third-year (1) students. No extreme values were recorded among fourth-year students. This trend suggests a growing homogeneity in self-assessed practical experience as students progress through their studies. In the first year, students arrive with varying backgrounds and expectations, which leads to a broader range of opinions. Over time, shared learning experiences, coursework, and collaboration contribute to a convergence of self-perceptions. The absence of outliers in the fourth year implies that the group has reached a higher level of consensus and similarity in understanding and evaluating their practical experience. The observed tendency for individual ratings to align more closely with the group average may be attributed to the process of socialization within the learning environment. Through shared experiences and interaction, students begin to form common reference points when evaluating their practical skills. This does not necessarily imply passive acceptance of a group norm, but rather a natural alignment of individual perceptions resulting from mutual learning and development.

To further investigate the influence of gender and year of study on students' perceptions of their practical experience with AI, an additional analysis was conducted using a four-layer ANN. The ANN was trained using the quasi-Newton method, with a hyperbolic tangent transfer function applied in the hidden layers. Although overall gender-based differences were not statistically significant, the ANN revealed an important relationship between gender, year of study, and the distribution of self-assessed practical experience with AI (Figure 11). The ANN indicated distinct patterns in how male and female students evaluate their AI experience, depending on their academic year – suggesting more complex interactions than what a simple mean comparison would show. In the early years, female students tended to give moderate ratings and avoided extreme values. However, as they progressed to the third and fourth year, more women reported either limited experience or high expertise in using AI tools. Among male students in the initial years, both low self-assessments and claims of advanced proficiency were present. Two distinct groups emerged – one with limited experience, and another showing high competence in AI use. In later years, this dichotomy decreased, and students with moderate practical experience increasingly filled the "middle zone" of the distribution. The findings from the ANN reveal an important dynamic in the acquisition of AI-related skills, which varies by gender and evolves over time. For female students, the pattern reflects a shift from moderate to more extreme self-assessments, while male students tend to move from early divergence toward greater homogeneity in perceived competence.

The analysis of factors influencing students' practical experience reveals a complex web of interdependencies, where each factor may interact with and be influenced by others. When calculating the practical experience index, it is possible to explore correlations between an excluded factor and the overall practical experience – even if no direct dependency has been established *a priori*. To test this, the practical experience index was calculated excluding factor P_7, which assesses recommendations of AI tools to others. The aim was to determine whether students' willingness to recommend AI tools is an independent behavior or strongly connected to their overall level of practical experience. After training a ANN, the

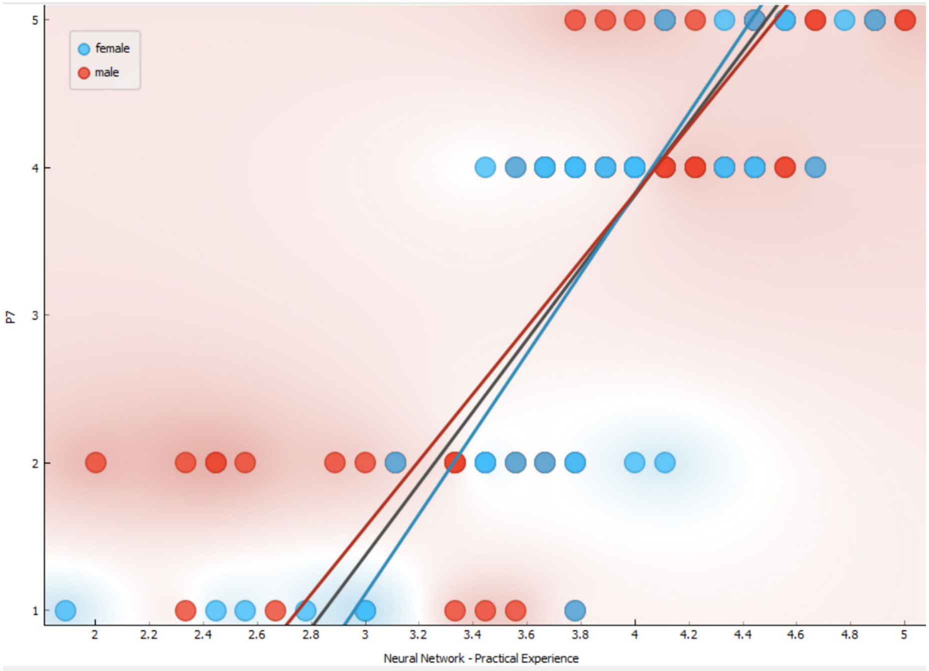

FIGURE 12
Relationship between recommendations and practical experience. The figure includes regression lines: blue (for female students), red (for male students), and black (overall average) (Orange v.3.25).

analysis of the relationship between the excluded factor P_7 and the practical experience index yielded clear results (Figure 12). A high correlation coefficient of 0.8 strongly indicates that recommending AI tools to peers is not random, but is closely tied to the student's own hands-on experience. These findings highlight an important social dynamic within the student community – trust built on shared, real-world experience and validated knowledge. This informal network for exchanging experience appears to play a crucial role in the organic, authentic, and sustainable adoption of AI technologies in education.

4.3 Students' perceptions of the benefits of using AI

To analyze students' perceptions of the benefits of AI, responses from Section 4 (B_1–B_{10}) were used, and the benefits index $\tilde{B}_k$ was calculated. Figure 13 presents the main results of this analysis. The analysis shows that students generally assign a moderately high rating to the benefits of AI applications. The largest proportion of students (40%, 55 individuals) rated the benefits between 4 and 4.5. The number of students who perceived significantly greater benefits was approximately half that (Figure 13a).

Students rated the ability of AI to support tracking of their individual learning progress (B_6) as the most valuable benefit, perceiving this functionality as a factor that boosts their confidence and self-esteem (Figure 13b).

The boxplot diagrams show a trend toward fewer extreme opinions as students advance through their studies (Figure 13c). While first-year students exhibit a slight tendency to overestimate the benefits of AI compared to the group average, in the second year, only one student gave a significantly more conservative rating. In the third and fourth years, the responses are more homogeneous and align more closely with the general perception.

The correlation matrix reveals a strong positive correlation (Pearson coefficient of 0.84) between perceptions of the impact of AI tools on predicting final course grades (B_9) and predicted graduation outcomes (B_{10}) on student motivation. This strong correlation is logical, as both factors relate to the motivational effect of predictive tools linked to future academic performance. All observed correlations in this group are easily interpretable and do not reveal any unexpected relationships that would alter the overall picture of students' perceptions of AI benefits.

The AI-based analysis of this section of the survey revealed that the values and distribution of the data support the use of a larger number of input variables for modeling. The training of predictive models for the AI Benefits Index $\tilde{B}_k$ showed significantly higher accuracy when using all factors from the group (B_1–B_{10}), along with students' gender and year of study as input features, i.e., $D = \{B_1, B_2, \ldots, B_{10}, Gender, Course\}$, compared to models trained with fewer input parameters (Figure 14).

Male and female students share similarly positive perceptions of the usefulness of AI, with only a few isolated cases showing lower ratings in both groups (Figure 15).

To determine whether students' overall positive perception of AI benefits influences their preference for traditional or innovative learning methods, an analysis was conducted using an ANN. The input data included all indicators from Section 4, along with gender and year of study. To eliminate any direct dependency between the model and students' specific preferences – and to enable a clearer observation of the influence of the overall AI benefits index on the choice of learning methods – the B_2 indicator, which directly assesses preferences for using AI instead of traditional learning methods, was excluded. The results of this analysis are presented in Figure 16.

The analysis of the relationship between the perceived benefits of AI ($\tilde{B}_k$) and preferences for innovative learning methods (B_2) reveals several interesting student groups. In the upper-right quadrant of the

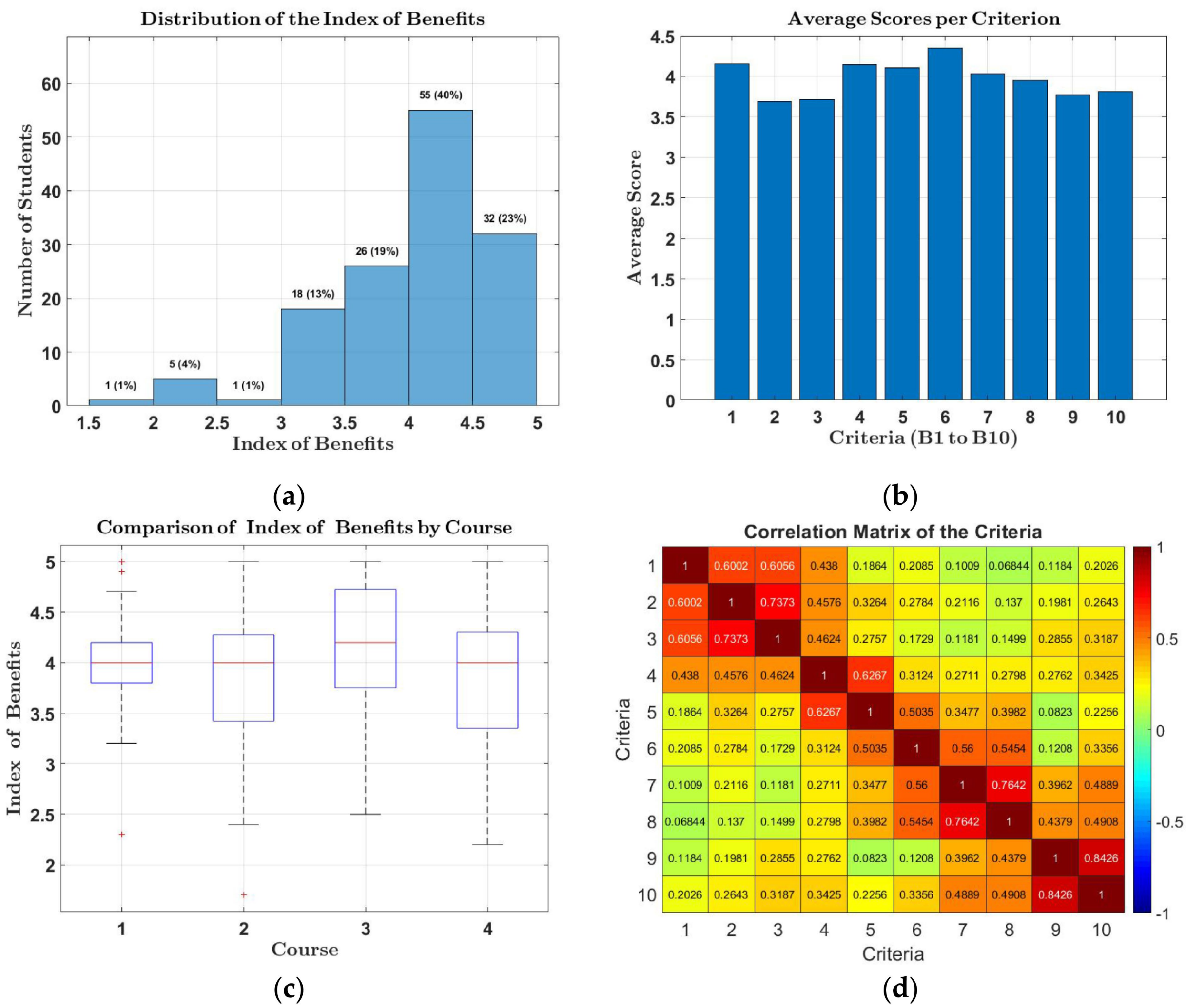

FIGURE 13
Analysis of the results for the AI benefits index: **(a)** histogram of the benefits index; **(b)** mean value of each criterion; **(c)** distribution of responses by year of study; **(d)** correlation matrix of the criteria (Matlab v.2018a).

(a)

Model	MSE	RMSE	MAE	R2
Neural Network - Confidence in Using AI	0.027	0.165	0.120	0.934
Random Forest	0.044	0.209	0.128	0.894
kNN	0.089	0.299	0.196	0.784
SVM	0.082	0.286	0.138	0.802

(b)

Model	MSE	RMSE	MAE	R2
Neural Network - Confidence in Using AI	0.456	0.675	0.513	-0.104
Random Forest	0.482	0.694	0.528	-0.166
kNN	0.443	0.665	0.499	-0.072
SVM	0.422	0.650	0.487	-0.022

FIGURE 14
Model errors with different input data sets *D*: **(a)** $D = \{B_1, B, \ldots, B_{10}, Gender, Course\}$; **(b)** $D = \{Gender, Course\}$ (Orange v.3.25).

diagram, a group of students stands out with high values for both indicators ($\tilde{B}_k \geq 4.5$ and $B_2 \geq 4$). These students are innovation-oriented, demonstrating a strong understanding of the benefits of AI and a clear preference for innovative learning methods. This expected correlation highlights that students who recognize the benefits of AI are more likely to adopt innovative approaches in the learning process.

Of particular interest is the group of cautious students who give moderate to high scores for AI benefits ($3 \leq \tilde{B}_k < 4$) but show low inclination toward innovation ($B_2 \approx 2$). These students acknowledge AI's potential but exhibit reservations or uncertainty regarding its practical application. Possible reasons for this caution may include lack of confidence in their AI-related skills, concerns about the effectiveness of new technologies, or a preference for traditional educational practices and teaching methods.

An interesting outlier is a student with a low benefits index ($\tilde{B}_k = 2.4$) who nevertheless shows a strong preference for AI-based learning methods ($B_2 \approx 4.1$). This case may reflect a student who sees AI as a useful educational tool, even though they are not fully convinced of its broader value. It's possible that the student appreciates

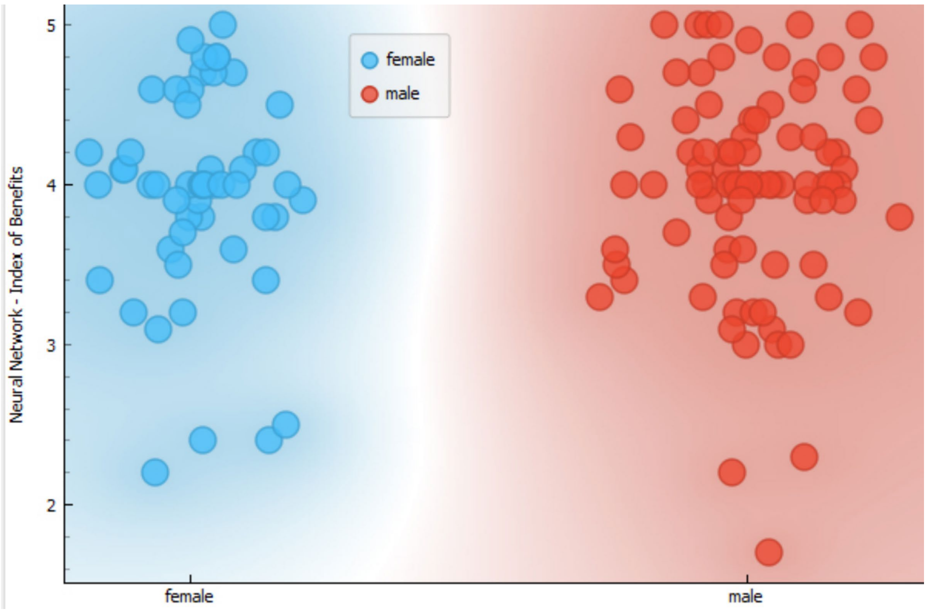

FIGURE 15
Students' perceptions of AI benefits analyzed by gender (Orange v.3.25).

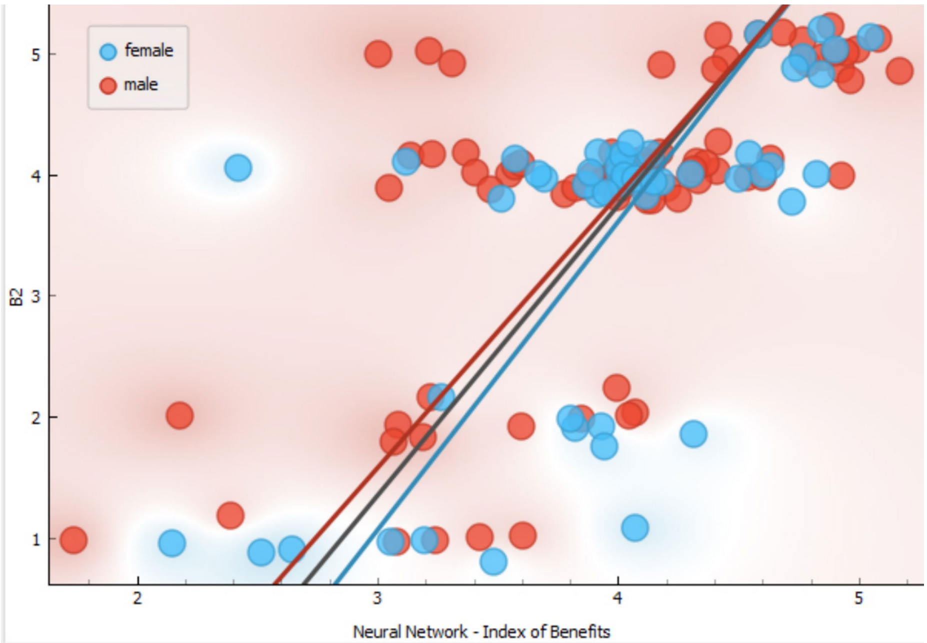

FIGURE 16
Influence of overall perception of AI benefits on preferred learning method (Orange v.3.25).

specific AI functionalities in the educational context but remains skeptical about its overall integration. This single case suggests that innovative methods can appeal even to students who are not fully on board with AI as a concept, underscoring the importance of demonstrating concrete benefits and practical use cases.

The largest concentration of students is found in the zone where both indicators are high ($B_2 \approx 4$ and $\tilde{B}_k \approx 4$). This group represents the core of the student population, who recognize the benefits of AI and are open to its active integration into the learning process. These students view innovation as compatible with effective learning and can play a key role in advancing the use of AI in academic practice.

4.4 Students' opinions on potential problems and challenges

To analyze students' opinions on the potential problems and challenges of using AI, responses to the questions in Section 5 (R_1–R_9) were used, and the risk index $\tilde{R}_k$ was calculated. This analysis provides a truly important and in-depth view of the risks and possible negative

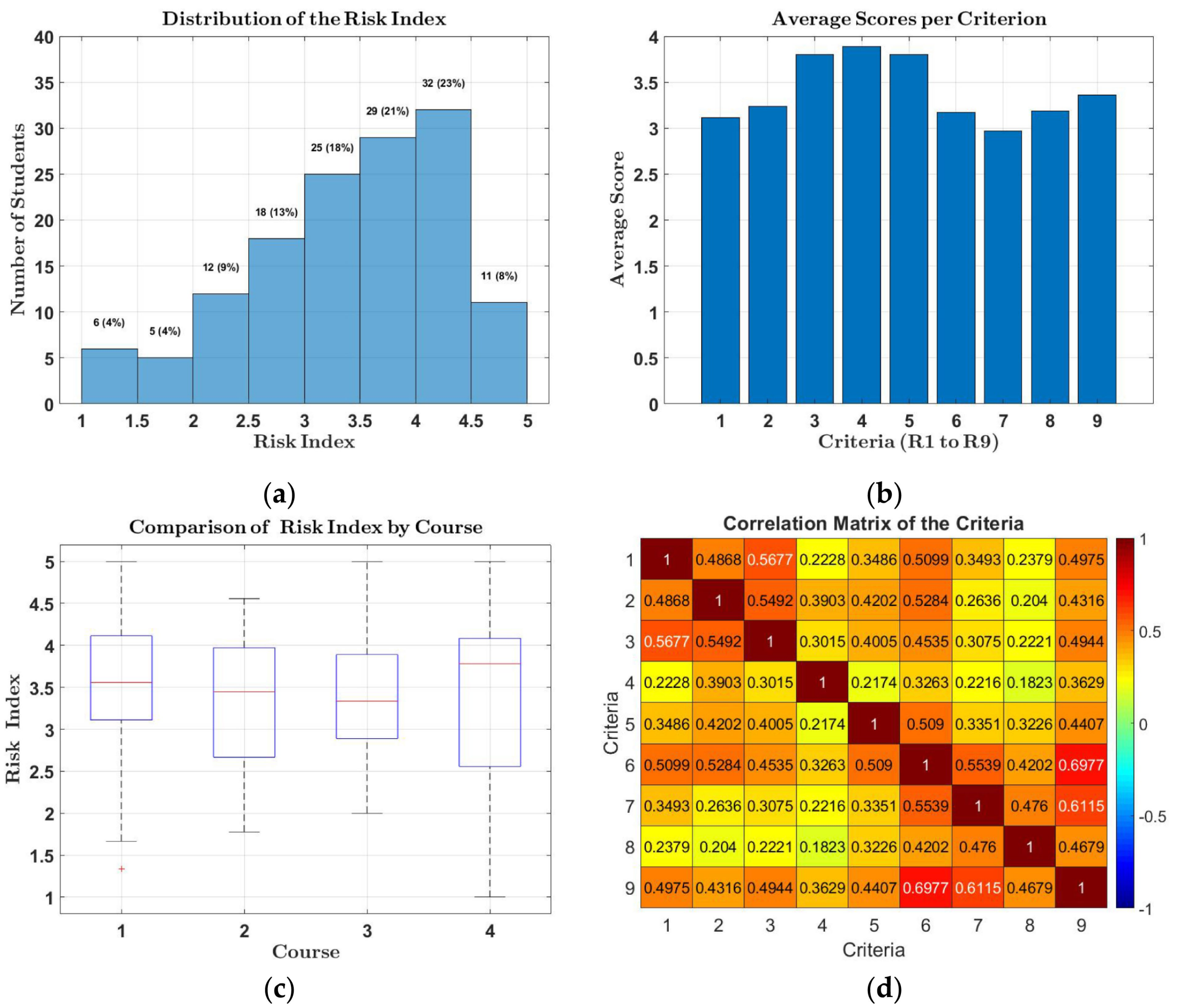

FIGURE 17
Analysis of the results regarding the AI risk index: **(a)** Histogram of the risk index; **(b)** Average value for each criterion; **(c)** Distribution of opinions by year of study; **(d)** Correlation matrix of the criteria (Matlab v.2018a).

consequences that may arise from the use of AI. Understanding these risks can help evaluate whether AI implementation is balanced and aligned with academic goals. Some of the results from the analysis are presented in Figure 17.

According to the calculated risk index $\tilde{R}_k$ (Figure 17a), students are divided into three main groups: students who perceive the risks as insignificant (8%, $\tilde{R}_k \in (1,2]$), students who perceive the risks as moderate (61%, $\tilde{R}_k \in (2,4]$), and students who perceive the risks as high (31%, $\tilde{R}_k \in (4,5]$). The significant proportion of students who perceive the risks as high highlights the need for discussions to address their specific concerns.

The calculated average risk values for the individual indicators (Figure 17b) and the overall average value of 3.39 indicate a moderately high level of perceived risk. The highest-rated risks include: the risk of dishonest use of AI during assessments ($R_4 = 3.89$), the concern over reduced critical thinking ($R_3 = 3.80$), and anxiety about data security ($R_5 = 3.80$). These high scores, given by the students themselves, emphasize their genuine concerns. The analysis also shows that students do not perceive the increase in inequality among students ($R_7 = 2.97$) as a particularly serious risk compared to the others, and the fact that $R_8 = 3.19$ suggests that some students see AI as "moderately" expensive for large-scale implementation.

An interesting finding from the Boxplot diagrams (Figure 17c) is that first-year students' perceptions of risk are almost evenly distributed, while fourth-year students show an asymmetric distribution, with 50% of them rating the risk below the calculated median (3.7).

The correlation matrix (Figure 17d) reveals a strong positive relationship (0.698) between ethical concerns (R_6) and potential misuse of AI (R_9), suggesting that these two risks are perceived as interrelated. A moderate to strong correlation is also observed between ethical concerns (R_6) and increased inequality (R_7), indicating that these concerns are often considered together.

Among the machine learning methods, ANNs again achieved the lowest error. After experimentation, the optimal architecture of the ANN was found to consist of three hidden layers with 17, 23, and 54 neurons in each layer, respectively. Training was carried out using the quasi-Newton method, and the transfer function in the neurons was the hyperbolic tangent.

The analysis of students' perceptions regarding the risks associated with AI does not reveal significant differences between male and female respondents (Figure 18). While men and women display similar central tendencies, women show a slightly higher inclination to report elevated levels of perceived risk. This

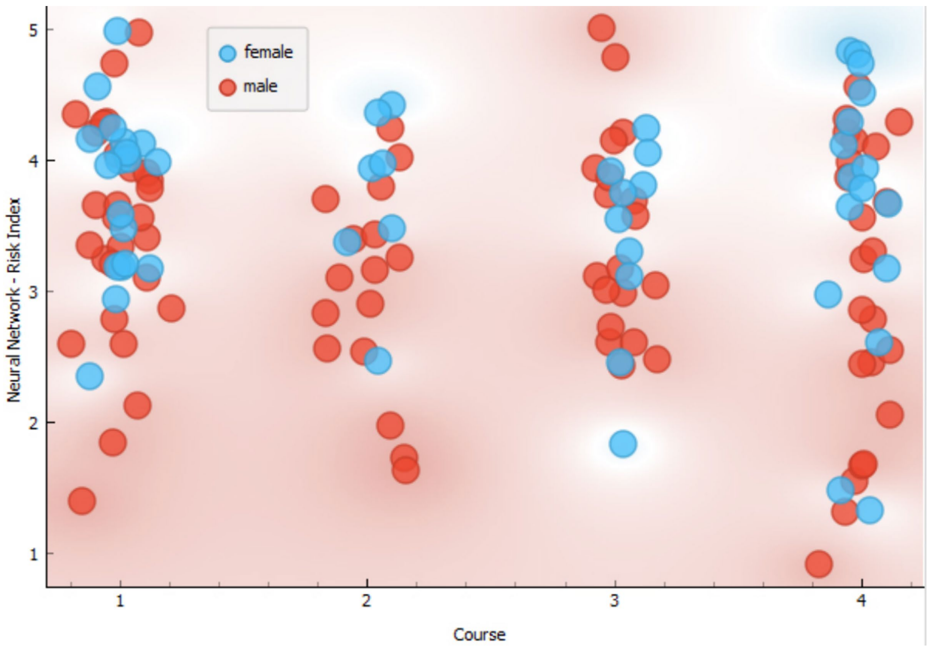

FIGURE 18
Distribution of the risk index by year of study and gender (Orange v.3.25).

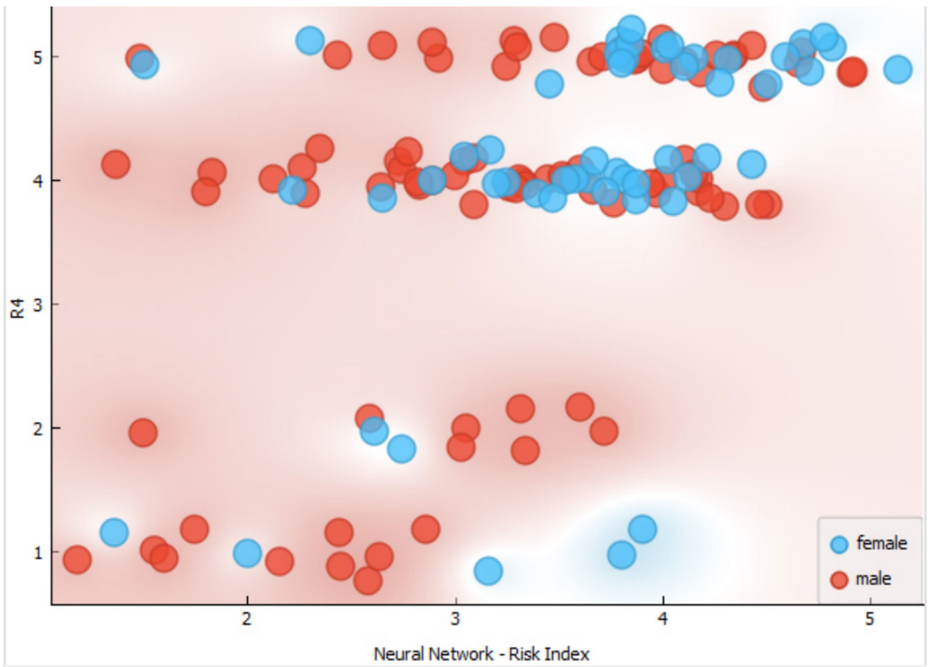

FIGURE 19
Influence of the overall risk perception on concerns about dishonest use during examinations (Orange v.3.25).

difference may reflect a broader perception spectrum of potential threats related to AI, more thoughtful consideration of possible negative scenarios, or greater emotional sensitivity. In the lower years of study (1st and 2nd year), men generally report slightly lower levels of concern regarding AI-related risks compared to women. This could be due to their limited hands-on experience with AI or a lower awareness of potential risks due to insufficient in-depth knowledge. Among students in the higher years (3rd and 4th year), a wider range of risk perception is observed. While some students still give low ratings, there is an increase in those who perceive AI not only as an inevitable element of the future but also as a technology that demands careful handling. Accumulated experience, deeper knowledge, and critical thinking likely contribute to a more conscious and analytical assessment of potential risks. This reflects their maturity, awareness, and readiness to face the challenges of AI – not with the naïve confidence seen in first-year students, but with an informed perspective developed over the course of their studies.

To examine the reverse dependencies of individual factors on the overall perceived risk, a ANN was repeatedly trained, with one factor excluded during each training iteration. After training, the relationship between the excluded factor and the predicted overall risk was analyzed. Figure 19 presents the relationship between the risk of AI being used dishonestly during examinations to manipulate student grades (R_4) and the overall risk index, obtained from training without the R_4 data, revealing interesting gender-based differences. Among female students – especially those with higher calculated levels of overall risk – a greater variability in R_4 assessments is observed. Some express significant concern about the potential for academic misuse of AI, while others do not see it as a serious threat. The higher R_4 scores among women may indicate greater concern for the ethical aspects of academic integrity and heightened sensitivity to potential injustices within the educational system. This trend may reflect women's stronger trust in rules and regulations, leading to higher concerns about their violation through AI. This characteristic is not coincidental. Their increased sensitivity to academic fairness largely aligns with concepts from social psychology and research findings, which suggest that women exhibit higher levels of empathy and compassion (McDonald and Kanske, 2023) and are more adept at recognizing social injustices compared to men.

On the other hand, male students – especially those in the lower years of study – generally demonstrate lower values for both overall risk and R_4. This may indicate greater trust in technology or a lower level of concern regarding academic integrity. It is also possible that this tendency is related to a higher willingness to experiment and greater confidence that existing control mechanisms will be effective in preventing misuse. Interesting insights also emerge from the analysis of students' sense of control over the situation and the development of critical thinking over the years. The distribution of R_4 scores (Figure 19) shows that two main groups of students are forming. One group shows low concern about the risk of dishonest use of AI in exams ($R_4 \leq 2$), likely due to trust in institutional control measures. The other group rates this risk as high ($R_4 \geq 4$), which may reflect greater skepticism toward technologies and concerns about their potential for abuse in the absence of adequate regulation. Students in the upper years of study have a higher risk index related to the impact of AI on critical thinking (R_3). This may be an indicator of increased critical awareness, resulting from accumulated experience and observations of real cases of academic dishonesty involving AI.

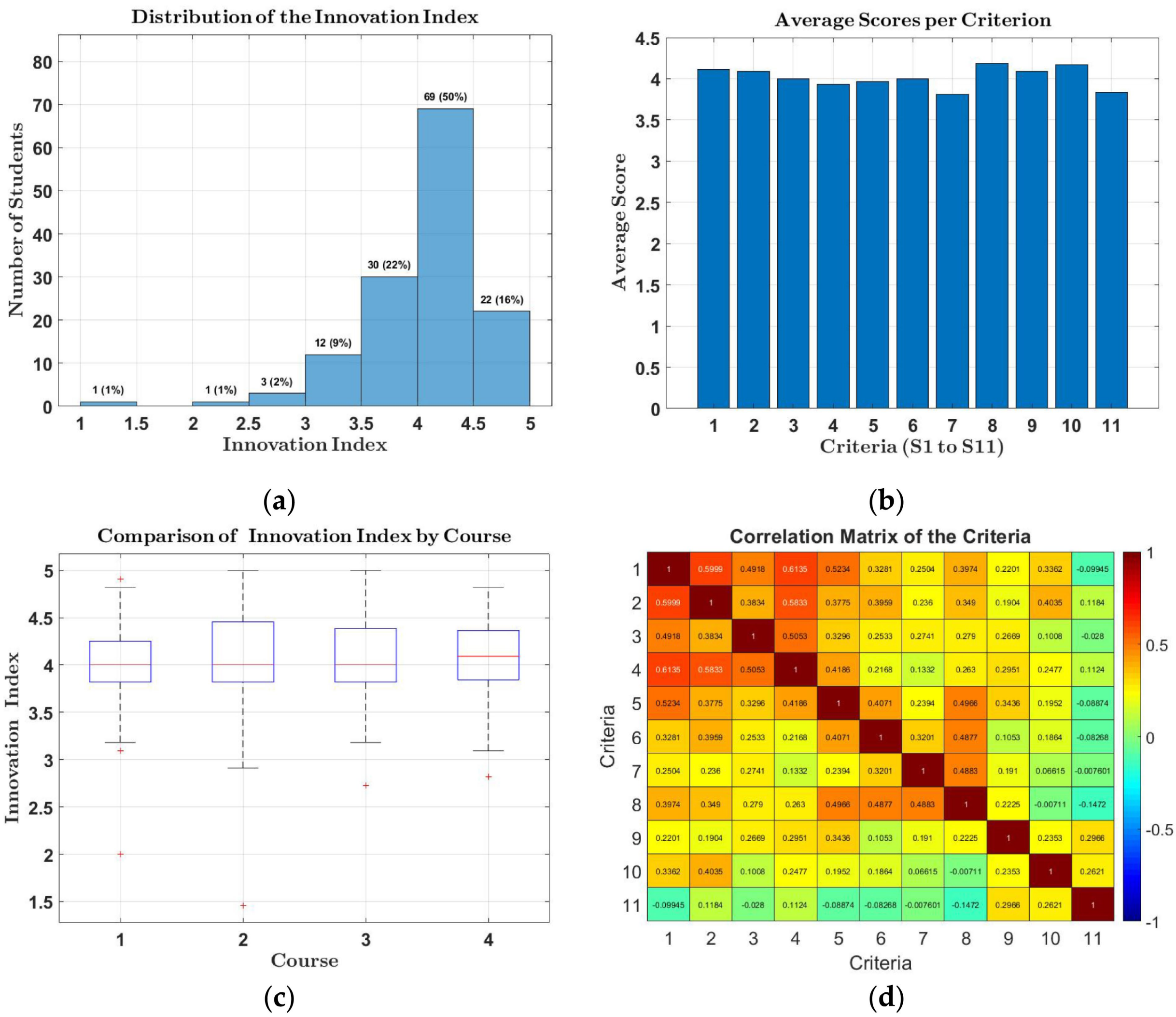

FIGURE 20
Analysis of the results regarding opinions on the need for innovation: **(a)** Histogram of the innovation index; **(b)** Mean value of each criterion; **(c)** Distribution of opinions by year of study; **(d)** Correlation matrix of the criteria (Matlab v.2018a).

4.5 Students' opinions on proposals for more effective use of AI tools

To examine students' ideas regarding the more effective use of AI tools, responses to the questions in Section 6 (I_1–I_{11}) were analyzed, and an innovation index ($\tilde{I}_k$) was calculated. The analysis of the responses shows that a very large proportion of students (50% in the group $\tilde{I}_k \in (4,4.5]$ and 16% in $\tilde{I}_k \in (4.5,5]$) strongly agree with the proposed innovations (Figure 20a). Only 4% of students expressed slight agreement or complete disagreement with the proposed innovations, which may stem from various reasons for disagreement (e.g., lack of trust in AI, financial concerns, or a lack of understanding of the proposed measures). The skepticism expressed by the group with a low innovation index ($\tilde{I}_k < 3$) highlights the need for open discussions about the benefits and risks of AI.

The histogram of the innovation index shows that the majority of students have high values, which emphasizes the need to prioritize proposals such as training (I_1), investment in AI (I_8), and personalized learning plans (I_6). Particularly notable is the strong support (from 50% of students) for the use of AI in creating individualized learning plans (I_6), highlighting the importance of adaptive learning as a key innovation. Due to this strong support, proposals such as I_6 and I_1 should be seriously considered by university administrators. The high average scores for ethical guidelines (I_9) and data transparency (I_{10}) clearly indicate the need to develop comprehensive policies for the use of AI. The strong support for AI investment (I_8) reflects an awareness of the potential of technologies to reduce social inequality. Based on the calculated average values of indicators I_1–I_{11}, the overall mean innovation support index is 4.01. This result indicates that, overall, the student community supports the proposed measures for more effective use of AI in education. The highest levels of support are seen for university investments in integrating AI technologies into education (I_8– 4.19), transparency in the use of data collected through AI tools (I_{10}– 4.17), and organizing training sessions for faculty and students on effective use of AI tools (I_1– 4.10). The lower average values for I_7 (chatbots) and I_{11} (strict regulations) suggest that students do not consider these top priorities or do not perceive sufficient added value in them. The lower rating for strict regulations may reflect a preference for a balanced approach between innovation and control, rather than excessive restrictions.

The analysis of scores across individual criteria (I_1–I_{11}) reveals a high degree of homogeneity in students' opinions regarding the need for innovation. The average values range from 3.813 to 4.194 (Figure 20b), indicating an overall positive perception of all proposed measures. Notably, none of the proposals received an average score below 3.5, confirming that all ideas are considered meaningful by students. Based on the results of the analysis of average values across the indicators, recommendations can be made for universities to invest more resources in integrating AI technologies into education, to establish clear policies and provide opportunities for discussions regarding the collection and use of data generated by AI tools, in order to build trust, and to organize seminars and training courses for students and faculty to ensure the effective use of AI in the learning process.

The quartile diagrams (Figure 20c) do not reveal significant differences or outliers that would allow for specific conclusions, except for the observation of similar median values among the different groups of students. A slight increase in expectations for innovation can be noted among 50% of fourth-year students.

The analysis of the correlation matrix (Figure 20d) reveals interesting relationships between the proposed innovations. A positive correlation (0.613) is observed between organizing training sessions for students and teachers (I_1) and student seminars for sharing experiences (I_4), suggesting that these two measures are perceived as complementary in promoting AI in education. A positive relationship (0.583) is also found between student seminars (I_4) and the need for regular evaluation of AI tools (I_2), highlighting the importance of continuous dialogue between students and institutions regarding the use of AI. Additionally, a positive correlation (0.6) is observed between investment in AI (I_8) and training (I_1), indicating a connection between the recognition of the need for resources and adequate preparation for working with AI. Based on these results, it can be concluded that in order to achieve the maximum effect from efforts to implement AI, measures should be taken to address all indicators with high positive correlations (I_1, I_4, and I_8). A weak or negative correlation is observed between strict regulations (I_{11}) and most other indicators, suggesting that proponents of regulation perceive innovation and control as opposing goals.

The ANN used in this part of the study consists of three layers with 10, 40, and 100 neurons, respectively, and was determined after experimenting with various architectures. The identity function $f(x)=x$ is used as the activation function in the neurons of the hidden layers, and the ANN is trained using the Adam optimization method.

The analysis shows that students' innovative attitudes remain consistently within the 4.0–4.5 range. High values of the innovation index (above 4.5) are observed across all academic years, suggesting that the adoption of innovation does not follow a strictly chronological pattern, but rather emerges spontaneously among students who are open to it. First- and second-year students tend to display more reserved attitudes, while in the later years (third and fourth), clearer lines of support or more well-founded reservations are observed. Students no longer simply accept or reject ideas uncritically – they observe, analyze, compare, and form opinions enriched by their academic experience (Figure 21).

It is important to note the early emergence of a high level of innovative thinking among some first-year students, highlighting the need for educators to identify and support these individuals. Gender-based analysis shows that female students display a more uniform distribution of innovation scores, while male students – particularly in the early years – show a wider range. This difference may be linked to various cognitive and social factors.

From a psychological perspective, the wider score range among men may reflect a greater tendency to adopt and assert extreme positions, whether in strong favor or complete rejection of a concept. Male students often exhibit higher cognitive self-confidence (regardless of how well-grounded it is), a predisposition toward polarized thinking, and greater freedom in expressing opinions without a strong need for external social validation. In contrast, female students may filter their evaluations through a social-ethical perspective ("What does this innovation mean for others?" or "How will the idea of innovation affect everyone in general?"), while male students are often more focused on functionality, efficiency, and utility – factors that may lead to more extreme assessments. They are more willing to take risks, more open to unfamiliar technologies, but also more likely to become disillusioned if expectations are not met – something that is reflected in their ratings of potential innovations.

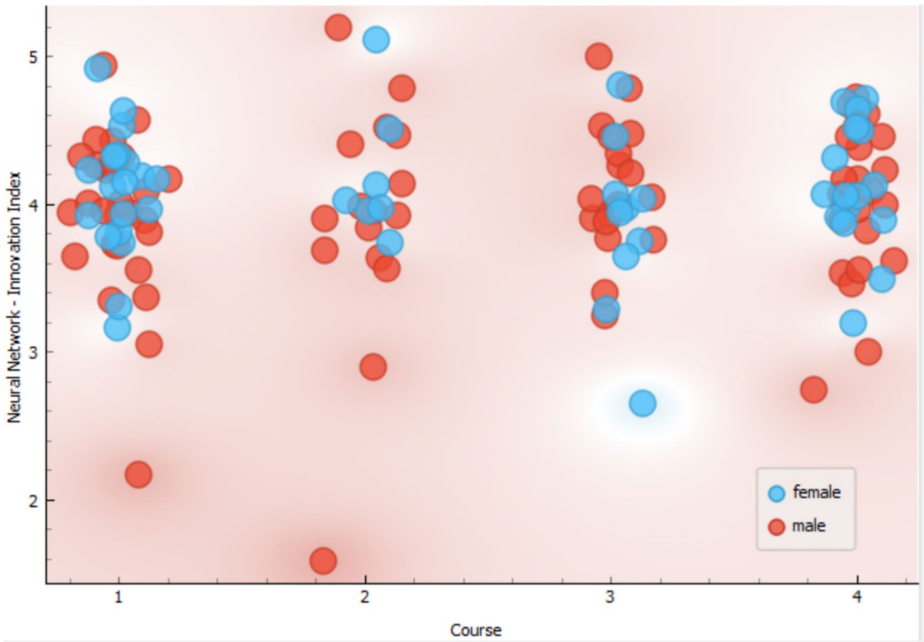

FIGURE 21
Students' innovative thinking by year of study and gender, as modeled by the ANN (orange v.3.25).

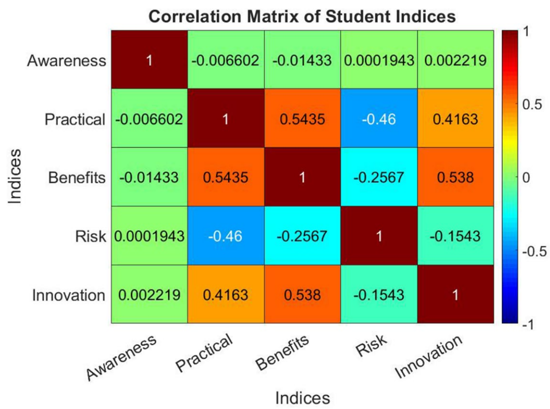

FIGURE 22
Correlation matrix of the individual indices (Matlab v.2018a).

4.6 Interdependence of the individual indices

In the final part of the analysis, the relationship and mutual influence among the individual indices for each student were examined (Figure 22).

The results indicate a positive correlation between the indices "Practical Experience" and "Perceived Benefits" ($r = 0.543$), suggesting that students who actively use AI in practice are the ones who most strongly recognize its advantages. This is expected, as direct interaction with the technology acts as a catalyst for developing positive academic attitudes toward AI.

There is also a positive correlation between the indices "Perceived Benefits" and "Innovation" ($r = 0.538$). This shows that students who recognize the benefits of AI are also the most open to change and to incorporating AI into more aspects of education. Conversely, positive attitudes toward technological innovation are often accompanied by a high perception of AI's benefits.

A positive correlation can also be observed between the indices "Practical Experience" and "Innovation," reinforcing the pathway: practice → perceived benefits → innovation. This relationship forms a solid foundation for an educational strategy aligned with a previously suggested recommendation to academia: more hands-on opportunities → increased innovative thinking.

The negative correlations with the risk index (Practical Experience: −0.460, Benefits: −0.257, Innovations: −0.154) confirm that fear of the unknown decreases with greater familiarity and a more positive perception of AI – the less students know, use, or trust AI, the more they perceive it as a threat. This finding highlights the need to familiarize students with the ways AI can be used, in order to disarm the fear of the unknown.

The near-zero correlation between the "Awareness" index and the other indices indicates that information alone is not sufficient to shape attitudes and behaviors. The main conclusion from the study is that personal experience plays a key role in changing perceptions and forming a positive attitude toward AI. Simply being aware of AI's existence is not enough. For awareness to have a real effect, it must be accompanied by practice and emotional engagement.

5 Discussion

The results of the analysis of the responses to the questions in Section 2 highlight that awareness is a key factor that motivates students to move from passive observation to active use of AI, and that knowledge is a prerequisite for action, while confidence in decision-making stems from a deep understanding of the context. The analysis based on a ANN (Figure 7c) clearly demonstrates an almost linear relationship between increased confidence and a higher awareness index. This indicates that the more informed students are about AI, the more confident they feel when using it.

On the other hand, the analysis of the responses to the question about using AI for self-study (Figure 8) shows a strong relationship between the actual use of AI for learning purposes and the awareness index, and that as awareness increases, so does the actual use of AI. These results allow us to provide a clear answer to RQ1 – the level of students' awareness regarding the possibilities of using AI in education is positively correlated with their confidence and actual use of AI tools.

Based on the results of the responses to the questions in Section 2, it is recommended that instructors pay attention to the connection between knowledge and activity, and encourage students to use AI by providing opportunities for its use during practical exercises.

The correlation matrix (Figure 9c) shows a strong positive correlation between P_4 (sense of confidence when using AI) and P_5 (improved learning effectiveness). Since learning effectiveness is likely associated with better understanding and handling of the study material, which in turn increases confidence, it can be concluded that greater practical experience leads to higher confidence. The analysis conducted when excluding factor P_7 (recommendation of AI tools) from the calculation of the practical experience index shows a high correlation coefficient of 0.8 between this factor and the overall practical experience (Figure 12). This provides strong evidence that students' willingness to recommend AI tools to their peers is closely linked to their own practical experience – i.e., students with more hands-on experience are more likely to recommend AI tools to others. The analysis also shows a positive relationship between P_2 (use of AI for self-study) and P_6 (better academic results). This suggests that students who have more practical experience using AI for self-study often believe it contributes to improved academic performance. Although this cannot be considered a direct correlation between the overall practical experience index and academic results, it is an example of a positive link between a specific form of practical experience (self-study with AI) and students' perceptions of better academic outcomes. Based on this, it can be concluded that the level of practical experience with AI in education is positively related to students' confidence, their tendency to recommend AI tools to others, and there are indications of a positive relationship between practical experience (particularly the use of AI for self-study) and students' perception of improved academic performance. To establish a more definitive connection between the overall practical experience index and actual academic outcomes (rather than just perceived ones), additional data on student achievement and analyses comparing the practical experience index with objective measures of academic performance (e.g., GPA, grades in specific courses, etc.) are needed. Results from other studies also show strong student confidence in their ability to use AI tools effectively (Balogh, 2024) and a positive student attitude toward AI tools (Idroes et al., 2023).

The results of the analysis of the questions in Section 3 indicate the need to encourage group discussions about AI, as this can enhance the exchange of experience both among learners and between learners and instructors, as well as promote and integrate the use of AI throughout the entire learning process in order to meet the needs of all student groups.

The analysis of the relationship between the AI Benefits Index ($\tilde{B}_k$) and preferences for innovative learning methods (B_2), presented in Figure 16, clearly shows that students who recognize the benefits of AI are more inclined to embrace innovative approaches in the learning process. The majority of students are aware of the benefits of AI and are inclined toward its active integration into the educational process. This provides a solid basis for a positive answer to RQ3 – awareness of the benefits of AI in education is positively associated with students' preferences for using innovative, AI-based learning methods. The obtained results correspond with findings from other studies, which show that students value the benefits of integrating AI tools into the learning process (Katsantonis and Katsantonis, 2024; Herawati et al., 2024; Khodeir et al., 2024; Asio and Gadia, 2024; Stoyanova et al., 2025).

Based on the analysis of the responses to the questions in Section 4, it is recommended to develop targeted programs aimed at engaging the group of students who recognize the benefits of AI and are inclined toward its active integration in the learning process, as "agents of change." This could include providing opportunities to participate in AI implementation projects and creating platforms for sharing experiences and best practices.

According to the calculated Risk Index ($\tilde{R}_k$), a significant proportion of students (31%) perceive the risks associated with the use of AI as high ($\tilde{R}_k \in (4,5]$), and a large share (61%) perceive them as moderate ($\tilde{R}_k \in (2,4]$). The analysis of the average risk values for individual indicators shows that the highest-rated risks are the potential for unfair use of AI in assessment ($R_4 = 3.89$), which is directly related to the danger of academic misconduct, concerns about the reduction of critical thinking ($R_3 = 3.80$), and worries about data security ($R_5 = 3.80$). The correlation matrix (Figure 17d) reveals a strong positive relationship (0.698) between ethical concerns (R_6) and potential AI misuse (R_9), indicating that students perceive these issues as interconnected. The analysis also shows that upper-year students (3rd and 4th year) have a higher risk index related to the impact of AI on critical thinking (R_3), suggesting increasing awareness of this risk as students advance in their studies. These findings support the conclusion that students perceive the use of AI in education as associated with several significant risks, including the reduction of critical thinking, ethical concerns, and the potential for academic misconduct. The fact that students in higher years show a higher risk index highlights the need for initiatives aimed at fostering critical thinking and ethical reflection from the early stages of university education. Similar concerns about AI use have also been expressed in other studies involving students (Brown et al., 2024; Gheţie et al., 2025; Herawati et al., 2024; Alzahrani, 2023; Saúde et al., 2024), which emphasize the need to initiate critical discussions about the risks and challenges of AI in higher education, as well as the development of clear guidelines for its use.

The fact that the average Innovation Support Index $\tilde{I}_k$ is 4.01 and that the mean values of all examined innovation indicators (I_1–I_{11}) range from 3.813 to 4.194 indicates that, overall, the student community supports the innovative use of AI in education and recognizes the need for the proposed measures to improve the learning process. The wide range of responses from first-year students and the internal tension between techno-optimism and techno-skepticism may generate a kind of energy which, if properly channeled by instructors, could certainly enrich the technological dialogue within the university's academic environment. It is advisable to engage students with more extreme positions on innovation in discussions that promote the exchange of experiences and perspectives on the future of education. The need to increase students' knowledge and confidence in working with AI to foster a more positive attitude toward the technology has also been identified in other studies (Kelly et al., 2023; Asio and Gadia, 2024; Bation and Pudan, 2024; Stoyanova et al., 2025).

It should also be noted that any differences observed when comparing the present findings with international studies may be partly attributable to the specific institutional and disciplinary profile of the surveyed sample, which consists of students enrolled in technology-oriented programs. Therefore, the results should be interpreted primarily within this academic context rather than as reflecting broader national or cultural characteristics.

The results of the present study outline several important conclusions for higher education institutions seeking the sustainable integration of artificial intelligence. First, the findings indicate that awareness alone is not sufficient to foster positive attitudes and responsible use of AI. Students' confidence, perceived benefits, and openness to innovation are instead shaped by concrete opportunities for hands-on interaction with AI. This suggests that institutional strategies should emphasize the guided use of AI tools within the learning process and the systematic integration of AI-based activities into curricula.

Second, the relatively high level of perceived risk, particularly with regard to academic integrity, critical thinking, and ethical concerns, highlights the need for clear institutional policies and transparent guidelines governing the use of AI in educational contexts. Rather than relying solely on restrictive measures, universities should combine ethical frameworks with training initiatives aimed at both students and instructors, in order to foster informed, reflective, and responsible use of AI.

Finally, the strong student support for innovation-oriented measures indicates their readiness to actively participate in the digital transformation of education. Educational policies that engage students as partners in this process—through feedback mechanisms, pilot projects, and the evaluation of AI tools, may enhance both the acceptance and the effectiveness of AI-based educational reforms.

6 Limitations of the study

This study was conducted at a specific point in time and reflects students' current attitudes toward AI tools. Due to the short time frame (1 month), only 138 students participated in the survey. The respondents were from two faculties (the Faculty of Physics and Technology and the Faculty of Mathematics and Informatics), and they are enrolled in degree programs related to computer science, computer engineering, and communications. Exploring their attitudes toward data privacy and automation in the workforce is crucial for promoting the responsible development and use of AI in HEIs; however, this also introduces certain limitations. Since AI is directly related to their fields of study and they possess more knowledge in computer science, programming, and mathematics – the foundations of AI – compared to students in other disciplines, they are expected to be more engaged with the topic and to provide more informed opinions about the possibilities, limitations, and potential risks of AI. For this reason, the findings reflect a specific context and should be interpreted with particular caution when attempting to generalize them to the broader student population of the university and in Bulgaria. All surveyed students have a basic knowledge of AI, and therefore their high levels of awareness and confidence in using AI for self-study may not reflect the attitudes of students in other majors. Furthermore, due to the use of an online questionnaire, the survey may have primarily sampled students with a heightened interest in digital innovation, which is reflected in the high overall innovation support index (4.01). Therefore, the results obtained represent a "best-case scenario" for AI adoption among technically competent students, rather than the opinion of a broad range of Bulgarian students.

Despite these limitations, the collected data provide a valuable snapshot of the surveyed students' attitudes toward the use of AI tools in higher education. These initial findings can serve as a starting point and foundation for future, larger-scale studies that explore the attitudes of students from different academic disciplines and those studying at other universities.

7 Conclusion

This study presents a survey on students' attitudes toward the use of AI in higher education. The main questions are divided into five sections, with most of them (46) assessed using a 5-point Likert scale. For each section, a numerical index was created to summarize the responses of each participant: Awareness Index ($\tilde{A}$); Practical Experience Index ($\tilde{P}$); Perceived Benefits Index ($\tilde{B}$); Perceived Risks Index ($\tilde{R}$); and Innovation Attitudes Index ($\tilde{I}$).

A variety of experiments were conducted to analyze the responses. Both classical statistical methods (correlation analysis, boxplots, histograms) and AI methods (ANNs, decision trees, SVM, Random Forests, KNN) were used.

The results show that a large proportion of students have a very high level of awareness regarding AI tools. At a maximum index value of 5, for 29% of the respondents, the Awareness Index ($\tilde{A}$) falls within the interval (4.5, 5], for 24% – (4, 4.5], 29% – (3.5, 4], and 18% – (3, 3.5].

The study of Practical Experience ($\tilde{P}$) indicates a moderate self-assessment among students regarding their hands-on experience with AI. Most students rate their practical experience with AI as relatively good (27%) or good (38%). Only 12% of students consider their practical experience to be excellent, while 9% have an index below 3, suggesting they may not actively use AI.

The analysis of students' opinions regarding the benefits of AI applications shows an overall moderately high assessment. The AI Benefits Index ($\tilde{B}$) values for over 60% of students fall within the range of 4 to 5; 39% also have a relatively positive view of the benefits, giving ratings in the range of 3 to 4, and only 6% do not consider the benefits of AI tools to be high.

According to the calculated Risk Index ($\tilde{R}$), which has a maximum value of 5, students can be divided into three main groups: those who perceive the risks as low (8%, $\tilde{R} \in (1,2]$), those who perceive the risks as moderate (61%, $\tilde{R} \in (2,4]$), and those who perceive the risks as high (31%, $\tilde{R} \in (4,5]$).

A large number of students – approximately 66%, strongly agree with the proposed innovations. A small proportion of students (4%) show weak agreement with the suggested innovations, which is likely due to a lack of trust in AI or uncertainty regarding the description of the proposed measures.

The average values for the indexes for all students indicate relatively high levels (around or above 4) of awareness, practical experience, perceived benefits, and expectations for innovation. The overall risk assessment (3.39) suggests that, in general, students are aware of the potential risks and hope that these can be mitigated through the advancement of AI technologies.

The results of this study offer insight into perceptions of AI among engineering students and open up several ideas for future research. Further studies should be conducted in the future to observe how student attitudes change over time and with greater integration of AI tools into curricula. Conducting similar studies among students across the university and/or other institutions in Bulgaria would enable more generalized conclusions to be drawn about student attitudes at the university/national level, which would be useful for introducing ethical guidelines and pedagogical strategies for the use of AI. Another avenue for future work is to investigate the attitudes of other stakeholders (leaders, faculty, administrators) towards AI, allowing for comparison of their perceptions and identification of gaps in expectations.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical approval was not required for the studies involving humans. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

KY: Writing – original draft, Writing – review & editing. SG: Writing – original draft, Writing – review & editing. EH: Writing – original draft, Writing – review & editing. SH: Writing – original draft, Writing – review & editing. MG: Writing – original draft, Writing – review & editing.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This study is financed by the European Union—NextGenerationEU, through the National Recovery and Resilience Plan of the Republic of Bulgaria, project "Digital Sustainable Ecosystems—Technological Solutions and Social Models for Ecosystem Sustainability—DUECOS", BG-RRP-2.004-0001-C01.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feduc.2026.1717886/full#supplementary-material

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