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Professional Education in AI

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1 Introduction

The growing demand for artificial intelligence professionals is driven by the rapid advancement of technology and its widespread adoption across industries. AI has become a transformative force, particularly in education, where it is improving teaching and learning through personalized and adaptive methods. In today's rapidly changing world, lifelong learning is essential, and AI plays a key role in supporting it by tailoring learning experiences to individual needs, helping learners remain relevant and agile [1].

This demand extends beyond education to other sectors, including healthcare, transportation, and finance, where AI is increasingly relied upon for innovative solutions. The shift from Industry 4.0 to Industry 5.0 emphasizes collaboration between humans and machines, underscoring the need for professionals who can develop AI technologies that align with human-centered values. In addition, AI has shown significant growth in specialized applications such as language learning, where intelligent tutoring systems, conversational agents, and automated assessments are becoming commonplace, further increasing the need for skilled professionals [2], [3].

Beyond the technical applications, AI also poses ethical challenges. Concerns about bias, accountability, and fairness in AI systems highlight the importance of training professionals in ethical frameworks to ensure responsible development. As AI becomes increasingly integrated into everyday life, having professionals equipped to address these issues is essential for creating technologies that are inclusive and equitable [1], [4]. Furthermore, the growing digital divide highlights the importance of democratizing AI education, preparing a diverse workforce that can develop solutions that benefit all members of society.

The growing demand for AI professionals stems from the transformative impact of AI across sectors, its ability to drive lifelong learning, and the ethical considerations it brings. Preparing students for careers in AI is crucial not only to meet workforce needs, but also to ensure the development of responsible, inclusive, and equitable technologies for the future [5].

As artificial intelligence continues to transform industries and societies, the first critical step to addressing the growing need for AI expertise is education. AI's rapid integration into many fields has created an urgent demand for skilled professionals capable of designing, developing, and implementing AI technologies. While AI proficiency spans a spectrum of expertise levels, higher education plays a foundational role in building a pipeline of talent to meet this demand.

Higher education institutions serve as the cornerstone for cultivating AI expertise by equipping students with both theoretical foundations and practical skills. Universities and colleges offer structured pathways for students to understand the principles of machine learning, data analysis, and AI ethics while providing opportunities to apply this knowledge through research and hands-on projects. This creates a vital entry point for developing a workforce capable of addressing real-world challenges associated with AI.

Given the strategic importance of higher education in preparing the next generation of AI professionals, research into AI education has become a key focus. Understanding how AI concepts can be effectively introduced, taught, and assessed within higher education settings is crucial for shaping curricula that align with industry needs while promoting ethical and responsible AI development. By emphasizing higher education as the initial platform for building AI literacy and competence, this research seeks to bridge the gap between the growing demand for AI expertise and the available supply of qualified professionals.

2 AI in Higher education

Artificial intelligence is making its way into higher education, offering innovative solutions to improve teaching, learning, and administrative processes. This part examines various applications of AI in higher education, highlighting benefits such as personalized learning, administrative efficiency, and increased student engagement. In addition, potential concerns and challenges associated with implementing artificial intelligence are examined.

As technology advances, the use of artificial intelligence in higher education is becoming more widespread. Universities have begun to use artificial intelligence to create personalized and more tailored classes, to streamline administrative processes, or to assist in research.

Intelligent learning systems

Intelligent learning systems can support classical ways of teaching. Using such systems, students can receive immediate feedback and assistance in strengthening their knowledge, especially in those aspects with which students perform less well. The use of ITS systems makes it possible to assess the level of students' knowledge and adjust educational content accordingly to ensure the best way to transfer knowledge to students. Among the most popular solutions based on intelligent learning systems, for example, are personalized learning systems (PLS). PLS systems perform real-time profiling of students, creating unique user profiles for each user. This approach allows the level and knowledge to be best matched to students, forcing a focus on weaknesses [6]. Adaptive learning systems are another example. In this type of system, artificial intelligence algorithms allow the content and level of knowledge to be adapted to the pace and style of each student individually. This feature is crucial for keeping students engaged and promoting effective learning [7].

Another possibility for extending teaching with intelligent tutoring systems is automatic feedback systems. These systems allow you to provide instant feedback on exercises and assessments. This allows students to immediately understand their mistakes, fostering a more conducive learning environment [8]. Artificial intelligence can also be used for the analysis of students' learning progress, and engagement rates. By analyzing this data, teachers can gain insight into individual and group performance trends, making informed decisions about pedagogical strategies and interventions [2].

Personalized Learning

In higher education, it is very important to have the right approach and personalized teaching suitable for students. AI can analyze student data to customize learning experiences, enabling personalized learning paths that can adapt to a student's pace and understanding. Platforms like Knewton or DreamBox Learning [9] evaluate student performance on various tasks, identifying areas of strength and weakness. They provide tailored resources and learning paths, enhancing engagement and mastery of subjects.

AI makes it possible to analyze vast amounts of data to gain insights into students' learning behavior. Predictive analytics can identify at-risk students early and recommend interventions to improve retention and success. By examining engagement patterns, teachers can effectively personalize instruction [10]. Natural language processing is used in language learning apps that customize exercises based on the user's skills and progress. With real-time feedback on vocabulary and grammar, students receive a personalized experience that supports language learning and fluency [11]. Artificial intelligence-based recommendation systems suggest educational materials adapted to individual students' interests and needs. This personalized approach can increase motivation and engagement, encouraging students to further explore relevant topics [12].

Administrative Efficiency

Integrating AI into administrative tasks in higher education institutions can positively impact workflow improvements [13]. In higher education, one of the elements affecting efficiency and student satisfaction is the efficiency of university administration. Tasks such as recruitment, financial aid, and student support can be time-consuming and resource-intensive. Using artificial intelligence, it is possible to automate repetitive and time-consuming tasks [14].

One possible task that can be supported by artificial intelligence is managing the recruitment process. Through artificial intelligence, it is possible to pre-evaluate candidates and using chatbots can relieve employees of the burden of answering repetitive questions. Such systems not only reduce the administration burden but also improve response times which affects the satisfaction of potential students. Another task in which it is possible to use artificial intelligence is to support students. Through virtual assistants and chatbots, it is possible to provide round-the-clock student support. This support ranges from answering basic questions to registering for subjects, etc., an example being George State University, where such chatbots have been implemented. Artificial intelligence can also help with data analysis and decision-making. With this application, it is possible to predict trends, and support decision-making.

Use of Chatbots

Another option for using artificial intelligence at universities is the use of chatbots. Chatbots have become an effective tool for providing round-the-clock assistance and can provide information on course content, university resources, and administrative processes. The use of chatbots in interaction with students can increase student satisfaction, as well as ease the burden on university administration. The main advantage of the availability of chatbots is that they are available 24/7, giving students virtually instant access to information at any time of the day. The use of chatbots relieves the administrative burden and has a significant impact on staff productivity. Interestingly, introducing chatbots fosters a sense of greater engagement and satisfaction among students, increasing the sense of belonging to the academic community [15]. Chatbots can also be used to support the educational process itself. They can be used to clarify doubts about courses, class materials, and deadlines, what is a significant convenience in the case of limited availability of instructors [16].

The introduction of chatbots also with it some difficulties and risks. The first is undoubtedly the problem of understanding queries by chatbots, of course, the continuous development of these technologies reduces these problems, but they can still occur. Another threat is the problem of adequate protection of personal data. In the case of chatbots supporting administrative processes, they must additionally comply with data protection regulations. There is also a risk of resistance to new technologies by both employees and students, which could translate into low levels of chatbot use [17].

Data-Driven Insights

Universities have long been collecting huge data sets on both students and the content taught. Developments in artificial intelligence methods, particularly machine learning, make it possible to extract patterns and trends from this data. This allows universities to make informed decisions, personalize the learning process, and improve productivity [18]. Typical example is the predictive analysis of academic performance – artificial intelligence algorithms can analyze historical student data to identify at-risk students and predict their future performance [19]. Universities also increasingly use artificial intelligence to create personalized educational programs based on individual student data [20]. Artificial intelligence can help tailor educational content and resources to students' needs, which can translate into improved outcomes. Analyzing student feedback using AI can help improve course design [21].

Assessment Automation

Traditional assessment methods in higher education can be time-consuming and labor-intensive, often distracting teachers from direct interactions with students. The desire to optimize and improve efficiency has made universities increasingly willing to use artificial intelligence in the process of automated student assessment [22].

It seems obvious to use automation in the assessment process of tests and quizzes, so students receive immediate feedback, and the risk of human error is minimized [23]. The use of NLP techniques enables the use of artificial intelligence in the evaluation of short answers and essays. Solutions such as Grading Assistant and Turnitin's Revision Assistant use machine learning models to assess content quality, relevance, and grammatical correctness [24].

Research Enhancement

The use of artificial intelligence also makes it possible to increase the efficiency of scientific research. Artificial intelligence algorithms excel at analyzing huge data sets and finding trends while providing innovative tools to improve scientific work [25]. Artificial intelligence algorithms can be applied to data analysis and pattern recognition, which often slows down the detection of relationships not apparent with traditional methods.

Artificial intelligence tools can assist researchers in their search for relevant literature, helping them navigate the growing number of scientific papers [26]. Tools such as Semantic Scholar and Connected Papers use artificial intelligence to suggest scholarly articles based on the data entered, minimizing the time it takes to review the literature.

Artificial intelligence used in social media platforms for scientists can help match scientists with similar interests. ResearchGate, for example, uses artificial intelligence algorithms to recommend potential collaborators and relevant research projects based on user profiles [27]. Artificial intelligence tools can also help generate hypotheses and design experiments. By using existing data to suggest new research directions, such as potential relationships between variables, artificial intelligence can accelerate the pace of scientific discovery.

Accessibility Improvements

The last issue of using artificial intelligence in higher education discussed is increasing the level of accessibility. With the implementation of tools such as speech recognition, text-to-speech conversion, and other assistive technologies, artificial intelligence can help adapt content for students with disabilities [28], [29], [30].

The discussed examples of the use of artificial intelligence in higher education show the usefulness of artificial intelligence methods. The use of AI in universities brings benefits both to students through easier access to information or personalized ways of transferring knowledge, but also to the university administration, reducing its burden and increasing productivity. It also improves the comfort of the work of scientists and academic teachers by relieving them of some tasks, such as automatic checking of students' tasks or support in conducting research. The continuous development of artificial intelligence methods also means that the possibilities of using AI at universities are also growing.

2.1 How to teach AI

This chapter examines various aspects of incorporating artificial intelligence into higher education curricula, focusing on educational strategies, pedagogy, ethics, competency development, and AI's transformative technologies. Key topics include AI-based educational technologies, ethical considerations, AI integration in engineering curricula, competency-based approaches, generative AI applications, and K-12 adaptations. The review highlights the diverse approaches proposed for leveraging AI to enhance learning environments and develop AI-related skills in students across multiple disciplines.

The subject of artificial intelligence within higher education can be categorized into several primary focal areas. Firstly, educational approaches center on AI-based technologies applied to both general education and specifically to HE. This encompasses various AI technologies deployed within educational frameworks, such as machine learning for content personalization and adaptive learning; augmented and virtual reality applications; learning analytics; and automated assessment systems [31].

The second major focus is pedagogy for teaching AI, covering foundational aspects through to engineering principles and advanced AI topics [32]. For engineering students, this area emphasizes

- mathematical foundations in AI,
- machine learning methodologies,
- optimization
- programming techniques,
- as well as further applications of AI within engineering contexts.

Additionally, AI ethics education [33] can be viewed as an independent discipline, engaging a broad audience with the ethical considerations and social implications of AI.

Cantú-Ortiz et al. [32] present an AI education strategy aimed at engineering and technology students. This strategy highlights:

- critical thinking,
- analytical problem-solving,
- big data analysis,
- human–computer interaction involving speech and image recognition,
- natural language processing,
- and gesture analysis,
- along with the development of wearable technologies,
- smart city solutions,
- autonomous vehicles,
- and decision support systems.

Their curriculum heavily utilizes advanced technology, supported by project-based and challenge-based learning methodologies.

Padovano and Cardamone [34] investigate collaborative AI-human curriculum development in engineering. They highlight the need for clearer career paths aligned with evolving industry standards and propose a competency-based curriculum supported by AI tools, including topic exploration, content benchmarking with peer institutions, and curriculum structuring around technology, human-centric, and sustainability subjects.

Southworth et al. [6] introduce a competency-based approach, integrating AI curricula into established educational structures. Their proposed AI curriculum comprises multiple courses:

- foundational AI concepts,
- applications of AI,
- advanced AI usage and creation,

- AI ethics.

For educator development, Ng et al. [35] suggest a framework for enhancing teachers' AI digital competencies. This framework addresses educators' professional engagement with AI, pedagogical competencies, and the facilitation of AI-related skills for learners.

2.1.1 Curriculum Structure and K-12 Adaptations

The structuring of AI curricula can take multiple forms, such as embedded curricula, where AI is integrated into existing content [6], or autonomous curricula, treating AI as an independent discipline [32]. Methodologies can vary between applied, theoretical, AI literacy, and competency-based focuses.

Bellas et al. [36] outline a two-year high school AI curriculum focusing on perception, actuation, representation, reasoning, learning, and collective intelligence, alongside sustainability, ethics, and legal aspects. Their instructional approach includes web-based investigation, intelligent applications, robotics, and IoT technologies.

Nwadinachi and Ivanov [37] propose an integrated AI educational model, encompassing AI technology, pedagogy, and systemic change, underpinned by pedagogical, learning, and domain-specific models. Chiu [38] presents a holistic curriculum design for K-12 AI education, incorporating aspects of content, process, and practical impact, emphasizing student relevance and teacher-student interaction.

2.1.2 AI-Aided Engineering and Certification in AI Competencies

Furthermore, entrepreneurial competencies related to high-tech startups are embedded as vital components of the AI curriculum. Specifically, the engineering curriculum covers symbolic AI (logic reasoning, knowledge representation), machine learning (tree and graph structures), natural language processing, ontology development, Bayesian uncertainty reasoning, symbolic programming (Lisp, Prolog), multi-agent systems, neural networks, deep learning, speech recognition, computer vision, fuzzy logic, robotic navigation, and evolutionary computing [32].

Nunez and Lantada [39] advocate for an "AI-aided engineering education" model, integrating AI across engineering programs, particularly in scientific and technological disciplines. This model incorporates AI for learning personalization, curriculum planning, sustainable teaching, automated assessment, and teacher assistance.

Finally, Jauregui-Correa and Sen [40] address AI competency certification within engineering education, proposing a curriculum based on theoretical, practical, and project-oriented pillars, with embedded certification within educational objectives.

How and Hung [41] emphasize AI-thinking competencies within STEM education, linking AI to mathematical foundations. The curriculum includes scientific concepts such as entropy within data, Bayesian networks in user-friendly AI tools, and AI applications in civil engineering, arts, and mathematics

A final key area is the integration of generative AI, recognized as an emerging trend in contemporary education [42], [43]. This includes the challenges and practical applications of generative AI within educational settings.

2.2 AI Curriculum for HE

Teaching AI in Higher Education can be approached in several ways, focusing on both the technical aspects of AI and its broader implications for society.

The curriculum design for study programmes in HE can be developed by following points of view:

- Integration of AI modules into existing courses - AI concepts can be woven into various disciplines, highlighting their relevance across different fields to expose students to the versatility of AI applications [44].
- Use AI learning platforms in education that provide hands-on experience with AI concepts and tools [45], [28]. Practical application can enhance understanding and encourage deeper engagement with AI.
- Development of dedicated AI programmes or specialisations integrated into study programmes – offer specialised courses and programmes focusing on AI principles, algorithms, and applications that will satisfy students seeking deep knowledge and expertise in AI [46].

2.2.1 Curriculum Development for IT Students

The rapid development of AI has highlighted the urgent need for AI literacy, especially among university IT students. Developing an AI-focused curriculum is essential to prepare students for the challenges and opportunities presented by this transformative technology. AI education should aim not only to familiarize students with AI systems but also to equip them with the skills to understand, evaluate, and responsibly create AI solutions.

AI literacy goes beyond technical proficiency; it encompasses the ability to critically analyze AI applications, recognize ethical implications, and understand their societal impacts. A well-rounded curriculum must balance theoretical knowledge, such as algorithms and data structures, with practical skills like programming, model training, and deployment. Furthermore, students should be encouraged to explore the ethical dimensions of AI, including issues like bias, accountability, and transparency, ensuring they are prepared to develop responsible and equitable AI systems.

A robust foundation in AI education is essential for higher education IT students, as it prepares them to understand, design, and implement AI systems effectively. The most critical components of this foundational phase include core concepts and programming skills, which lay the groundwork for advanced applications and innovations in AI.

The curriculum should begin by introducing students to fundamental AI concepts, ensuring they develop a deep understanding of the principles and methodologies underlying AI technologies [47], [36], [48]. Key topics include:

- Machine learning to cover supervised, unsupervised, and reinforcement learning paradigms, students learn how algorithms like decision trees, support vector machines, and neural networks process data to make predictions or decisions.
- Deep learning offers a deeper dive into neural networks, including architectures like convolutional neural networks for image processing and recurrent neural networks for sequential data analysis, is crucial for understanding cutting-edge AI advancements.
- Natural language processing explores techniques for processing and analyzing human language, such as sentiment analysis, machine translation, and chatbot development.
- Computer vision covers topics like image recognition, object detection, and facial recognition introduce the use of AI in visual data interpretation.
- Robotics explores how AI integrates with robotics to enable perception, decision-making, and autonomous operations provides a practical understanding of AI's role in hardware systems.

Proficiency in programming is a cornerstone of AI education, as it enables students to translate theoretical knowledge into practical solutions [49], [48]. The curriculum should emphasize languages and tools widely used in the AI field, with a focus on:

- Python with its extensive libraries (e.g., TensorFlow, PyTorch, scikit-learn) and simplicity, serves as an ideal starting point for AI development.
- R and Java can be used for specialized applications, exposure to additional languages like R for statistical computing or Java for scalability can broaden students' capabilities.
- Students should engage in structured coding activities, such as implementing basic machine learning models, to build hands-on experience. For example, a task like creating a linear regression model to predict housing prices teaches core AI principles and programming syntax.
- Capstone projects encourage students to apply their skills in realistic scenarios. Developing an AI-based image classifier or a sentiment analysis tool offers opportunities to integrate various aspects of AI knowledge, from data preprocessing to model evaluation.

To fully engage IT students and prepare them for the challenges of a rapidly evolving AI landscape, it is crucial to emphasize the real-world applications of AI. Demonstrating how AI impacts various sectors and incorporating hands-on projects can bridge the gap between theoretical knowledge and practical skills, ensuring students grasp the relevance and potential of their learning. Practical skills in utilizing existing AI tools and platforms for various tasks can be achieved by datasets and practical solutions focused on:

- Education where AI-powered tools such as intelligent tutoring systems, adaptive learning platforms, and automated grading systems enhance personalized learning and streamline administrative tasks.
- Healthcare where applications like AI-driven diagnostic tools, predictive analytics for patient care, and robotic surgery demonstrate how AI improves medical outcomes and efficiency.
- Finance to identify fraud detection systems, algorithmic trading, and customer support chatbots highlight AI's role in enhancing security and optimizing financial operations.
- Transportation focused on autonomous vehicles, traffic management systems, and predictive maintenance solutions underscore AI's potential to revolutionize mobility and logistics.
- Entertainment with their recommendation systems on platforms like Netflix or Spotify and the use of AI in gaming or content creation illustrate its creative and commercial value.

To encourage innovation, students should progress from evaluating existing systems to creating new AI solutions that address real-world problems responsibly [50], [51]. This includes:

- Creative problem-solving - students can engage in projects such as developing a natural language processing model for low-resource languages, addressing linguistic diversity.
- Interdisciplinary thinking - encouraging collaboration with fields like sociology or psychology helps students design AI systems that account for human behavior and societal impact.
- Iterative development - teaching iterative design principles ensures that students refine their solutions through testing and feedback, building robust and scalable AI models.

Developing higher-order thinking skills is a crucial aspect of AI education, enabling students not only to assess AI systems critically but also to design and develop innovative solutions. This requires a strong emphasis on the evaluation of AI’s effectiveness, limitations, and ethical dimensions, as well as fostering creativity in building responsible and impactful AI systems.

Students must be trained to evaluate AI systems' performance, scalability, and alignment with intended goals. Key aspects include [52], [53], [54]:

- Students learn to analyse **effectiveness** by metrics such as accuracy, precision, recall, and F1 scores to assess how well an AI model performs in each context. For example, evaluating a spam detection algorithm based on false positive and false negative rates can reveal its real-world utility.
- Teaching students to identify and articulate an **AI system's limitations** - such as data quality issues, lack of generalizability, or susceptibility to adversarial attacks - ensures they can recognize areas for improvement. For instance, students might critique a facial recognition system's accuracy disparity across demographic groups.
- By integrating **ethical analysis** into evaluation, students explore questions about privacy, fairness, and accountability. A critical review of AI-driven hiring systems, for example, might uncover algorithmic bias that disadvantages certain candidates.

Addressing the ethical dimensions of AI development is vital to ensure that students approach their work responsibly and with societal impact in mind. Algorithmic bias is a critical challenge in AI, as it can perpetuate and even amplify societal inequalities [1], [4] , [55]. Students must be encouraged to think critically about fairness, privacy, and accountability in AI systems. Key educational strategies include:

- Analyzing **real-world examples and case studies** helps students understand how biased datasets and algorithmic decisions can lead to discrimination.
- Structured debates and **critical discussions** on topics like facial recognition in policing or AI-driven content moderation foster analytical thinking about the societal impacts of AI.
- **Practical assignments** that require students to identify and mitigate bias in datasets or models - such as ensuring balanced training data for gender classification – in still practical awareness of fairness considerations.

Equipping students with knowledge of ethical frameworks and responsible AI practices ensures they can build systems aligned with societal values. Key components include [56], [57]:

- Students should learn how to design AI systems that provide clear, understandable outputs to achieve **transparency and explainability**.
- Emphasizing the **importance of human-in-the-loop** approaches helps students balance automation with accountability. For example, teaching how human review can validate AI decisions in healthcare applications ensures a safety net against errors.
- Familiarizing students with global frameworks and **ethical guidelines** like the European Union's AI Ethics Guidelines or UNESCO's AI Recommendations fosters an understanding of principles such as accountability, safety, and inclusivity.

2.2.2 Pedagogical Approaches

Effective AI education requires adopting diverse pedagogical approaches to address different learning styles, foster deeper understanding, and equip students with both theoretical knowledge and practical skills. Below are detailed explanations of six key pedagogical strategies used in AI education:

- **Constructivism** emphasizes student-centered learning, where educators act as facilitators rather than direct instructors. In this approach, students are encouraged to construct their understanding of AI concepts through exploration, interaction, and problem-solving. For example, instead of merely explaining how a neural network works, a teacher might guide students to build a simple neural network using a visual tool like TensorFlow Playground. This approach allows students to see how adjustments to parameters influence outcomes, promoting an active discovery process. By engaging in hands-on activities and reflecting on their learning experiences, students develop a deeper understanding of AI principles.

Constructivist methods are particularly effective in teaching complex and abstract AI concepts, as they enable learners to connect theoretical ideas to real-world applications [58], [59].

- **Direct instruction** involves a structured, teacher-led approach where concepts are explicitly explained, and students are provided with clear examples and demonstrations. This method is often used to introduce foundational AI topics such as algorithms, machine learning models, or the ethical implications of AI. For instance, an instructor might use slides and code examples to explain the gradient descent algorithm, demonstrating how it minimizes errors in machine learning models. Direct instruction ensures that all students receive a consistent baseline of knowledge and is particularly useful for clarifying complex concepts or equations. While it may seem traditional, this method is highly effective when paired with interactive tools like coding notebooks or simulations, which help reinforce understanding [52].
- **Participatory learning** focuses on active student involvement through discussions, debates, and group activities. This approach encourages critical thinking and the exploration of diverse perspectives on AI-related topics. For example, a class discussion could center on the ethical dilemmas of AI in surveillance or healthcare, where students are tasked with arguing for or against specific viewpoints. Such debates not only deepen students' understanding of the ethical dimensions of AI but also help them develop soft skills like communication and argumentation. Participatory learning is particularly effective in addressing societal and philosophical aspects of AI, as it engages students in exploring the broader implications of technology [52], [60].
- In **project-based or problem-based learning**, students tackle real-world AI problems or develop projects that apply AI concepts. This approach emphasizes critical thinking, creativity, and problem-solving. For instance, students might work on a project to create a chatbot using natural language processing or analyze datasets to predict trends using machine learning models. These activities mirror the challenges professionals face in AI fields, providing students with practical experience and a portfolio of work. PBL also fosters autonomy and ownership of learning, as students must research, experiment, and iterate to achieve their goals. This method is particularly valuable in AI education because it aligns theoretical knowledge with real-world application, preparing students for industry demands [61], [62].
- **Collaborative learning** involves teamwork and peer interaction to solve problems, share ideas, and build projects together. In an AI course, students might work in groups to design and train simple AI models to leverage the diverse skills and perspectives within the group, encouraging knowledge sharing and cooperative problem-solving. Collaborative learning not only enhances technical skills but also builds interpersonal skills critical for AI professionals who often work in multidisciplinary teams [63]. Platforms like GitHub and Kaggle can be incorporated to facilitate collaboration, allowing students to learn version control, dataset sharing, and collaborative coding practices.
- **Hands-on learning** focuses on giving students practical experience with AI tools, programming languages, and platforms. This approach allows students to directly interact with technologies like Python, TensorFlow, or Jupyter Notebooks, solidifying their technical expertise. For example, a hands-on session might involve training a simple machine learning model to classify images. Through such activities, students gain familiarity with the end-to-end AI workflow, including data preprocessing, model training, evaluation, and deployment. Hands-on learning bridges the gap between theoretical knowledge and practical application, making it an indispensable component of AI education [64]. It is particularly effective in building confidence, as students see the tangible outcomes of their efforts.

2.2.3 Learning Tools

A diverse array of learning tools is essential for supporting effective AI education. These tools, encompassing both hardware and software, provide students with the opportunity to engage in hands-on experimentation and practical learning. By integrating these resources into the curriculum, educators can bridge theoretical knowledge with real-world application, fostering deeper understanding and skill development.

Hardware tools play a pivotal role in offering tangible, hands-on experiences with AI concepts [6], [65]. These tools allow students to explore the integration of AI with physical systems and gain insights into real-world applications.

- **Robotics kits** like Arduino, Raspberry Pi, or LEGO Mindstorms provide an accessible introduction to robotics and AI. Students can program robots to perform tasks such as object detection, obstacle avoidance, or speech recognition, enabling them to connect AI algorithms with physical actions. For example, programming a robot to navigate a maze using AI algorithms helps students apply machine learning to solve spatial problems.
- **Sensors and IoT devices** equipped with sensors for temperature, motion, or light detection offer opportunities to explore data collection and AI-based analysis. Students might use IoT devices to develop predictive maintenance systems or environmental monitoring applications, reinforcing their understanding of AI's role in smart technologies.
- **Other physical devices** such as drones or robotic arms introduce students to specialized AI applications like autonomous navigation or automated manufacturing, providing insight into industry-specific use cases.

Hands-on experimentation with hardware not only reinforces theoretical knowledge but also cultivates problem-solving skills, creativity, and adaptability, all of which are crucial for AI professionals.

Software tools are indispensable in AI education, offering powerful platforms for designing, testing, and implementing AI models [52], [66]. These tools cater to various skill levels and learning objectives, making them versatile resources for students.

- **Programming languages** – Python is the most widely used language for AI education due to its simplicity and extensive libraries, such as TensorFlow, PyTorch, and scikit-learn. The libraries allow students to experiment with machine learning, deep learning, and data visualization.
- **AI platforms** like Google Colab, AWS AI, and Microsoft Azure Machine Learning provide cloud-based environments for developing and deploying AI models to enable students to work on large-scale datasets and gain experience with real-world workflows.
- **Simulation tools** such as OpenAI Gym or Unity ML-Agents allow students to experiment with reinforcement learning and simulate environments for training AI agents. For instance, students can program an AI agent to play games, solve puzzles, or optimize strategies within a virtual environment.
- **Educational apps and games** like Code.org or AI Dungeon incorporate gamification to teach foundational AI concepts, keeping students engaged while learning complex topics. For example, educational apps might simulate AI decision-making processes or guide students through building basic models step-by-step.

2.2.4 Teacher Training and Support

The success of AI education depends significantly on the preparedness and support of educators. Teachers must possess a combination of technical expertise, pedagogical strategies, ethical awareness, and access to ongoing professional development to effectively teach AI concepts and tools. This multifaceted approach ensures that educators are equipped to deliver engaging, responsible, and up-to-date AI education [67].

To teach AI effectively, educators need a solid foundation in the technical skills, tools and platforms commonly used in the field. Teachers should be **adept at using AI programming languages** like Python and platforms such as TensorFlow or scikit-learn [68]. This allows them to guide students in developing and testing AI models. Hands-on **familiarity with AI tools and environments**, such as Google Colab or

Jupyter Notebooks, ensures that teachers can troubleshoot issues and provide real-time support to students during projects. Training workshops and certifications can help educators gain these technical skills [69].

Integrating AI concepts into the classroom requires an understanding of effective **teaching strategies** tailored to AI education [70]. Educators should be skilled in creating lesson plans that balance theoretical knowledge with practical applications. Understanding how to use interactive methods, such as group projects, simulations, or gamified exercises, helps teachers make complex AI topics more accessible and engaging [71]. Teachers should be trained to address varying levels of student proficiency, ensuring that both beginners and advanced learners benefit from the curriculum.

Ethical considerations are central to AI education, and teachers must be prepared to address these topics thoughtfully [72], [73]. Educators need knowledge of critical ethical concerns, including algorithmic bias, data privacy, and accountability in AI systems. This enables them to guide discussions and projects that incorporate ethical reflection.

Teachers should facilitate debates and case studies on real-world ethical dilemmas, such as the fairness of AI in hiring processes or the implications of facial recognition technology to encourage students to think critically about the societal impact of AI. Familiarity with global guidelines, such as the European Union's AI Ethics Guidelines, equips educators to teach students about responsible AI development.

Given the rapid pace of advancements in AI, continuous professional development is essential for educators to stay current. Regular participation in training programs, webinars, or certification courses ensures teachers are familiar with the latest AI tools, techniques, and educational practices.

Encouraging collaboration among educators through professional networks or communities of practice allows teachers to share resources, strategies, and experiences. Providing them with updated teaching materials, research, and access to AI tools fosters confidence and effectiveness in the classroom [74].

Investing in teacher training and support is crucial to the success of AI education. By equipping educators, we can ensure that students receive high-quality, responsible, and impactful AI education.

2.3 AI Curriculum: Case Study

The literature on AI integration in higher education reveals several emerging themes and directions, clustering around competency development, personalized learning, generative AI tools, and ethical considerations.

A significant focus in the literature is on designing AI curricula that incorporate **key skills and competencies** needed for the digital transformation era. Studies advocate for the integration of AI into curricula to support the development of critical thinking, problem-solving, and technical skills relevant to engineering and technology. There is an emphasis on competency-based education models, ensuring that curricula are structured to build foundational and advanced AI skills progressively.

AI tools are increasingly used to **personalize the learning experience**. Intelligent tutoring systems, chatbots, and adaptive learning platforms allow for customized educational pathways tailored to student needs and performance. This trend highlights AI's potential to enhance learning efficiency and engagement through targeted, real-time feedback and support mechanisms. The clustering of studies suggests a strong move toward AI-enabled instructional design that focuses on student-centered learning experiences.

The **integration of generative AI**, such as chatbots and other interactive technologies, is identified as a growing trend. These tools are used to facilitate learning, automate administrative and grading processes, and provide immediate feedback. The literature indicates a move towards incorporating these technologies not only as educational aids but also as core components of the learning process, fostering both engagement and efficiency.

The literature consistently addresses the **ethical implications and challenges** associated with AI integration in education. Concerns about bias, academic integrity, and data privacy are prevalent, leading to calls for the development of comprehensive guidelines and ethical frameworks. The findings suggest that while AI has transformative potential, its implementation must be managed carefully to mitigate risks and promote fairness.

Another cluster of findings emphasizes **the importance of integrating AI literacy early** in educational settings, particularly in K-12 contexts. Studies advocate for embedding AI into curricula at the primary and secondary levels, ensuring that students acquire fundamental AI skills and literacy before entering higher education. This trend suggests a strategic focus on building AI competency as a continuous developmental process from early education through to HE.

In summary, the literature indicates a comprehensive approach to AI in education, encompassing early integration, personalized learning, competency development, and the ethical management of emerging technologies. Future directions include refining AI curricula, enhancing AI literacy from early education onwards, and developing robust ethical guidelines to ensure the responsible and effective use of AI in educational environments.

2.3.1 Adapting Curriculum for AI Practice

The FITPED-AI project undertook a comprehensive initiative to design a curriculum structure that is in line with the growing demands of AI education. In preparing the project, the partners proposed an AI course structure as a basic framework for integrating AI into higher education, with the aim of ensuring that students graduate with both theoretical knowledge and practical skills. The project outputs reflect the contributions of all participating partners, emphasizing collaboration and alignment with modern AI practices.

The curriculum structure proposed by the FITPED-AI project is organized into three core areas:

- AI prerequisites ensure coverage of basic topics such as mathematics, programming, and computational thinking to ensure that students have the necessary knowledge to engage with advanced AI concepts.

- AI fundamentals cover basic topics such as data preparation, knowledge discovery, AI methodologies, and machine learning. These courses provide students with a strong theoretical and technical foundation in AI.
- The AI application areas focus on exploring practical applications of AI in domains such as natural language processing (NLP), educational data analytics, and cybersecurity, allowing students to connect theoretical knowledge with real-world problems.

These courses have been carefully designed to enhance students' highly specialized AI skills, with over 3,000 students participating in the project.

To maximize the impact of the FITPED-AI project, the curricula of the participating university partners have been synchronized, aligning their programs with the newly designed structure:

- Constantine the Philosopher University (UKF) aligned its Applied Informatics program with the defined curriculum structure in 2022. The integration ensures that students receive a well-rounded education in AI and prepares them for the demands of the field.
- The University of Silesia (US) and Mendel University in Brno (MENDELU) have incorporated the developed content into selected courses and recommended additional courses as supplementary education. This approach has enriched their programs while providing students with the flexibility to explore AI topics in greater depth.

The synchronization effort has strengthened the educational offerings of the partner institutions, but also set a precedent for joint curriculum development across universities.

The application of the FITPED-AI curriculum at Constantine the Philosopher University has resulted in a structured program covering both the bachelor's and master's degrees of the applied computer science program. This structure can serve as a model for other universities seeking to enhance their AI-related offerings, demonstrating the potential of collaborative projects to address evolving AI education needs.

Table 1. Structure of subjects covering AI in the Applied Informatics study program at the UKF in Nitra

Course (subject) name	Content description	Semester of study
Encoding and Representation of Information	Introduction to methods of encoding and representing data, including binary systems, multimedia encoding, and efficient data compression techniques.	Bc - 1
Programming	Fundamental programming concepts, including algorithms, control structures, and data structures, using Python.	Bc - 1
Programming Seminar	Practical programming sessions focusing on problem-solving, debugging, and implementing projects to enhance coding skills.	Bc - 1
Database Systems	Design, implementation, and management of relational databases, including SQL queries, normalization, and database optimization techniques.	Bc - 2
Mathematical Principles of Language Processing and Machine Learning	Covers foundational mathematical concepts such as linear algebra, probability, and statistics as they apply to natural language processing and machine learning.	Bc - 2
Data Processing in Python	Techniques for data preprocessing, analysis, and visualization using Python libraries like Pandas, NumPy, and Matplotlib.	Bc - 2
Formal Languages and Automata	Study of formal grammars, languages, automata theory, and their applications in computer science and compiler design.	Bc - 3

Course (subject) name	Content description	Semester of study
Computational Complexity of Algorithms	Analysis of algorithm efficiency, computational complexity classes	Bc - 4
Computer Data Analysis	Introduction to data analysis techniques using statistical tools and computational methods to extract insights from datasets.	Bc - 5
Artificial Intelligence	Fundamentals of AI, including search algorithms, knowledge representation, decision-making systems, and introduction to machine learning and neural networks.	Bc - 6
Internet of Things	Overview of IoT technologies, including sensor networks, device connectivity, and applications in smart homes, cities, and industries.	Bc - 6
Introduction to Machine Learning	Basics of machine learning, covering supervised, unsupervised, and reinforcement learning, with hands-on examples using real-world data.	MS - 1
Social, Moral, and Economic Aspects of Informatics	Examination of the societal, ethical, and economic implications of information technologies, including AI ethics and privacy concerns.	MS - 1
Cloud Technologies	Principles of cloud computing, including cloud architecture, virtualization, and services like IaaS, PaaS, and SaaS.	MS - 1
Introduction to Information Visualization	Basics of visualizing complex data using charts, graphs, and other visual tools to enhance data interpretation and decision-making.	MS - 1
Knowledge Discovery	Techniques for discovering patterns, trends, and insights in data, focusing on data mining and predictive analytics.	MS - 2
Neural Networks	Introduction to artificial neural networks, including perceptrons, feedforward, and convolutional networks, with practical examples.	MS - 2
Virtual Reality	Concepts and applications of virtual reality, including 3D modeling, VR system design, and immersive user experience creation.	MS - 2
Big Data Processing Technologies	Tools and techniques for processing large-scale data, including Hadoop, Spark, and distributed computing methods.	MS - 2
Deep Data Analysis	Advanced data analysis techniques using machine learning and AI to uncover deep insights and predict future trends.	MS - 3
Introduction to Natural Language Processing	Basic concepts in NLP, including text tokenization, sentiment analysis, and language modeling with AI tools.	MS - 3
Augmented Reality	Study of AR technologies and their applications in blending virtual objects with real-world environments for enhanced interaction.	MS - 3
Educational Data Mining	Focus on extracting patterns and insights from educational data to improve teaching strategies, learning outcomes, and academic performance.	MS - 3

2.4 AI Benefits in the Educational Process

Artificial intelligence is transforming the way students learn and engage with educational content, making the study process more personalized and efficient. AI-powered tools, such as intelligent tutoring systems and adaptive learning platforms, provide tailored feedback and guidance based on individual learning needs. Through natural language processing, AI enables interactive experiences, such as chatbots and virtual assistants, to answer questions and support students in real time. Additionally, AI can analyze learning patterns to identify areas where students struggle, offering targeted resources and strategies to improve understanding.

AI has the potential to fundamentally transform education and bring many benefits, such as personalization of teaching, automation of assessments, support of teachers and students, or improvement of the availability of educational materials. This can fundamentally change the way teachers approach teaching. At the same time, however, it is important to carefully consider the ethical and practical issues associated with this technological progress. Educational systems should be designed so that AI supports teachers and students, but at the same time the importance of the human factor and personal approach in teaching remains. The human factor in teaching remains key, especially when building relationships with students and solving complex pedagogical situations. Artificial intelligence should be a tool that supports teachers, not replaces them.

Holmes and Tuomi [75] propose a taxonomy of AI applications in education (AIED), structured by target audience and commercialization level:

- student,
- teacher,
- institution.

Student-centered AIED applications include intelligent tutoring systems, AI-enabled applications, simulations, AI tools for supporting learners with disabilities, automated essay scoring, chatbots, automated formative assessments, learning network orchestrators, dialogue-based tutoring systems, exploratory learning environments, and lifelong learning assistants facilitated by AI.

Teacher-focused AIED tools encompass plagiarism detection, curated educational content platforms, classroom monitoring, automated summative assessments, and AI teaching assistants (inclusive of assessment support).

For institutions, AIED applications target student admissions (e.g., selection processes), course planning, scheduling, timetabling, security management, identifying students at risk of dropout, and digital proctoring systems.

2.4.1 Student Benefits

Artificial Intelligence is revolutionizing education, offering transformative ways for students to learn and grow academically. AI can help students to learn in a variety of ways. AI enables the customization of learning experiences, tailoring educational content to the specific needs, and learning styles of individual students.

Personalised learning

This approach focuses on areas where students need more support while accelerating through familiar topics. Based on the analyse of student data AI can create **personalised learning paths** tailored to each student's needs, preferences, and learning style [44], [76], [77]. This means students can learn at their own pace, focusing on areas where they need more support and moving more quickly through topics they already understand [78], [79]. AI can also suggest relevant learning materials and strategies to students based on their individual learning styles and academic performance data [80].

AI-powered learning platforms can offer **adaptive content** delivery that adjusts to the student's pace, learning style, and knowledge gaps to resonate the learning materials with learners' preferences and aptitudes [76], [81]. For example, platforms using AI can monitor a student's progress and, based on this, offer him study materials and practice tasks that are suitable for him, which improves the effectiveness of learning.

AI can also **adapt assessments** to the individual learning paths of each student, allowing teachers to quickly and effectively address specific learning gaps [78]. For assessment personalization, AI shows promise in providing real-time feedback, highlighting areas requiring intervention, and tracking progress by analyzing student work processes and responses [76], [82].

AI can also be used in the **intelligent tutoring systems development** that provide students with personalized feedback and support. These systems can adapt to the student's level of understanding and provide targeted instruction that helps them to master the material and act as digital mentors, guiding learners toward mastery of complex concepts [83], [84].

Increased engagement and motivation

AI is making learning environments **more interactive and engaging**, helping students stay motivated and invested in their studies. For example, gamification techniques integrated with AI create immersive learning experiences that blend fun and educational value, rewarding students as they achieve milestones [44], [78], [81]. Interactive AI tools often adapt to student preferences, ensuring the learning experience feels personalized and meaningful.

Real-time feedback systems powered by AI keep students informed of their progress. This transparency allows learners to adjust strategies and stay on track toward academic goals [85], [86], [87]. Additionally, AI platforms can modify learning environments to cater to different accessibility needs and learning styles, ensuring inclusivity and a tailored approach for all [76].

AI also supports the **development of self-regulated learning** (SRL) skills, which are critical for success, especially in online learning contexts. By equipping students with tools for goal-setting, progress monitoring, and self-reflection, AI encourages independence and deeper engagement with the learning process. These SRL strategies are particularly valuable in environments that demand high levels of autonomy from learners [80], [85], [88].

Impact of generative AI tools

ChatGPT and other generative AI tools are having a significant impact on education from the students' perspective. They have sparked a complex mix of excitement and concern among students, leading to differing perspectives on their impact on education.

Here are some of the key ways GAI tools are positively impacting students:

- **Language learning and communication skills** – ChatGPT clones can be particularly beneficial for language learning by offering a platform for students to practice dialogue and receive feedback, helping them improve their speaking skills and reduce anxiety [2], [89]. Students may also use these tools to draft essays and other assignments and get feedback on their work, which can be especially helpful for students who are not confident in their writing abilities [90], [91]. Students report that the instant feedback provided by these tools is very helpful [2], [92].
- **Personalised learning** – generative AI tools can facilitate personalised learning by tailoring content and learning paths to individual student needs and providing personalised feedback [2], [93]. Students are positive about the potential for AI to provide cheaper and more engaging learning opportunities and these, who lack access to human advisors may particularly benefit from AI expert systems [94].
- **Accessibility** – AI tools can enhance accessibility for students with disabilities. For example, they can provide automatic **speech recognition, text-to-speech and sign language interpretation** [95]. There is also potential for AI to help alleviate academic stress for students with disabilities [96].
- **Student supervision and support** – AI chatbots can be used to scale mentoring for students, especially those on work placements [97]. Students value the potential of AI to create

personalised supervisory relationships that enhance their research progress and foster critical thinking [98]. AI can also help develop creative thinking and problem-solving skills. Modern AI systems can create new, unexpected combinations of ideas and approaches, which can inspire and encourage students to find their own innovative solutions. In some cases, students can work with AI to solve complex problems, allowing them to improve their analytical skills and better understand complex situations [99].
- **24/7 availability** – AI chatbots and virtual assistants are available to students 24/7, providing a valuable resource for those who need support outside of traditional classroom hours. Studies show that some students even view AI as more approachable than human tutors [89], [100], [101].

However, alongside their benefits, generative AI tools also raise important concerns and challenges in the educational context. These include issues related to academic integrity, over-reliance on AI, and the potential for uneven access to these technologies among students.
- **Academic integrity** – one of the most significant concerns surrounding generative AI is its potential for misuse in academic work. Students are worried about plagiarism and cheating, as AI tools can easily generate essays and assignments that are difficult to distinguish from original work. There is also concern about the authenticity of students' work and the development of critical thinking skills if students rely too heavily on AI for content generation [102], [103], [104].
- **Over-reliance and dependency** – while AI can be beneficial, there is a risk of over-reliance on AI tools, potentially hindering the development of critical thinking and problem-solving skills [105], [104]. Some students worry that becoming too dependent on AI for answers and feedback could lead to a decline in their own analytical abilities and motivation to learn independently [106], [107].
- **Impact on human connection** – some students are concerned about the potential loss of human connection in learning if AI takes on a more prominent role [108], [109]. They value the personal interaction and mentorship provided by human educators and fear that excessive AI integration could lead to a less engaging and fulfilling learning experience [104].
- **Bias and accuracy** – AI models are trained on vast datasets, which can contain biases and inaccuracies [110], [109], [104]. Students are aware of the potential for AI-generated content to reflect these biases, leading to misinformation and skewed perspectives.

Despite the concerns, a large portion of students have a positive attitude towards the use of AI chatbots in education. However, the study in source [110] found statistically significant differences in attitudes across genders and fields of study. Female students and students from the humanities and medicine were more likely to express negative attitudes and concerns, while male students and those in technology and engineering displayed higher usage and optimism. This suggests that different groups may experience the impact of AI on education differently [111], [112], [113].

It is evident that students are navigating a complex landscape as they try to understand and adapt to the integration of generative AI in education. The overall sentiment appears to be cautiously optimistic, with students acknowledging both the potential benefits and challenges of these tools. Students are particularly interested in how AI can be used to personalise their learning experiences and enhance efficiency, but they are also mindful of the potential risks to academic integrity, critical thinking skills, and the human element of education. As AI continues to evolve, it is crucial for educators and policymakers to address these concerns and work collaboratively with students to ensure responsible and ethical integration of these powerful tools into the learning process.

2.4.2 Teacher Benefits

AI can assist teachers in numerous ways, streamlining tasks, enhancing teaching strategies, and offering valuable insights into student learning. The sources highlight the following benefits of using AI in education. These tools provide educators with innovative solutions to enhance lesson planning, improve student engagement, and streamline administrative tasks. By integrating AI into their teaching strategies, teachers can focus more on fostering creativity, critical thinking, and personalized support for their students.

Reduced workload and administrative tasks

Student assessment is a time-consuming activity that often takes up a large part of teachers' working time. Artificial intelligence can greatly simplify this activity, especially when evaluating routine tasks such as grading tests or providing feedback to students. Automated systems can quickly and accurately correct tests, homework or exercises, freeing up teachers' hands and allowing them to spend more time on teaching [2]. In addition, some systems can provide students with immediate feedback, which is key for their further development. This applies, for example, to language teaching, where AI systems can correct grammar, language style and pronunciation in real time. The time thus saved can be used by teachers for the preparation of new materials, individual consultations with students or work with those who require additional support.

Reduced workload and administrative tasks are probably the most important impact of AI on a teacher's job. AI can automate routine tasks such as grading, lesson planning, and handling student inquiries [114]. This automation frees up teachers' time, allowing them to focus on more creative and engaging aspects of teaching. For example, AI-powered chatbots can address frequently asked questions, schedule appointments, and provide basic support to students, thereby reducing the administrative burden on teachers [89], [115].

Helping to prepare personalized education and support

Lesson preparation is one of the most time- and mentally demanding parts of a teacher's work. AI can facilitate this process by offering lesson structure suggestions or recommending suitable learning materials. Some systems allow teachers to enter the objectives of the lesson and, based on them, create a proposal for the structure of the lesson, which is suitably adapted to specific educational objectives.

AI algorithms can analyze student data to identify individual learning needs and provide tailored learning materials and support. This **enables teachers to accommodate different learning styles** and paces, ensuring all students could succeed [2], [116]. Adaptive systems and personalization are key areas of AI research in education, with AI being used to tailor content delivery, recommend personalized learning pathways, and represent knowledge through intuitive concept maps [3], [117].

Preparation of improved assessment and feedback

Teachers can use the assistance of AI in assessing student learning more efficiently and effectively [115], [118]. Automated grading systems save time and provide objective, error-free assessments [114]. Additionally, AI algorithms can deliver personalized feedback to students, highlighting areas needing improvement [2], [119]. These tools allow teachers to offer more targeted support and helps students better understand their strengths and weaknesses.

Enhanced student engagement and motivation

AI can create more interactive and engaging learning experiences. This is achieved through AI-powered games, simulations, and virtual reality experiences, which make learning more enjoyable and relevant for students. Such technologies boost motivation and engagement, encouraging active participation in educational activities [89], [120], [121].

Distance education and virtual assistants

AI can help improve communication between teachers and students, especially in remote learning environments. Virtual assistants using AI can provide real-time support to students, both in finding the right materials and answering questions [122]. Virtual assistants, or chatbots, can be available to students 24/7 to answer their questions, provide basic support with solving problems with assignments, or explain more complex concepts. This allows teachers to focus on more complex questions and direct interaction with students, while AI takes care of routine questions. These tools can significantly improve the effectiveness of learning and reduce dependence on the teacher, which is especially useful in situations where the physical presence of the teacher is not possible [123], [124].

Data-driven insights and decision-making

Another advantage of AI is the ability to analyze a large amount of data about the progress of learning and create comprehensive overviews of student progress based on it. This data can include not only test results, but also data on how long it took the student to process certain material, where he made the most mistakes, or what type of learning suits him best [125]. In this way, teachers can quickly obtain information about how students are progressing, where the most common problems appear, and in which areas additional teaching needs to be focused. AI systems can also predict which students might have trouble completing a course and suggest steps to take to avoid those problems. This kind of predictive analytics allows teachers to quickly intervene and provide students with the support they need before problems escalate [126], [127].

By analyzing data about students' previous results and performances, AI can recommend materials or exercises that are adapted to their individual learning pace. AI enables teachers to gain a deeper understanding of their students' learning processes. Learning analytics platforms use AI algorithms to collect and analyze data on student behavior and performance [128]. This data helps identify areas where students struggle, track progress over time, and support data-driven decisions about teaching strategies.

Adaptive learning platforms that use AI are another important area in which this technology can enrich education [129]. These platforms learn based on student behavior and adjust content and learning methods to best suit individual needs. For example, AI can recognize when a student repeatedly makes mistakes in a certain topic, and based on this, provide him with additional explanations or more exercises to help him understand the material better.

Challenges to AI integration in education

Despite the enormous potential of artificial intelligence in education, there are also challenges and ethical issues that need to be addressed. One of them is the **issue of privacy and protection of personal data**. The collection and analysis of large amounts of student data raises concerns about who has access to that data and how it is used. Teachers need to be mindful of the ethical implications of using AI in education. This includes safeguarding data privacy, addressing algorithmic bias, and ensuring AI does not reinforce existing inequalities [2], [73].

Another ethical question is possible **dependence on AI**. Relying too much on technology can lead to a decline in skills that are necessary for interpersonal communication and interaction [130].

Critics also point to the risk that AI will promote standardized education at the expense of creativity and individuality [131]. Although AI can be useful in recognizing patterns and providing targeted support, it can also lead to the loss of the human touch that is often necessary to support students' emotional and social development.

Teacher training and skills development is necessary part of effective use of AI tools. Teachers must be adequately **trained to use AI tools effectively** and incorporate them into their teaching practices [132], [133]. A lack of technical knowledge and concerns about AI ethics can hinder the development and adoption of AI-based curricula [133], [134].

AI-powered tools may **shift some authority from teachers to AI systems**, raising concerns about the evolving nature of teacher-student relationships [133]. Teachers must navigate these changes carefully, maintaining their roles as educators and mentors while using AI as a supportive tool.

Despite these challenges, AI has the potential to significantly enhance the teaching and learning experience. By automating tasks, personalizing learning, and providing valuable insights into student progress, AI empowers teachers to become more effective and efficient in their roles.

2.4.3 Recommendations for Applying AI in Education

The integration of AI in education requires strategic and thoughtful application to ensure that it effectively supports teaching and learning processes. Below are key recommendations for teachers to make the most of AI tools in education. By applying these recommendations, teachers can effectively leverage AI to enrich the educational experience, improve student outcomes, and foster a balanced, ethical approach to technology use in the classroom.

- Develop AI literacy at the student and teacher level – equip both groups with the knowledge and skills to understand AI technologies, interact with them, and critically evaluate outcomes, with an emphasis on raising awareness of the ethical and societal implications of AI [135], [136]. Before implementing AI tools, teachers should familiarize themselves with their capabilities, strengths, and limitations. To maximize AI’s potential, teachers need ongoing training and support. Staying updated on advancements in AI tools helps educators refine their approaches and integrate new technologies effectively. Understanding what AI can and cannot do ensures realistic expectations and appropriate use. For example, AI can automate assessments and generate personalized content, but it can struggle with ambiguous decision-making or ethical considerations. Ensure participation in workshops or training on AI tools relevant to education and engage with case studies or resources to gain practical insights.
- Choose AI tools in line with learning objectives and learning strategies. Adaptive learning platforms are great for personalizing instruction, while AI chatbots can effectively handle common questions or provide on-demand support. Evaluate AI tools based on their ability and usefulness to meet curriculum requirements, increase student engagement, and provide useful information aligned with learning content and appropriate methodologies [137], [138], [139].
- Leverage AI for personalized learning [87]. With AI algorithms able to analyze student performance data to identify strengths, weaknesses, and preferred learning styles, it is possible to provide content based on students’ individual needs, ensuring that no student is left behind [140]. Teachers can also use this information to provide personalized feedback, adjust plans, and recommend customized learning materials. Also, emphasize self-regulated learning – encourage students to develop metacognitive skills and strategies to manage their learning using AI tools. This will teach students to take responsibility for their learning process [141].
- Encourage reflective practices – help students understand how AI works, its benefits and limitations, which will support their digital literacy and prepare them to use AI responsibly in academic and professional settings. Encourage students to critically analyze their interactions with AI and consider the implications for their learning and future careers [142], [143].
- Teachers play a crucial role in supporting the ethical and responsible use of AI in education by addressing key issues such as bias, privacy, and the potential impact of AI on the workforce. These topics should be openly discussed with students to raise awareness and sensitivity to their implications [144]. Encouraging critical thinking about AI's applications and limitations is essential, along with fostering responsible development and ethical use. Transparent communication about how AI tools are utilized and what data is processed builds trust and helps students understand AI’s role in their education. Furthermore, it is important to ensure that AI-powered educational tools are accessible to all students,

regardless of their background or abilities, which includes addressing biases in AI systems and promoting equitable access to technologies to avoid exacerbating existing inequalities [145].

- AI is designed to enhance, not replace, the role of the teacher in education. It should be viewed as a complement to traditional teaching methods, enriching the learning experience while preserving the essential human element [124], [146]. Students should be encouraged to collaborate with AI tools rather than passively rely on them. For example, AI can assist in brainstorming, drafting essays, or solving complex problems, but it is critical that students evaluate and refine the outputs to foster deeper understanding and critical thinking. Assignments that require students to creatively use AI tools while emphasizing their own input and analytical skills can highlight the importance of the human role in the process. Additionally, AI tools can automate repetitive tasks such as grading or lesson planning, freeing up teachers' time for more creative and interactive teaching activities. However, the outcomes of these automations should be closely monitored to ensure they align with educational goals and maintain quality [23], [130].
- Collaboration with school administrators, IT staff, and fellow educators is essential for the successful implementation of AI tools in education. Teachers should work as part of a team to evaluate, implement, and scale AI tools across the institution. Sharing best practices, experiences, and lessons learned within this collaborative framework ensures a smoother integration process and supports the effective use of AI to improve educational outcomes [147], [148].
- Institutional development and support are essential for the sustainable integration of AI in education. Providing teachers with ongoing training and professional development opportunities is critical to equipping them with the skills needed to effectively integrate AI into their teaching practices. This includes developing competencies in data interpretation, implementing adaptive tools, and addressing ethical issues related to AI use. Collaboration between educators and technologists should also be prioritized to bridge the gap between pedagogical needs and technological solutions. Interdisciplinary collaboration is equally important, fostering the development of innovative and pedagogically sound AI-powered learning tools that align with educational goals and principles, ensuring meaningful and effective AI integration [149], [150].

3 Active Learning

Active learning is a teaching methodology that prioritizes active student engagement, fostering a dynamic learning environment where students participate in constructing their own knowledge. Unlike traditional models of passive instruction, such as lectures where information flows unidirectionally from teacher to student, active learning places students at the center of the educational process, encouraging interaction, exploration, and critical reflection.

Scholars define active learning as instructional methods that involve students directly in the learning process. Prince [151] describes it as "any instructional method that engages students in the learning process," while Bonwell and Eison [152] emphasize its focus on “students doing things and thinking about what they are doing.” These definitions highlight the multifaceted nature of active learning, which includes hands-on activities, collaborative efforts, and real-world problem-solving scenarios [153].

This approach aligns closely with constructivist theories of learning, such as social constructivism, which suggest that knowledge is actively constructed through social interactions and meaningful engagement with the environment. Active learning strategies such as problem-based learning, where students tackle real-world challenges in collaborative settings, and teamwork-based collaborative learning, which promotes communication and interpersonal skill development, exemplify this philosophy [154].

The benefits of active learning are well-documented, ranging from enhanced student engagement and motivation to improved critical thinking and problem-solving skills [155], [156], [157]. By actively participating in the learning process, students develop a deeper understanding of the material, retain knowledge longer, and gain confidence in their abilities. Furthermore, the incorporation of technology, including AI-driven platforms and tools, has expanded the scope of active learning. AI can facilitate personalized feedback, adaptive content delivery, and interactive environments that resonate with individual student needs [107], [137], [158].

Active learning is thus an essential approach for modern education, bridging the gap between theoretical knowledge and practical application while preparing students with the skills and confidence they need to succeed.

3.1 Key Characteristics

Active learning is characterized by specific elements that differentiate it from passive learning approaches. These features collectively create an engaging, participatory, and interactive learning environment that fosters deeper understanding and skill development:

- Student participation – active learning prioritizes student involvement through activities such as reading, writing, discussions, and problem-solving. These activities require students to actively engage with the material, shifting the focus from passive reception of information to active exploration and application [159].
- Engagement and understanding – by experiential and interactive tasks students learn through hands-on activities, problem-solving, discussions, and collaborations. They actively engaging with the material, develop a better understanding of the subject and retain information more effectively [160]. This hands-on approach encourages curiosity and deeper cognitive processing, which enhances long-term retention.
- Knowledge construction based on active learning emphasizes the construction rather than its transmission. Students actively create meaning by interacting with the content, engaging with peers, and participating in activities that challenge them to think critically and apply their knowledge [161].
- Active learning promotes higher-order thinking by engaging students in activities that require critical thinking, analysis, synthesis, and evaluation, allowing them to apply their

knowledge and develop problem-solving skills. Additionally, research shows that active learning methods significantly improve information retention compared to traditional passive approaches [162], [163]. By involving students in meaningful and interactive tasks, active learning fosters stronger connections to the material, making it easier for students to recall and apply what they have learned.

- Facilitated by technology – technology, including AI-powered tools, can play a key role in supporting and enhancing active learning. For example, AI-based chatbots can provide personalized feedback, guidance, and interactive learning experiences. Platforms that allow for real-time tracking of student progress during classroom coding exercises can also support active learning [154], [164].

3.1.1 Active Learning Techniques and Benefits

Active learning offers a diverse range of techniques designed to foster participation, collaboration, and critical thinking. Active learning can be facilitated through various methods, including interactive teaching methodologies that incorporate web-based and face-to-face instruction. These methods can be adapted to various educational environments to maximize engagement and learning outcomes:

- Flipped classrooms where students review lecture material or readings before class, freeing up in-class time for active learning activities like problem-solving, discussions, or group work [165]. This approach works well in both face-to-face and online settings.
- Interactive labs, experiments and simulation based learning offer hands-on activities in laboratory settings allow students to test hypotheses, analyze data, and draw conclusions [166]. These activities are common in STEM education and foster experiential learning. They are also suitable for solving problems by AI tools [146].
- Collaborative learning – many active learning strategies incorporate collaboration, such as group work, discussions, or peer feedback. This teamwork helps students develop interpersonal skills, improve communication, and learn to work effectively in diverse groups [159].
- Collaborative digital tools are covered by platforms like Google Workspace, Padlet, or discussion boards and can enable collaborative editing, brainstorming, and sharing of ideas in virtual environments. These tools are essential for remote and blended learning contexts [70].

In addition to techniques in virtual environments, “classical” techniques based on face-to-face communication, are sometimes also used [159]:

- Case studies – analyzing and discussing real-world cases to apply theoretical knowledge or practice skills.
- Role-playing – students act out scenarios to explore concepts in real-world contexts.
- Peer learning – students teach or learn from their peers, reinforcing their understanding of the material.
- Short class discussions – focused, interactive conversations to clarify and deepen understanding.
- Debates – structured arguments that encourage critical thinking and the exploration of multiple perspectives.
- Group projects – collaborative tasks where students work together to achieve shared objectives.
- Think-pair-share – a quick strategy where students think individually, discuss with a partner, and share their ideas with the group.
- Just-in-time teaching – adjusting instructional content based on student feedback or performance right before the lesson.

Active learning, grounded in cognitive learning theories, emphasizes the active role of learners in constructing their knowledge. It aligns closely with self-regulated learning, where students take initiative, monitor their progress, and adapt strategies to achieve learning objectives. This approach offers a wide array of benefits that contribute to deeper understanding, skill development, and overall student success.

Increased engagement and motivation

Active learning creates a dynamic and interactive educational environment, making learning more relevant and stimulating for students. By engaging directly with the material through hands-on activities, discussions, and problem-solving, students find the process more enjoyable and meaningful [153], [167]. This heightened engagement often leads to increased motivation, as students see the value of their participation and the relevance of the content to real-world scenarios [168].

Deeper understanding and improved retention

When students actively engage in the learning process, they are more likely to process and internalize the information deeply. Active learning encourages students to connect new concepts with prior knowledge, apply theoretical ideas in practical contexts, and reflect on their learning. These processes enhance comprehension and lead to better retention of information compared to passive learning methods, where knowledge is simply absorbed without interaction [157], [169].

Development of critical thinking and problem-solving skills

Active learning challenges students to analyze information, evaluate options, and make decisions, fostering critical thinking and problem-solving abilities. Activities such as case studies, debates, and role-playing push students to explore multiple perspectives and devise creative solutions to complex problems are essential for success not only in academics but also in professional and real-world contexts [153], [167].

Enhanced collaboration and communication skills

Many active learning techniques involve group work, peer interactions, and discussions, which help students develop collaboration and communication skills. These activities require students to articulate their ideas clearly, listen actively, and work effectively within a team. The ability to collaborate and communicate effectively is a transferable skill that benefits students in academic, social, and professional settings [157], [167].

Increased student confidence and self-efficacy

Active learning empowers students to take charge of their education, boosting their confidence in their abilities. By actively participating in their learning journey and achieving success through their efforts, students develop a sense of self-efficacy [159], [170]. This belief in their capability to learn and solve problems translates into improved performance and a more positive attitude toward learning.

Development of transferable skills

Active learning fosters the development of skills that extend beyond the classroom. Activities such as group projects, problem-solving tasks, and collaborative discussions help students cultivate teamwork, adaptability, and effective communication [157], [171]. These transferable skills are invaluable in various settings, including higher education, the workplace, and everyday life.

3.1.2 Role of AI in Active Learning

Artificial intelligence plays a transformative role in fostering active learning by enhancing learner engagement, personalization, and interactivity. By aligning with the principles of active learning, AI offers innovative tools and methodologies that empower students to take an active role in their education, promote critical thinking, and facilitate meaningful knowledge construction.

Interactive assessment and real-time feedback

AI can power interactive tools and simulations that engage students in hands-on activities, problem-solving, and critical thinking [172], [173]. Real-time feedback from AI systems is a key component that supports active learning. Traditional feedback was often delayed, reducing its effectiveness. Providing rapid feedback from learning systems improved the learning experience for students, but if the assessment required more than just comparing the correct answer with the student's answer, the feedback again depended on a live teacher. The first swallow showing the possibilities of AI was the integration of tools that allowed for automatic evaluation of the correctness of source code. Artificial intelligence brought interaction instead of static tests with AI-driven tools that adapt questions based on their answers and ensure the optimal level of challenge. It has also enabled the creation of tasks that are not limited to multiple-choice questions, but can include simulations, scenario-based problem-solving, and even real-time coding challenges in both IT and STEM education [174].

Personalized learning experiences

Personalization is one of the most significant contributions of AI to active learning. By analyzing vast amounts of data, AI systems can identify individual learning preferences, strengths, and areas for improvement [172], [173]. This enables customized learning paths that keep students engaged at the right level of challenge. Personalization also applies to pacing, ensuring that students don't feel overwhelmed or bored. Adaptive learning systems adjust the difficulty level of tasks in real time, allowing advanced learners to progress more quickly while providing additional support for struggling students. AI-powered platforms can also adapt to different learning styles [175]. For example, visual learners can benefit from infographics or video tutorials, while auditory learners can benefit from podcasts or voice explanations. This allows each student to actively participate in their learning in a way that aligns with their individual needs.

Student self-control and agency

AI empowers students to take ownership of their learning process, and through adaptive platforms, students can customize their learning paths and decide what, how, and when they learn.

Content systems typically provide access to educational content from anywhere, anytime. This gives students the ability to learn at their own pace while also reinforcing their sense of efficiency and self-discipline [176]. By allowing students to control the timing, content, and delivery, these tools align with the principles of active learning. For example, a language learner can choose grammar exercises, practice speaking through AI-powered voice assistants, or take real-time quizzes. This level of customization helps students feel more in control of their learning outcomes, which is key to maintaining engagement and motivation [177].

AI systems typically encourage students to explore their interactions with the technology itself through their features. They allow them to track their own learning, errors, progress towards correct solutions, and distribution over time. Through the visualization of educational data, they support students in understanding what is happening in the system and how to evaluate student behavior [173], [178].

Critical thinking and problem solving

AI can power a range of interactive learning tools and resources, such as educational games, simulations, and virtual labs. These environments can provide students with opportunities to apply knowledge in engaging and meaningful ways. For example, AI can be used to create realistic scenarios in which students can practice problem-solving, decision-making, and collaboration, critical thinking, and teamwork skills. Simulations place students in real-world contexts where they must analyze data, evaluate options, and make decisions. These activities align closely with the principles of active learning because they require students to engage deeply with the content [179], [180].

For example, medical students can use AI-powered simulation to diagnose and treat virtual patients, receiving real-time feedback on their decisions. This hands-on experience not only reinforces theoretical knowledge, but also hone practical skills in a risk-free environment [181]. Similarly, role-playing scenarios powered by artificial intelligence can help students explore complex issues such as ethical dilemmas or policy decisions, fostering critical analysis and creative problem-solving.

Supporting personalized content with generative AI

Generative AI tools like ChatGPT allow students to explore topics interactively and dynamically by asking questions, requesting explanations, and changing their perspective on a given issue. By engaging in discussions with AI, students can delve deeper into the subject and actively build their knowledge. Chatbots can answer questions, clarify doubts, and offer advice or prompts to keep students engaged and moving forward. This on-demand support supports self-directed learning and helps students overcome challenges on their own [154], [182], [183].

On the other hand, these tools also help students create original content like essays, presentations, or reports. By providing advice on structure, style, and argumentation, AI improves the quality of students' output and teaches them subconsciously.

Monitoring student progress and intervention

Artificial intelligence can continuously monitor student progress during active learning activities, serving not only the needs of individual students but also teachers and the wider educational process [172]. These systems enable the tracking of engagement, performance and areas of interest, and offer insights into learning patterns. AI provides teachers with detailed data on student behavior, helping to identify areas where students may need additional support. Virtually real-time feedback enables early intervention and personalized guidance, ensuring students stay on track and receive the help they need. In addition, ongoing research is focused on improving AI's ability to predict potential risks, such as early course completion or underperformance, enabling proactive strategies to support student success [127], [184].

3.1.3 Active Learning Shortcomings

While active learning offers significant advantages, it's important to acknowledge its potential shortcomings, particularly regarding implementation and scalability:

- **Increased time and effort** – active learning often requires more preparation and planning time for teachers compared to traditional lecture-based approaches. Designing engaging activities, developing resources, and facilitating group work can be time-consuming. Teachers may also need to invest additional time in providing individualized feedback and support to students [185], [186].
- **Challenges in large classrooms** – implementing active learning strategies can be challenging in large classrooms. Managing group dynamics, ensuring participation from all students, and providing adequate individual attention can be difficult with a high student-to-teacher ratio [187].
- **Resistance from students and teachers** – students accustomed to passive learning environments might initially resist the shift to active learning. They may feel uncomfortable with increased participation and responsibility for their learning. Similarly, some teachers may be hesitant to adopt active learning approaches due to unfamiliarity, time constraints, or concerns about classroom management [89], [185].
- **Assessment challenges** – assessing learning outcomes in active learning environments can be more complex than in traditional settings. Active learning often focuses on developing higher-order thinking skills and problem-solving abilities, which may not be easily measured using traditional assessment methods [181], [187].

- **Resource requirements** – implementing some active learning strategies may require additional resources such as technology, materials, or dedicated learning spaces. For example, problem-based learning often requires access to real-world data, simulations, or case studies, which may not always be readily available [185], [186].

Despite these shortcomings, the benefits of active learning generally outweigh the challenges. Educators must carefully consider these limitations and plan accordingly to ensure successful implementation. However, by fostering student engagement and promoting deeper understanding, active learning can significantly enhance the educational experience for both teachers and students.

3.2 Project FITPED-AI: Case Study

Following part was published as a part of the article based on FITPED project activities at the DLCC 2022 conference to explain proposed and implemented solution to support active learning in AI education.

In research connecting AI and education, the authors aim most often on AI contribution and application in education [188], adoption of AI in the university environment [189] or to specific scientific or educational areas in which AI tools are used [190], [191].

A study [190] shows widespread agreement that introductory AI courses are generally challenging to teach in engineering programs despite growing enthusiasm for AI education. According to [192], [193], the reason is wide broad of AI and its complexity caused by many advanced topics and techniques. A secondary reason is the constant updating of content due to the research and creation of new types of AI applications, which is related to the rapid obsolescence of knowledge, often within a very short period.

Integrating AI into the engineering study brings many advanced topics such as pattern identification, decision-making, and combining them into higher levels of reasoning abilities, sequential control, plan generation and integrated intelligent agents. Langley [193] defines the following requirements supporting integration:

- Present a system perspective that shows how mechanisms interact to produce intelligence (to combat views that AI is a collection of disconnected algorithms).
- Give students experience with encoding representational content that mechanisms interpret to produce behaviour (to clarify the centrality of structured representations in intelligent agents).
- Present topics in a cumulative manner, with later material layered on the earlier content, much as calculus builds on algebra, which draws on arithmetic (to emphasise the hierarchical character of intelligence).
- Teach students not only how to use AI methods but how to construct them from simpler components (to give them the ability to develop their own mechanisms when existing ones do not suffice).
- Cover important abilities exhibited in human intelligence even when they are challenging to formalise (to show the link between AI and psychology that address many of the same core phenomena).

The reason for these requirements is a lack of understanding of the basic principles of AI, the solution of isolated (partial, abstract) problems, as well as the fact that AI teaching is currently mainly oriented to the use of existing libraries without the necessity of an internal understanding of their principles. According to [190], pedagogical research on the design of curriculum and teaching methods for AI training is relatively rare.

Considering the scope of the AI introduction curriculum, a typical representative of which is, e.g. book [194], used to teach in more than 1500 universities, integrating the above requirements is almost impossible. However, preparing educational content that can capture and retain the interest of students less skilled in abstract thinking is a constant challenge for authors. This statement is evidenced by the number of publications aimed at providing basic knowledge in the field of AI [195], [196], [197], [198].

A popular output aimed at popularising artificial intelligence to the public is the course Elements of AI (https://www.elementsofai.com/) developed by the University of Helsinki and first launched in Finland in 2018. This course presents elements, problems, and selected solutions from the field of AI at the level of high school knowledge in an exciting way. According to [199], the overall experience setting up and running the course was very interesting and rewarding. Moreover, its impact was considerable, with many companies requesting the opportunity for their employees to participate in the course.

Based on modern principles of digital content creation [200], [201], authors' experiences [202] and the popularity of Elements of AI, the requirements for the effective provision of essential knowledge for the broadest possible community of AI users (and consumers) can be defined as follows:

- active learning – the emphasis must be on dynamic content; the content creator must prefer explanations using examples and solving tasks,
- allow students to make mistakes and look for better solutions - prioritise content in the form of activities allowing them to make mistakes, optimise the solution, improve, and compete with each other,
- prioritise practicality at the expense of abstractness, even if the practical solution does not quite correspond to the theoretical basis - especially in the introductory chapters, where it is necessary to "build the user's relationship with AI",
- put less emphasis on the amount of content versus more focus on understanding it and building practical skills,
- divide the content into smaller units and "close them", thanks to which the student will have the feeling that he has already mastered some areas, even if they are only a prerequisite for understanding other topics,
- to support the mutual evaluation of students' solutions, the benefit of which is the understanding of different ways of thinking and approaches to solutions.

Even though, we can find many courses focused on AI and specific areas of AI on educational portals (Table 2), they mostly do not meet the above-mentioned requirements. The reason is that the creation of such content is demanding and laborious, and there is a risk that during the preparation of the learning materials, the content will become outdated before they are completed. As a result, linear courses in the form of video lectures or video tutorials of varying quality are created. Moreover, despite the success and indisputable quality of the content, they often include the shortcomings mentioned in [193].

Table 2. The number of some types of AI-focused courses/educational materials on selected educational platforms (August 2022). The content of AI and Data science often overlaps in the courses, so this area was also included in the survey (Other popular portals, e.g. Khanacademy.org, and Udacity.com, contained a significantly smaller number of courses covering the given areas).

Educational portal	**Artificial Intelligence**	**Data Science**	**Machine Learning**	**Deep Learning**	**Natural Language Processing**
Coursera.org	731	1.506	676	269	79
Edx.org	242	345	208	224	12
Udemy.com	353	2.593	624	238	97
number of users in Udemy courses	*2.435 mil. learners*	*6.5 mil. learners*	*7.0 mil. learners*	*1.75 mil. learners*	*0.565 mil. learners*
Total	**1.316**	**4.444**	**1.138**	**731**	**188**

The data in Table 2 shows a strong interest in AI and selected areas that overlap or are part of it.

3.2.1 Learning Forms Suitable for Teaching AI

The primary target group of university students focused on IT expects an effective acquisition of knowledge and practical skills, emphasising simplification. In other words, they wish to learn highly specialised knowledge and skills in AI following their habits to be ready for a career in AI (regardless of whether they finally choose it). Therefore, increasing the level of highly specialised knowledge and skills of students who consider or have already decided on a career in AI will be realised using a work-based learning strategy with elements of active-based, collaborate-based and problem-based learning.

Active learning, which transfers responsibility for progress in the educational process to the student, is one of the most effective and probably the most suitable form of education for building knowledge and skills in AI. According to [203], active learning as an instructional approach includes different forms of activation, such as increased physical activity, interaction, social collaboration, deeper processing, elaboration, exploration of the material, etc. Active learning from this point of view is defined and viewed mostly through student activation. Other authors [204] proved that active learning leads to better outcomes than comparatively passive forms of instructions.

If it is considered that studying AI represents the same leap in thinking as learning to program, then it has to be also taken into account the results of flipped classroom experiments [205], [206], [207]. This method is one of the few that undoubtedly improves student results. However, its success is strongly conditioned by strict adherence to defined rules and measures that ensure students do their homework honestly [184].

Another provably functional and currently functioning approach is microlearning supporting and enabling study within short time intervals [208]. Moreover, if it is supplemented with appropriate gamification elements, it will demonstrably increase the satisfaction and motivation of students [209].

Based on [210], it can be stated that the combination of micro-learning, gamification, immediate feedback, and the automatically evaluated program assessment increased the quality of the training of experts in the field of programming. These elements represent the basis, integrated into the educational environment, enabling self-study with the automatic evaluation of results within the framework of microlearning, as well as automatic evaluation of programs and provision of feedback. The virtual learning environment Priscilla [211] can serve as an example and starting solution.

What does teaching AI require in addition to teaching programming? Suppose the teaching of AI follows the teaching of programming supported by an educational system with the features mentioned above. In that case, it is appropriate to integrate AI content into the same environment.

As a result, students meet a familiar environment and are not distracted by unknown functionalities and rules. They can thus fully concentrate on studying the content. However, from the view of the system creators, it is essential to identify the modules necessary to explain the initial problems of AI and thus ensure the closest possible connection between the perception of the real world and its transformation into tasks. For this purpose, the careful development of interactive modules enabling various kinds of experimentation (decision making, deductive reasoning, genetic algorithms, heuristic algorithms, etc.) is necessary.

The work of a data scientist is very often intertwined with the use of an environment using Jupyter notebooks where students write code that processes data and generates outputs prepared for interpretation. Sometimes the work ends at this point, and sometimes, the result is a model that will be deployed to solve the problems of the given class. If the student should follow these steps, he needs a tool that allows him to experiment with data, obtain the created model, verify its functionality, success, overfitting, speed, etc.

In the context of the existing educational system supporting the teaching of programming and the requirements mentioned above for the education of AI, the learning objects for AI courses can be defined as follows:

- microlearning – introduction to the issue, familiarisation with terms, presentation of superficial relationships and practice of simple tasks,

- automatic source code evaluation – will be available to prepare assignments, especially in the case of initial familiarisation with libraries,
- domain- and problem-specific independent modules enabling the solution of specific tasks defined as snapshots of reality; this part represents the most time-consuming activity of creating tasks focused primarily on motivating and building the educator's relationship with AI,
- Jupyter notebook ecosystem – represents an environment in which students, who master the essential topics, can experiment and transform real-world problems into it; mastering this environment is also a prerequisite for applying in the field of data science and/or AI, where Jupyter notebooks are widely used,
- collaboration, competition, and gamification – the training of AI professionals should be implemented through a learning strategy integrating the parts of active, collaborative and problem-based learning, using gamification and competition, which can make learning more interesting, more fun, more friendly, and more practical.

3.2.2 Technological Background for AI Learning Environment

As the output of the FITPED and FITPED-AI project consortium consisted of universities and SME organisations, the educational model and virtual learning environment focused on teaching programming languages were designed and implemented [212], [211].

The system combines microlearning and automatic evaluation of source codes, but it was designed to support the integration of other elements and activities as efficiently as possible. The system includes a web development environment that allows writing, running, and debugging programs without installing any supporting applications on the computer (Figure 1). Instead, the code is saved, executed and run on the server.

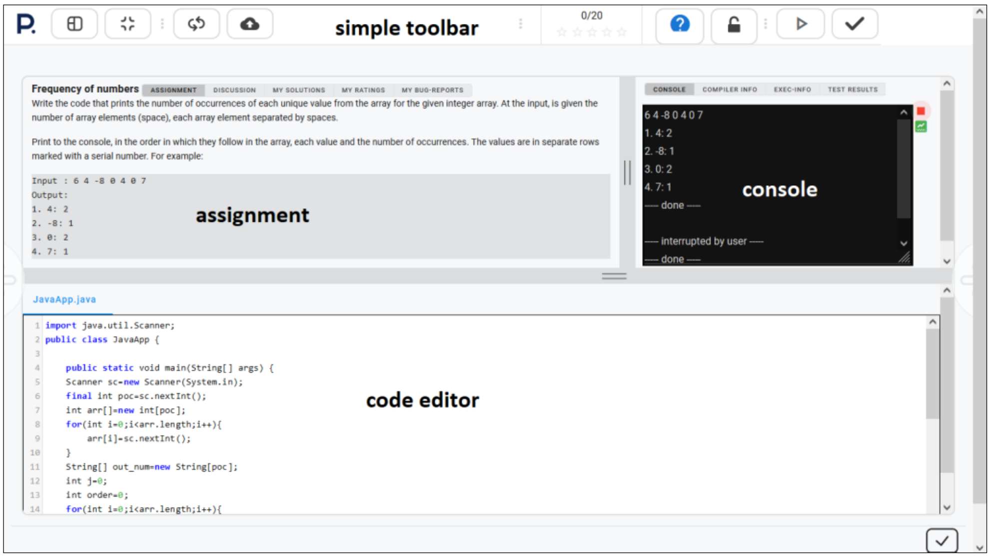

Figure 1. Web interface dedicated to solving and code writing in PRISCILLA system.

To leave task solving to powerful server processors is a standard approach even in environments oriented to solving AI tasks. The primary reason is that to obtain a result, the programs, in many cases, need high performance and a long time, which cannot generally be provided on local devices.

The requirement for solving tasks and experimenting with data is currently most often implemented by Jupyter notebook technology [213]. Thanks to its openness, simplicity, and constant development, it has become a popular tool in teams focused on data science and AI. Currently, it is used not only as a format used in the processing of data in science but also in the education [214]. Its strength lies in combining text, source code and editing and running this code any time with a single click. Furthermore, the results are or can be displayed as part of the document content.

Jupyter server/notebook technology has a significant disadvantage, which was recently identified by the authors during its maturation – to use the computing and processing components, it is necessary to run the content from the given server – because notebooks could work via localhost by default [215]. This approach made cooperation with other systems and front-end applications difficult or impossible.

The Jupyter Kernel Gateway (JKG) technology is currently used as one of the alternatives enabling the communication between an independent front-end and a Jupyter server running on the backend. According to [216], JKG is a web server that provides headless access to Jupyter kernels. As a result, the independent applications communicate with the kernels remotely through REST calls and websockets rather than ZeroMQ [217] messages.

Thanks to JKG, it was possible to implement modules that ensured communication with the Python language kernels, usually used to solve data science and artificial intelligence tasks. A single kernel can be simultaneously connected to one or more front-ends.

To integrate the Jupyter infrastructure into the used Priscilla system and enable communication with Python kernels, it was necessary to create a clone of the design of a standard Jupyter notebook and enrich it with possible additional features (the ability to stop the program, friendly insertion of input data into the running program, the ability to combine with rich text, etc.) An example of the prepared content (from the FITPED-AI project) is presented in Figure 2.

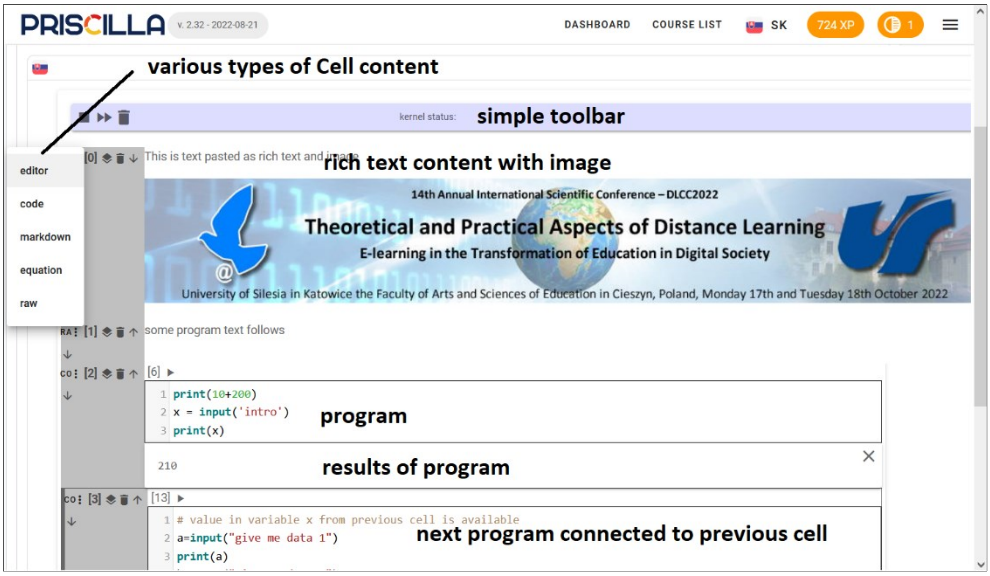

Figure 2. Integration of the Jupyter notebook design into the Priscilla system (a case study of the FITPED-AI project)

Integration of the Jupyter notebook clone environment with the backend technology of the Jupyter server in connection with the proven features of the Priscilla system provides the new system with all the original benefits (microlearning, gamification, automatic evaluation of source code, communication between users, etc.). A new logical and communication structure is presented in Figure 3.

The key part of the model is the Learning environment, which provides the content for the user/student and communicates with other modules with the aim of, e.g. checking the answer correctness, logging the student's activity and attempts, providing assistance or help etc.

The Learning environment also includes separate modules dedicated to code writing or AI task solving in the Jupyter microenvironment (presented in Figures 1 and 2). These modules require communication with modules executing programs.

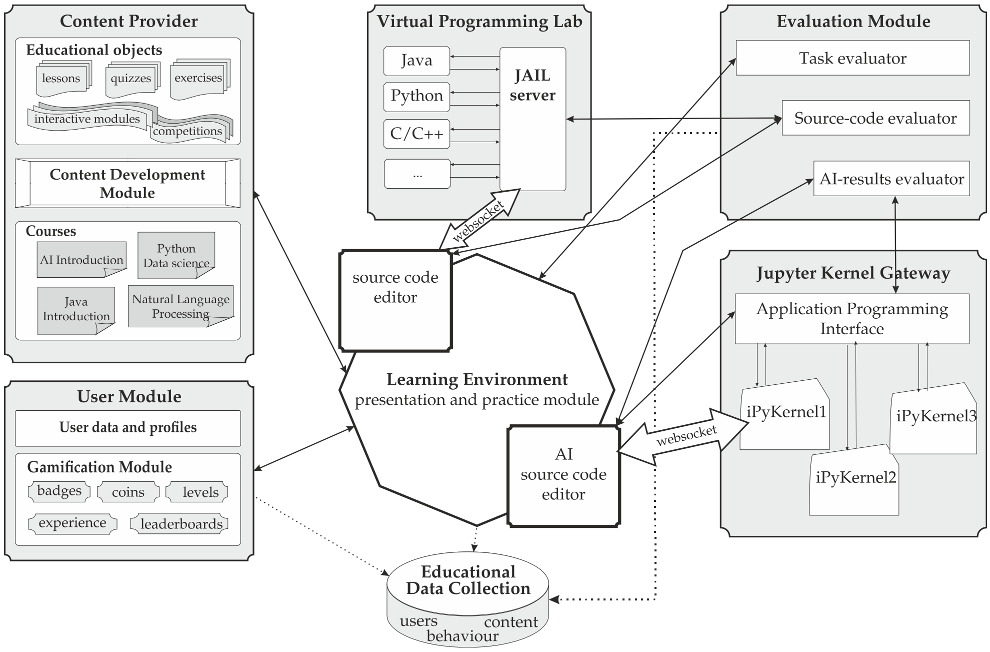

Figure 3. Logical and communication structure of the technological solution ensuring coverage of the requirements of the educational model over the Priscilla system (a case study of the FITPED-AI project)

The first module is the web interface of the source code editor, with the backend covered by the Virtual Programming Lab server [218], which supports the execution of programs in various codes. Communication starts initially via REST API, then continues via websocket. The results of the program can be verified against the expected inputs, or the environment allows only program execution and communication through the console (entering inputs and reading outputs).

AI source code editor is defined by a structure consisting of cells that can contain various forms of text (images or equations) and source code currently in Python. The code in each cell can be executed independently, or the cells can contain pieces of code that follow each other. Each cell can be run separately and any number of times. When the code is started for the first time, a kernel is created on the server (via the REST API) in **Jupyter Kernel Gateway**. This kernel then communicates with the user via websocket. Listing of results and loading of inputs takes place in its own front-end interface. The results are always listed under the cell whose code was run.

The evaluation module checks the correctness of the answers on three levels at the moment when the user decides to submit the task. Currently, three types of verification are available - validation of the solution from microlearning (compares against the database of correct answers), verification of the correctness of the program and verification of the results of the AI program (compares against the defined correct outputs for the prepared inputs).

All user attempts and responses are stored by the **Educational Data Collection module** tools, scored concerning gamification rules in the **Gamification module**, and logged as problematic in case of non-standard behaviour within the System module.

The **Content provider** is an essential part of the system. It ensures the creation of content based on individual types of educational objects and enables their organisation into lessons, chapters, courses, competitions, etc. In addition, questionnaires and discussions about the content are part of the module.

New modules of the system are currently in pilot operation, and content creation for courses in AI has been started.

3.2.3 Educational model

The main output of the project FITPED-AI is an educational model for building highly specialised skills at the university stud programs focused on AI. The model should increase IT students' interest in artificial intelligence by better understanding and mastery of educational content, increasing the level of highly specialised knowledge and skills of graduates and developing students' vocational and lifelong learning habits.

Newly developed modules needed to teach artificial intelligence courses will provide immediate feedback and support students' projects in artificial intelligence. The created educational content will consist of lessons for learning prerequisites of AI, classes for teaching basics of AI (data preparation, knowledge discovery, artificial intelligence, machine learning) and courses for teaching application domains of AI (natural language processing, educational data, cybersecurity). In addition, educational data will be collected within several rounds of courses, which will be used for identifying students' behaviour and problem areas in the educational content and teaching process.

The steps leading to the creation of a mature graduate of a study covering the field of artificial intelligence with an IT orientation can be defined in two layers:

- Artificial intelligence demystification – on the one hand, artificial intelligence is not expected to solve all the world's problems. But on the other hand, many tabloid authors present it as the greatest danger for future generations. The content and activities should answer questions about what AI really is, its potential, and its risks for society.
- Knowledge and skills development to create solutions based on artificial intelligence mastery of AI technologies – the training courses should provide all the knowledge needed to understand the principles and design their solutions based on AI. They should also present specific solutions in knowledge discovery, cyber security, recommender systems, natural language processing and learning analytics.

The FITPED-AI project not only supports the development of specialized AI skills, but also integrates modern pedagogical approaches such as active learning and AI-based education to enhance the learning experience. By leveraging active learning, the project ensures that students are deeply engaged in the learning content through activities such as problem solving, projects, and real-world applications. These strategies foster critical thinking, collaboration, and knowledge creation, which are essential for mastering complex AI concepts.

Artificial intelligence plays a central role in the FITPED-AI learning model, which offers personalized learning experiences tailored to the individual needs of students. Through AI-powered tools, students receive immediate feedback on their progress, allowing them to adjust their strategies and focus on areas that require improvement. This real-time feedback ensures that learning is dynamic and responsive, supporting students as they work on projects and acquire basic and advanced AI skills.

System analytics powered by learning analytics provide insights into student behavior, engagement, and performance, allowing educators to refine their teaching approaches and effectively address problem areas.

Active learning methodologies are integrated into the curriculum of the subjects covered by the courses, ensuring that students actively apply their knowledge, fostering deeper understanding and long-term retention of AI concepts. Scenarios and case studies are also used to simulate real-world challenges and prepare students to solve complex problems in areas such as cybersecurity, natural language processing, and educational data analytics.

The FITPED-AI project emphasizes the collection and analysis of educational data over multiple course iterations. This data-driven approach identifies trends in students' learning patterns, highlights areas of concern, and informs continuous improvement of content and teaching methodologies. By addressing these insights, the project ensures that the educational framework evolves to meet the needs of current and future students.

Integrating AI into the teaching process is consistent with the broader goal of preparing students for the workforce by developing their professional and lifelong learning habits. AI systems not only help deliver knowledge, but also foster the cultivation of critical skills such as adaptability, problem-solving, and innovation. These skills are essential in an AI-driven world where technological advancements require continuous learning and application.

The project also underscores the importance of demystifying artificial intelligence to create a realistic understanding of its potential and limitations. Educational activities aim to dispel misconceptions, highlighting practical applications and ethical considerations of AI, while addressing societal concerns about its risks. This balanced perspective allows students to critically engage with AI technologies and their implications.

The integration of generative AI tools like ChatGPT offers opportunities for further elaboration. Students will be able to dynamically interact with the content by asking questions, receiving personalized explanations, and generating project ideas.

4 AI Literacy

Artificial intelligence has quickly become a transformative force across sectors, reshaping industries, labor markets and the future of work. In education, AI technologies are used to personalize education, improve teaching methods and streamline administrative processes. The role of AI goes beyond technological innovation; is critical to preparing students for a future dominated by data-driven decision-making and automation. As AI continues to evolve, students must not only understand these technologies, but also be equipped to engage with, develop, and critically evaluate AI applications.

The arrival of ChatGPT, a sophisticated language model developed by OpenAI, marked a turning point in the development - and especially in the perception - of AI not only among experts, but also within society as a whole. Its ability to hold conversations that are almost indistinguishable from humans, produce creative text, and perform a wide variety of tasks has garnered much public attention and brought AI into the mainstream of discussion and attention.

Before the introduction of ChatGPT, AI was primarily used for specialized fields such as medical diagnostics, financial analysis, or self-driving cars. Although these applications have demonstrated the enormous potential of AI, they have often remained inaccessible to the general public. The complex nature of AI algorithms and the specialized knowledge required to interact with them presented an insurmountable barrier to understanding by the lay public.

With ChatGPT's user-friendly interface and conversational style, as well as subsequent solutions like Bard, Claude, Jasper, etc., these tools have broken barriers and made AI accessible to a wide audience. By presenting useful ideas and functional answers to everyday tasks, ChatGPT helped create a more positive perception of AI technology.

The growing popularity of AI has had and is likely to have a significant economic impact in the long term. Investments in AI startups and research have soared, creating new jobs and business opportunities. Industries such as healthcare, finance and manufacturing are increasingly adopting AI solutions to improve efficiency, reduce costs and gain a competitive advantage.

But the rise of AI has also raised many questions about the future of work, privacy and ethics. As AI systems become more capable, concerns are growing about their potential to displace human workers and exacerbate existing inequalities. The collection and use of personal data by AI-powered systems also raises privacy concerns. Addressing these challenges will require careful consideration of the ethical implications of AI and the development of appropriate regulations and safeguards to prevent misuse across sectors.

The fulfilment of these tasks will be handled by experts in job positions that are still being created. These professionals, probably current university students, are preparing for careers not only in IT, but also as managers, teachers, translators and other professionals. The aim of this article is to map their readiness and attitudes towards artificial intelligence and, in particular, to explore how selected factors related to the current perception of AI and students' career orientation are interconnected.

Research questions are defined as follows:

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

The study considers the following research hypotheses:

- H1: Years of study are associated with greater perceived satisfaction in learning AI.

- H2: Men tend to experience greater satisfaction in learning AI that women.
- H3: Study program has a significant impact on satisfaction levels in learning AI.
- H4: Between 2022 and 2024, the level of satisfaction associated with learning AI evolved significantly.
- H5: Men tend to demonstrate higher levels of AI readiness compared to women.
- H6: IT student demonstrate higher levels of AI readiness compared to other study programs.
- H7: Men tend to demonstrate higher levels of AI relevance compared to women.

4.1 Structure of AI Literacy

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

4.1.1 AI Literacy

According to a survey [219], AI literacy can be understood at three basic levels:

- **Knowing and understanding AI** – involves educating students to acquire basic concepts, skills, knowledge and attitudes, even if they have no prior knowledge. This basic level of knowledge is considered essential. In addition to being end users of AI applications, students should also understand the underlying technologies that drive these systems. This understanding is also supported by the works [220] and [221] emphasizing the ability to understand the basic techniques and concepts of AI in various domains of products and services so that students not only use AI tools, but also have an overview of how they work and how they evolve.
- **Apply AI** – emphasizes the importance of teaching students how to apply AI concepts and tools in different contexts [222], [223]. At this stage, it is important for students to understand how AI applications affect everyday life and to be aware of ethical issues related to AI technologies. At this level, AI education is based on computational thinking, focusing on the development of logical reasoning and algorithms as tools for understanding and using knowledge bases for problem solving, semantic processing, and manipulation of unstructured data.
- **Evaluate and create AI** – in addition to understanding and using AI concepts and practices, AI literacy can extend to other competencies, such as the ability to critically evaluate AI technologies and to effectively communicate and collaborate with AI systems. Multiple studies described how students improved their AI based science and technology knowledge, which they then applied in research-based learning to solve practical problems [224], [225]. By being able to evaluate and create AI, students were able to infer, connect, manipulate and categorize AI concepts in innovative ways.

Findings highlight that basic AI knowledge and skills significantly increase career motivation and interest [226], [227], [228]. Studies [229], [230], [231] suggest that introducing AI literacy early in education promotes a more inclusive understanding of the role of AI in society. They advocate for the integration of AI curricula into school systems to better prepare students for careers that will increase rely on AI.

In addition to ethical considerations and the responsible use of AI, AI literacy encompasses a broader set of competencies. These enable individuals to critically assess AI technologies as well as effectively communicate and collaborate with AI systems [229]. Tuomi extends the concept by introducing "critical AI literacy" which includes not only technical knowledge but also the ability to critically evaluate the social, ethical, and economic impacts of AI [232], [75].

4.1.2 Students' Attitudes Toward AI

Several recent studies provide valuable insights into student attitudes toward AI and their readiness to engage AI tools in both academic and professional settings. These studies usually focus on specific areas of AI deployment or application.

A study [233] investigated the factors influencing students' behavior and attitudes towards the use of AI in higher education. While perceived risks had a negative effect on attitudes, factors such as performance expectancy and facilitating conditions had a strong positive effect on attitudes and behavioral intentions to use AI in education. Interestingly, perceived effort was not a significant factor in shaping attitudes towards AI. These results suggest that students are aware of the potential of AI to enhance performance, especially when given adequate support, despite some concerns about its risks.

The study [234] found that social science students have a generally positive view of AI, emphasizing its emotional dimension in particular. Their willingness to use AI in the future was strongly associated with positive emotional and cognitive attitudes, with overall feelings of security about technology playing a significant role.

Several surveys of medical students have revealed a strong interest in AI, although they also point to a significant lack of education on the topic within their curriculum. Many students report that they feel they do not fully understand the basic computational principles of AI or its limitations, evoking the conclusion that AI is currently underrepresented in the medical curriculum. Most students expressed support for incorporating AI education into their studies, with the vision that such additions could better prepare them for future challenges in AI-driven medical advances [235], [236], [237].

In a study of medical students' attitudes toward AI and medical chatbots, participants showed strong support for the use of AI in administrative tasks and research involving health data. However, concerns have been raised about data protection and the potential for increased monitoring in the workplace. The results suggest that while medical students are open to integrating AI into their field, they remain wary of privacy issues and the ethical implications of AI technologies [238].

A survey of 399 students in Hong Kong [239] showed a generally positive attitude towards ChatGPT in higher education. Students appreciated its ability to provide personalized learning support, help with writing and brainstorming, and enhance research opportunities. However, significant concerns have been raised regarding accuracy, privacy, ethical implications, and potential impact on personal growth and societal values. The study highlighted the importance of the need for careful integration of AI technologies into educational environments to ensure that they effectively enhance the learning experience.

A survey of 5,894 students from Swedish universities [240] revealed significant differences in attitudes towards AI chatbots based on gender, field of study and academic level. More than a third of students reported regular use of AI chatbots such as ChatGPT, but many expressed concerns about their future implications. Students and engineering students showed more frequent use and positive attitudes, while humanities students, and especially medicine students, expressed more concern about the accuracy of the results generated.

A case study on the use of AI in academic writing among Indonesian students showed a generally positive acceptance of AI tools such as grammar checkers and plagiarism detectors. Students recognized that these tools help improve their writing skills, increase self-efficacy, and promote academic integrity. However, some have expressed concern that an over-reliance on AI could potentially stifle creativity and critical thinking [241].

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

4.1.3 Career Motivation

Although AI presents many opportunities for application in various sectors, it also retains a significant role for human employees. Their contribution ranges from managing communication with AI systems to developing new models, methods and integrating AI elements into various applications.

From a career perspective, AI can be examined through two primary lenses. The first includes careers directly related to AI, focusing on tasks such as data management, data analysis, AI model development, or AI integration into various applications. Professionals in this field are expected to have strong analytical skills and a scientific mindset, constantly being forced to update their knowledge to keep up with new trends and technologies [242].

The second category includes specific industries where AI is becoming – or is expected to become – an important part of work activities. Typical examples are fields such as medicine, meteorology, marketing, graphic design and even programming. In these areas, employees who lack basic AI skills can quickly find themselves at a disadvantage, not because they will be replaced by AI, but because they will be overtaken by colleagues who can use AI capabilities effectively. This shift creates a new perspective on employment structures that require future employees to have skills that combine human and machine capabilities [243].

Preparing students for this work environment is not solely the responsibility of higher education. Research [226] and [227], suggests that laying the foundation for AI literacy and future career readiness must begin in elementary school. Early exposure to AI concepts, ethics, and societal implications can build confidence in students and reassure them that AI will not replace all jobs, but creates new.

Incorporating AI into early education helps alleviate concerns about job security, equipping future professionals with the skills needed to thrive in emerging fields and also supports their active role in shaping how AI will be used in various industries [244].

Research [245] created a multidimensional model of the perceived usefulness of artificial intelligence from the students' view of emerging jobs, the perception of its usefulness in studies, the students' view of future job skills, and their view of emerging jobs. The main findings highlight the need to emphasize teaching the meaning and importance of AI, integrating AI into courses, strengthening quantitative skills, and developing future job skills that are in line with new trends in data and AI.

According to [246], access to training in complementary skills and technologies can significantly influence the impact of AI on employment. While AI has the potential to further polarize the labor market, evidence suggests that occupations affected by AI will see, on average, a modest but positive change in wages without significant changes in employment levels. In addition, the research highlights a positive correlation between wages and the demand for software and analytics skills, as well as a strong relationship between the defined impact of AI on employment and wages.

The results of a systematic literature review [247] suggest that factors such as usefulness, expected performance, attitudes, trust, and expected effort significantly and positively influence behavioral intentions, willingness, and actual use of AI in various industries. However, in certain cultural contexts, AI cannot fully replicate or replace the essential need for human interaction, regardless of its perceived usefulness or ease of use.

According to the survey reported in [248], students expressed a strong interest in careers in AI-related fields, highlighting the potential for innovation and social impact as primary motivators of their interest. This enthusiasm reflects the growing recognition of AI's transformative role across sectors and underscores the importance of preparing the next generation for careers in this evolving environment.

4.1.4 AI Anxiety

New technologies often raise concerns about deployment in some segments of the population, and artificial intelligence is no exception. As AI technology advances rapidly, individuals are increasingly expressing their concerns about its implementation and implications. Concerns range from job loss and transformation and privacy issues to ethical considerations regarding decision-making and bias in AI systems [249], [250].

In accordance with this coverage, AI anxieties can be divided into the following categories:

- **Loss of control and existential risk** Loss of control and existential risk include concerns about AI systems gaining autonomy and operating independently of human supervision. Exacerbating these concerns is the possibility of the development of artificial consciousness, which could lead to systems becoming unpredictable and uncontrollable. In such cases, human intervention would no longer be required and AI systems could adopt solutions or behaviors that are beyond human understanding or control [250], [251], [252]. The historically highest level of threat is thus a super-intelligent AI that could surpass human intelligence and potentially lead to catastrophic consequences, including the risk of destroying humanity [253], [254].
- In addition to the fear of the unknown, a much more practical question lies in the **interpretability and explainability of AI decisions**. AI researchers have long focused on addressing the opacity of AI operations and decision-making processes. Difficulties in verifying and checking the correctness of solutions after deployment of AI models bring unpredictable risks. The lack of transparency in "black box" models thus significantly affects trust and acceptance of AI. The push for explainability, interpretability and comprehensibility of AI solutions stems from the need to increase transparency, which is critical to fostering wider trust and acceptance of AI systems [255], [256].
- Another set of concerns involves various **ethical and humane dimensions**. A key problem is that AI is not bound by the rules of human ethics, which can lead to serious violations. The most devastating idea is the use of autonomous weapons that can take life without human supervision [257]. AI systems also pose privacy risks due to operational breaches or deliberate collection despite laws and regulations to protect personal and sensitive data [258]. There is growing discontent among content creators that their works are being used to train AI models without proper consent, which can lead to extensive lawsuits without clear rules. A significant problem is also the use of fake AI-generated content – news, photos or videos – that can manipulate public opinion or lie through fictitious media [259].

4.2 Research Methodology

The research methodology is based on the more general CRISP-DM methodology and has the following steps [260]:

- **business understanding** – understanding the problem and its context in connection with the collected data, selecting specific measure tool, setting requirements and procedures for analyzing data,
- **data understanding and preparation** – description of the data acquisition and preparation process
- **data analysis** – implementing specific analytical steps to obtain answers to RQs
  - examination of constructs and comparison of their values between individual groups (RQ1) and with each other (RQ2)
- **understanding of the results** – evaluation of the results of the analysis and determine the answers to the research questions,
- **application of the research outcomes** – description of the application possibilities of the obtained results.

4.2.1 Business understanding

Current and future education programs should focus on strengthening students' readiness for the AI era. As a rapidly developing technology, AI is often presented in the context of its complexity and progress, which may excite some students but intimidate others [261]. A validated questionnaire based on the following constructs was selected to examine students' readiness and acceptance of AI [262]:

- AI literacy reflects an individual's knowledge and awareness of AI applications such as image and speech recognition, AI-enabled tools such as translations and voice assistants, etc.
- AI readiness measures the degree to which individuals feel ready to use AI in their daily lives, their confidence in AI's ability to assist and stimulate personal growth and thought processes.
- The importance of AI captures an individual's understanding of AI's potential to impact the world, the perceived usefulness of learning AI, and how closely AI relates to their future career and personal interests.
- Career motivation assesses the degree to which students believe that learning AI will benefit their future career and help them find a good job and achieve their long-term goals.
- Social goods measure the desire to use AI for the greater good, such as helping others and contributing to the well-being of humanity, with a focus on ensuring that AI serves the interests of the majority.
- AI anxiety captures feelings of worry and uncertainty about how AI may affect an individual's future, including concerns about the potential negative impact of AI on their career or overall life.
- Confidence reflects a student's belief in their ability to succeed in AI-related courses, including mastering both basic and complex concepts and achieving good grades.
- Satisfaction measures how satisfied individuals feel after learning about AI, including feelings of accomplishment, enjoyment, and personal reward from AI-related courses.
- Intrinsic motivation assesses students' natural curiosity and drive to pursue challenging AI topics and their desire to thoroughly understand AI concepts for personal satisfaction.
- Behavioral intention indicates a student's intention to continue learning about AI, to be informed about its applications, and to actively use AI tools to solve problems and improve learning.

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

659 participants took part in the research, including 395 students whose specialization is related to the IT field, 15 STEM teachers, 130 teachers of other specializations, 33 language specialists, 38 management and marketing students, and finally 48 students of other specializations. In total, there were 276 women and 383 men in the survey.

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

4.2.2 Data understanding and preparation

Participants, in addition to providing basic demographic information (gender, country, age, and study program), responded to items corresponding to the constructs described above using a 5-point Likert scale (ranging from 1 to 5). If participants were unable to provide a response, a value of 0 was used, which was excluded from subsequent data analysis.

Study programs across the participating universities, despite differing in names and focus, were manually categorized into the following fields: education, IT, IT education, languages, management, other, and STEM. Additionally, based on age, participants were grouped into age categories as follows: 18-20, 21-25, 26-30, 30-40, and 40+.

4.3 Data Analysis

In the first step, our focus will be on descriptive statistics, which will provide an overview of the collected data. This phase involves summarizing and organizing the dataset to identify trends, patterns, and distributions. Key measures will be inspected to gain a clear understanding of the basic characteristics of the data. Additionally, visualizations like histograms, bar charts, and scatter plots will be used to present the data in an accessible and interpretable format. These foundational insights will serve as the groundwork for more advanced statistical analyses.

Next, we will delve into sociological statistics, where the emphasis will be on testing hypotheses derived from our research objectives. This phase will involve employing inferential statistical methods to determine whether the observed data supports the proposed hypotheses. Statistical tests will be applied to examine differences and relationships within the data. For instance, we may explore how demographic variables like age or gender influence specific constructs, or test whether there are significant variations in responses across different groups. This step will help us draw conclusions about the broader population based on our sample data, adding depth to our understanding of the underlying sociological phenomena.

Finally, we will focus on identifying relationships between individual constructs, moving towards more sophisticated statistical techniques like correlation analysis and regression modeling. This phase aims to uncover the connections and interdependencies among various constructs within the dataset. For example, we will investigate how variables such as satisfaction, motivation, and performance are interrelated, and whether certain constructs act as predictors for others.

4.3.1 Descriptive Statistics

Descriptive statistics offer a detailed overview of the data, highlighting central tendencies and variability. The key features are summarized in Table 1 and visualized in Figure 1 for better clarity and understanding.

Table 1. Descriptive statistics for individual constructs.

	count	mean	std	min	25%	50%	75%	max
AI Literacy	659	4.110	0.711	1	3.75	4.25	4.75	5
AI readiness	659	4.094	0.751	1	3.75	4	4.75	5
Relevance of AI	659	3.820	0.710	1	3.5	3.833	4.333	5
Social Goods	659	3.802	0.736	1	3.5	4	4.25	5
Career motivation	659	3.640	0.857	1	3.25	3.75	4.25	5
Anxiety	659	2.675	0.939	1	2	2.6	3.2	5
Intrinsic motivation	659	3.572	0.683	1	3.333	3.572	4	5
Satisfaction	659	3.582	0.666	1	3.225	3.582	4	5
Confidence	659	3.962	0.792	1	3.667	4	4.5	5

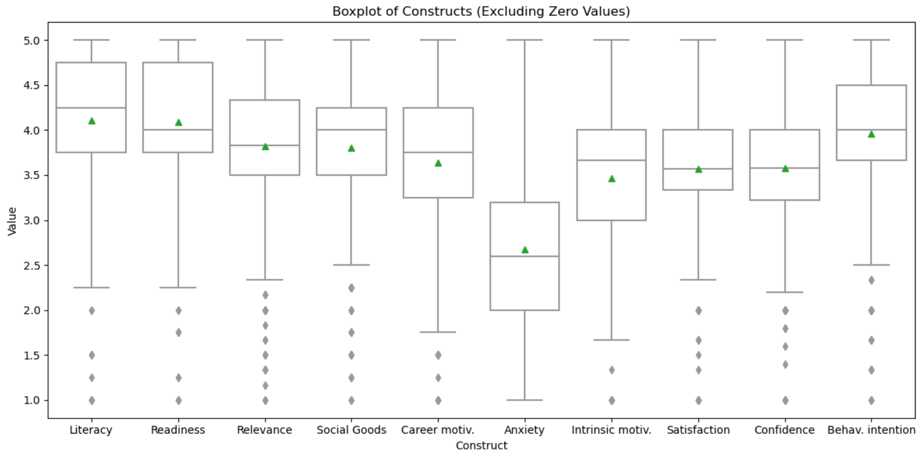

Figure 1. Visualization of individual constructs.

An analysis of the dataset reveals the following insights about individual constructs:

- AI literacy (AVG: 4.11, SD: 0.71) – participants demonstrate a relatively high level of AI literacy, with average scores indicating a general understanding of AI concepts and applications. The standard deviation indicates some variability in responses, with a quarter of participants scoring below 3.75.
- AI readiness (AVG: 4.09, SD: 0.75) – similar to AI literacy, readiness to engage with AI technologies and use them in everyday life is also high among participants.
- Relevance of AI (AVG: 3.82, SD: 0.71) – participants recognize the relevance of AI and score above the middle of the scale. However, the slightly lower mean compared to literacy and preparedness suggests that while participants see AI as important, there may be concerns or reservations about its applicability or impact.
- Social goods (AVG: 3.80, SD: 0.74) – the perceived social benefits of AI are rated positively, indicating an understanding of AI's potential to contribute positively to society.
- Career motivation (AVG: 3.64, SD: 0.86) – the mean score for career motivation indicates that while participants see learning about AI as beneficial for their future, this construct has the greatest variability among responses, indicating different levels of motivation to pursue an AI-related career.
- AI Anxiety (AVG: 2.68, SD: 0.94) is recorded as a concern with a mean score below the midpoint, indicating that although some participants feel anxious about AI, many do not perceive it as a significant threat. The variability of responses suggests that levels of anxiety vary widely among participants.
- Satisfaction (AVG: 3.57, SD: 0.68) with AI-related learning experiences is rated as medium. This suggests that participants generally find AI education fulfilling, although there is a space for improvement, as evidenced by the variability of responses.
- Confidence (AVG: 3.58, SD: 0.67) – the level of confidence in understanding AI concepts is moderate, indicating that while participants generally believe in their ability to understand AI-related materials, some may still feel insecure.
- Behavioral intention (AVG: 3.96, SD: 0.79) – participants show a strong intention to engage in AI in the future and score near the upper end of the scale. This result suggests a proactive approach to learning and applying AI technologies.

In the context of the individual constructs, the dataset reveals high levels of AI literacy and readiness for working with AI among respondents. This is further supported by strong indications of behavioral intent, suggesting that respondents are not only prepared but also motivated to engage with AI in practical contexts. The construct of AI anxiety shows relatively low values; however, this observation is influenced by the wording of the related survey questions. When the perspective is reversed, AI anxiety matches the levels observed in the other constructs, providing a more balanced view of this factor.

The visualization of the dataset highlights the balanced distribution of the individual constructs, suggesting consistency in the competencies and attitudes of the respondents. This balance is likely influenced by the demographic composition of the sample, with a significant proportion of respondents coming from IT-related fields, where knowledge of AI concepts is typically higher. This background likely contributes to the overall confidence and readiness observed in the dataset.

While these descriptive insights are valuable, deeper insights are likely to emerge from sociological analysis. Such analysis can explore the subtle relationships between constructs, demographic factors, and contextual variables. For example, it can reveal how AI literacy interacts with anxiety or behavioral intention across different groups of respondents, or identify patterns that are not immediately apparent from descriptive statistics alone. This step will provide richer interpretations and improve our understanding of the implications of the data set.

4.3.2 Sociological Metrics

The first section of the questionnaire focused on sociological metrics, covering questions about:

- Grade (year of study)
- Age
- Gender
- University
- Study program
- How many hours of AI-related courses have you taken (from 0 to many, not per week, summary in your study)

The year of data collection probably influenced the responses, as the questionnaire was available from 2022 to 2024 – a period marked by rapid advancements in AI and the widespread adoption of large language models (LLMs) and AI chatbots. Therefore, we also keep this information in the data.
The frequency tables of responses to each question on the sociological metric are presented in Tables 1-6.

Table 2. Frequency table of responses for Grade

	Number	Cumulative Number	Percent	Cumulative Percent
1	292	292	24.44	24.44
2	432	724	36.15	60.59
3	272	996	22.76	83.35
4	129	1125	10.79	94.14
5	56	1181	4.69	98.83
6	9	1190	0.75	99.58
7	5	1195	0.42	100
Missing	0	1195	0	100

Table 3. Frequency table of responses for Age

Age	Number	Cumulative Number	Percent	Cumulative Percent
17	13	13	1.09	1.09
18	22	35	1.84	2.93
19	87	122	7.28	10.21
20	229	351	19.16	29.37
21	276	627	23.10	52.47
22	192	819	16.07	68.54
23	133	952	11.13	79.67
24	76	1028	6.36	86.03

Age	Number	Cumulative Number	Percent	Cumulative Percent
25	39	1067	3.26	89.29
26	19	1086	1.59	90.88
27	12	1098	1.00	91.88
28	4	1102	0.33	92.22
29	10	1112	0.84	93.05
30	6	1118	0.50	93.56
31	6	1124	0.50	94.06
32	2	1126	0.17	94.23
33	6	1132	0.50	94.73
34	2	1134	0.17	94.90
35	5	1139	0.42	95.31
36	5	1144	0.42	95.73
37	2	1146	0.17	95.90
38	7	1153	0.59	96.49
39	4	1157	0.33	96.82
40	3	1160	0.25	97.07
41	2	1162	0.17	97.24
42	4	1166	0.33	97.57
43	1	1167	0.08	97.66
44	2	1169	0.17	97.82
45	2	1171	0.17	97.99
46	4	1175	0.33	98.33
47	5	1180	0.42	98.74
48	3	1183	0.25	99.00
49	1	1184	0.08	99.08
50	3	1187	0.25	99.33
51	1	1188	0.08	99.41
52	3	1191	0.25	99.67
53	2	1193	0.17	99.83
54	1	1194	0.08	99.92
56	1	1195	0.08	100
Missing	0	1195	0.	100

Table 3. Frequency table of responses for Gender

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

Table 4. Frequency table of responses for University

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

	Number	Cumulative Number	Percent	Cumulative Percent
UA	2	1195	0.17	100
Missing	0	1195	0	100

Table 5. Frequency table of responses for Study program

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

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

Table 6. Frequency table of responses for Year

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

As can be seen from the above tables, there are 1195 students in total, with no missing data. Most students are in years 1 through 3, comprising the majority (83.35%) of the sample. Years 6 and 7 have the fewest students, collectively making up just over 1% of the total, suggesting a low continuation rate in later years.

The sample is predominantly composed of young adults, university-aged individuals, as shown by the concentration of ages between 20 and 24. The presence of older individuals in smaller numbers might indicate a mix of traditional and non-traditional students or participants in a specific educational or professional context. The most common ages are between 20 and 22, which together account for the majority (58.33%) of the respondents. Specifically, age 21 has the highest frequency, representing 23.1% of the total sample. Respondents aged 25 and above make up a much smaller portion of the sample (approximately 14%).

The sample is male-dominated, with roughly twice as many male respondents as female respondents. The sample has a higher proportion of male respondents, with 793 individuals (66.36%).

The sample is highly concentrated around a few universities, primarily in Slovakia and Poland. Other countries contribute a smaller portion, indicating that the sample may have a strong regional focus, particularly within Central and Eastern Europe. The largest group of respondents is from SK (Slovakia), with 682 students, representing 57.07% of the total. PL (Poland) is the second most represented university group with 295 students, making up 24.69%. CZ (Czech Republic) follows with 106 respondents (8.87%). ID (Indonesia) has 65 respondents (5.44%), and LT (Lithuania) has 36 (3.01%). TR (Turkey), FR (France), and UA (Ukraine) have a minimal presence, each with fewer than 10 respondents and collectively representing only about 0.92% of the total.

The sample is heavily concentrated in IT, the majority of respondents (69.21%). Education programs are the second most common, with 185 respondents, accounting for 15.48% of the sample. Other programs, such as IT education (1.84%) and STEM education (1.17%), are represented by smaller groups.

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

Most respondents provided their data in 2022, with 532 individuals, representing 44.52% of the total. In 2023, the participation significantly decreased, with only 110 respondents, accounting for 9.21% of the total. In 2024, there was a substantial increase in responses, with 553 respondents, which constitutes 46.28% of the total. All this information will be used in the following analysis.

AI Learning Satisfaction

We will begin our analysis by examining how respondents rated their satisfaction with AI learning. The questions addressing this topic were as follows:

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

Respondents answered questions on a five-point scale

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

The box plot of responses to the questions depicted in Figure 1 shows no big differences among individual responses. The question S3, 'I find learning AI to be very interesting,' received a slightly higher rating compared to the others.

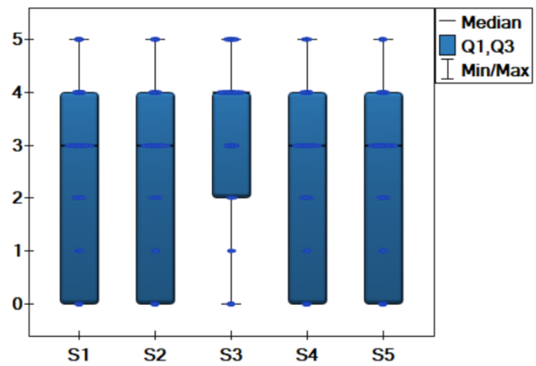

Figure 1. The box plot of responses for questions S1-S5

In order to answer the first research question "To what extent does the year of study impact perceived satisfaction with learning AI?" based on the collected data, seven independent samples were created. As the measurement scale is ordinal, the Kruskal–Wallis test was performed to verify the hypothesis that the median scores in the independent samples are significantly different. Thus, the null hypothesis was that there was no statistically significant difference in the median responses for the question for S1-S5 (the test was conducted separately for each question) in groups defined by year of study. The results obtained, test statistics and the p-value, are given in Table 7. The test confirmed a significant difference (we can reject the null hypothesis) in medians for all questions. Thus, it can be concluded that the year of study significantly affects satisfaction with learning AI.

Table 7. Results for the Kruskal–Wallis test and questions S1-S5, groups defined by year of study

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

A post-hoc test (Dunn Bonferroni) was then performed, the results are shown in Tables 8-12.

Table 8. p-value of the post-hoc Dunn Bonferroni test for question S1 with respect to year of study

p-value	1	2	3	4	5	6	7
1		1	0.187765	0.000522**	0.002319**	1	1
2	1		0.009205*	0.000015**	0.000304**	1	1
3	0.187765	0.009205*		0.734132	0.402194	1	0.831358
4	0.000522**	0.000015**	0.734132		1	1	0.237937
5	0.002319**	0.000304**	0.402194	1		1	0.134464
6	1	1	1	1	1		1
7	1	1	0.831358	0.237937	0.134464	1	

Table 9. p-value of the post-hoc Dunn Bonferroni test for question S2 with respect to year of study

p-value	1	2	3	4	5	6	7
1		1	0.000034**	0.000034**	0.000208**	1	1
2	1		<0.000001**	0.000001**	0.000024**	1	1
3	0.000034**	<0.000001**		1	1	0.574417	1
4	0.000034**	0.000001**	1		1	0.285412	1
5	0.000208**	0.000024**	1	1		0.124416	1
6	1	1	0.574417	0.285412	0.124416		1
7	1	1	1	1	1	1	

Table 10. p-value of the post-hoc Dunn Bonferroni test for question S3 with respect to year of study

p-value	1	2	3	4	5	6	7
1		0.734047	1	1	0.041264*	1	1
2	0.734047		0.103142	0.054471	0.000352**	1	1
3	1	0.103142		1	0.153495	1	1
4	1	0.054471	1		1	1	1
5	0.041264*	0.000352**	0.153495	1		1	1
6	1	1	1	1	1		1
7	1	1	1	1	1	1	

Table 11. p-value of the post-hoc Dunn Bonferroni test for question S4 with respect to year of study

p-value	1	2	3	4	5	6	7
1		1	0.000024**	0.000183**	0.002237**	1	1
2	1		<0.000001**	0.000013**	0.000586**	1	1
3	0.000024**	<0.000001**		1	1	0.676747	1
4	0.000183**	0.000013**	1		1	0.475547	1
5	0.002237**	0.000586**	1	1		0.29718	1
6	1	1	0.676747	0.475547	0.29718		1
7	1	1	1	1	1	1	

Table 12. p-value of the post-hoc Dunn Bonferroni test for question S5 with respect to year of study

p-value	1	2	3	4	5	6	7
1		1	0.290762	0.391928	0.947839	1	1
2	1		0.001255**	0.009491*	0.112451	1	1
3	0.290762	0.001255**		1	1	1	1
4	0.391928	0.009491*	1		1	1	1
5	0.947839	0.112451	1	1		1	1
6	1	1	1	1	1		1
7	1	1	1	1	1	1	

As can be seen, depending on the question, different groups of homogeneous responses were recognized. For question S1, the homogeneous groups are the following years of study {1, 2, 6, 7}, {1, 3, 6, 7}, {3, 4, 5, 6, 7}. For question S2, the homogeneous groups are the following years of study {1, 2, 6, 7}, {3, 4, 5, 6, 7}. For question S3, the homogeneous groups are the following years of study {1, 2, 3, 4, 6, 7}, {3, 4, 5, 6, 7}. For question S4, the homogeneous groups are the following years of study {1, 2, 6, 7}, {3, 4, 5, 6, 7}. For question S5, the homogeneous groups are the following years of study {1, 2, 5, 6, 7}, {1, 3, 4, 5, 6, 7}. Thus, for some questions, a distinction can be made between the initial stage of study and the higher years of study. However, increased satisfaction with learning AI was not observed in the higher years of study; in fact, satisfaction tends to diminish slightly in the later years. This trend is illustrated in Figures 2-6 displaying the box plot of responses to each question.

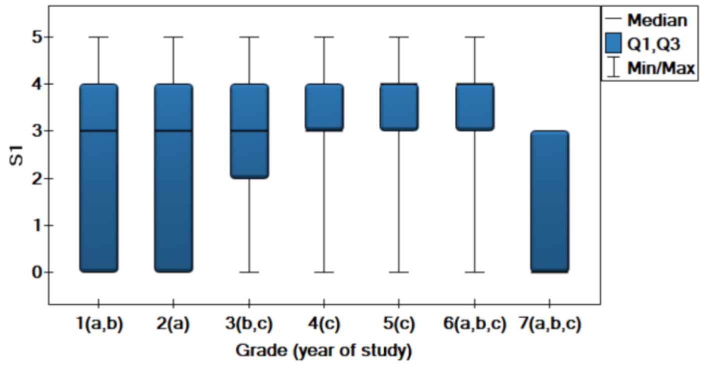

Figure 2. The box plot of responses for questions S1 with respect to year of study

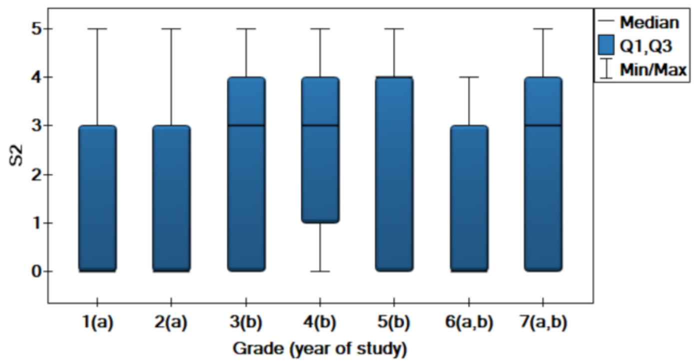

Figure 3. The box plot of responses for questions S2 with respect to year of study

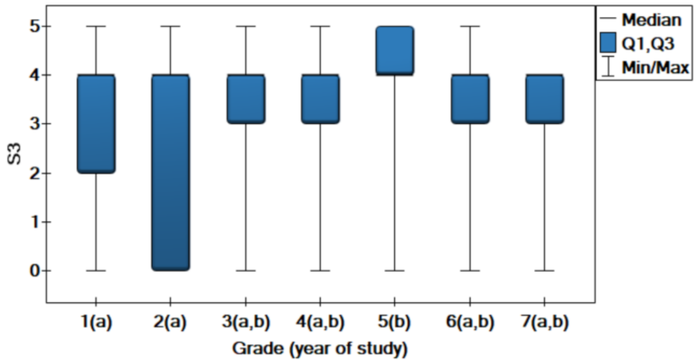

Figure 4. The box plot of responses for questions S3 with respect to year of study

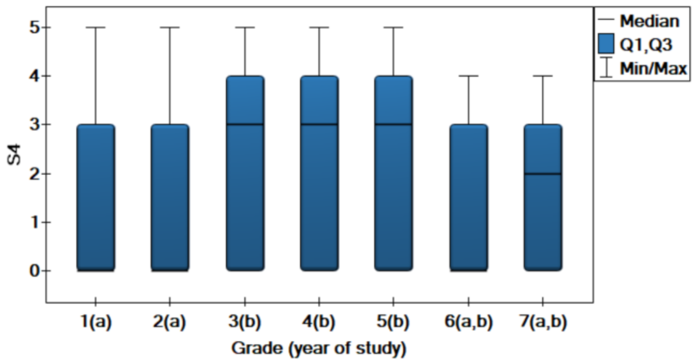

Figure 5. The box plot of responses for questions S4 with respect to year of study

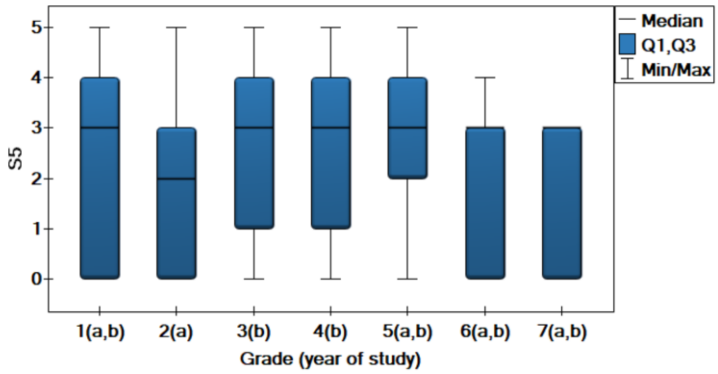

Figure 6. The box plot of responses for questions S5 with respect to year of study

In conclusion, this confirms the hypothesis that years of study are associated with greater perceived satisfaction in learning AI.

In order to test whether satisfaction levels are significantly different in the populations for different genders of respondents, the dataset was divided into two independent samples: women with 402 and men with 793. As before, the scale of the dependent variable is ordinal so in order to verify the null hypothesis that there are no significant differences in satisfaction levels for men and women, the Mann-Whitney test will be performed. The results obtained, test statistics and the p-value, are given in Table 13.

Table 13. Results for the Mann-Whitney test and questions S1-S5, groups defined by gender

	Z statistic	p-value
S1	3.20	0.0014**
S2	4.32	0.0001**

	Z statistic	p-value
S3	3.58	0.0003**
S4	4.69	0.0001**
S5	3.52	0.0004**

As can be seen, a significant difference in level of satisfaction from learning AI was detected in all tested aspects in populations of men and women. Figures 7-12 shows the box plot graph, which indicates that it is definitely men who feel higher satisfaction with AI learning. This confirms the second hypothesis H2: Men tend to experience greater satisfaction in learning AI that women.

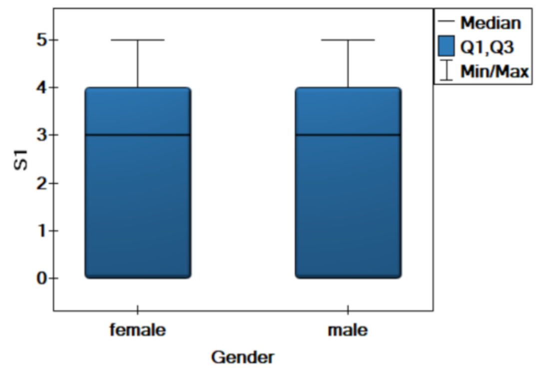

Figure 7. The box plot of responses for questions S1 with respect to gender

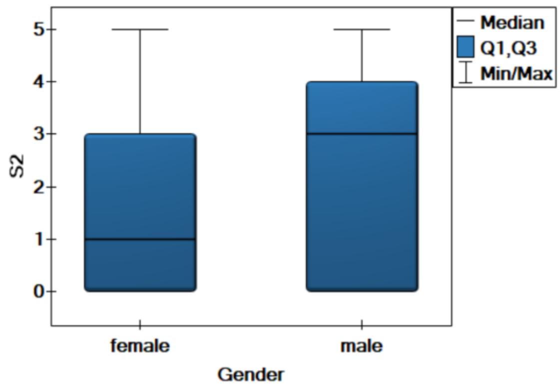

Figure 8. The box plot of responses for questions S2 with respect to gender

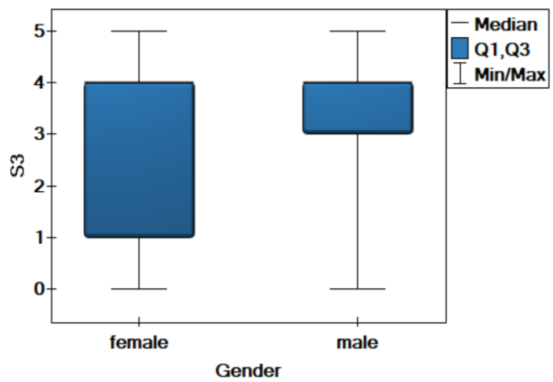

Figure 9. The box plot of responses for questions S5 with respect to gender

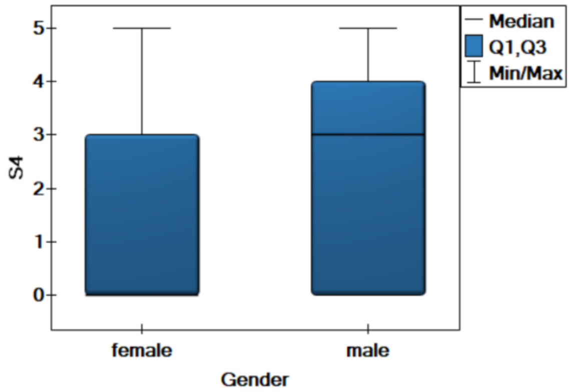

Figure 10. The box plot of responses for questions S5 with respect to gender

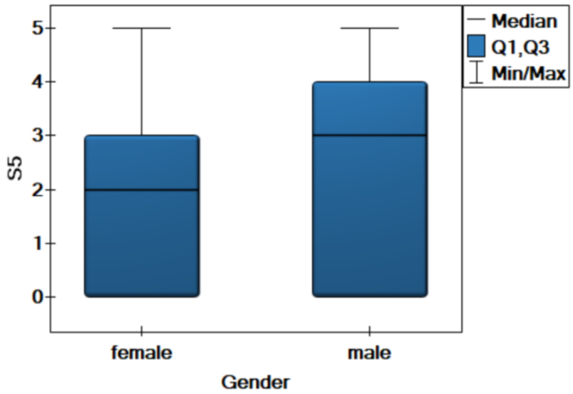

Figure 11. The box plot of responses for questions S5 with respect to gender

In the next stage of our analysis, we will examine whether the study program influences perceived satisfaction with AI learning. It is hypothesized that students enrolled in IT-focused programs may exhibit greater interest in learning about these topics, as they probably aligned with these interests, hobby. Initially, we created seven independent groups, each for a different study program: IT, education, IT education, STEM education, language, management and other. To verify the hypothesis that there are statistical differences in learning AI satisfaction levels grouped by study program, the Kruskal–Wallis test was performed. The results obtained, test statistics and the p-value, are given in Table 14.

Table 14. Results for the Kruskal–Wallis test and questions S1-S5, groups defined by study program

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

Thus, it can be concluded that in all studied aspects (questions S1-S5) of AI learning satisfaction, a significant difference in levels between at least two groups defined by the study program was noted. In order to verify between which groups there is a statistical difference in satisfaction levels, post-hoc tests were performed. The results are shown in Tables 15-19.

Table 15. p-value of the post-hoc test for question S1 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.011	1	0.430	1	0.016	1
education	0.011		0.439	1	1	1	1

p-value	IT	education	IT education	STEM education	other	language	management
IT education	1	0.439		0.243	1	0.040	1
STEM education	0.430	1	0.243		1	1	1
other	1	1	1	1		0.841	1
language	0.016	1	0.040	1	0.841		1
management	1	1	1	1	1	1	

Table 16. p-value of the post-hoc test for question S2 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.0001**	1	0.570	0.002**	0.001**	0.360
education	0.0001**		1	1	1	1	1
IT education	1	1		1	0.765	0.110	1
STEM education	0.570	1	1		1	1	1
other	0.002**	1	0.765	1		1	1
language	0.001**	1	0.110	1	1		1
management	0.360	1	1	1	1	1	

Table 17. p-value of the post-hoc test for question S3 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.002**	1	0.247	1	1	1
education	0.002**		0.182	1	1	1	1
IT education	1	0.182		0.107	1	1	0.968
STEM education	0.247	1	0.107		1	1	1
other	1	1	1	1		1	1
language	1	1	1	1	1		1
management	1	1	0.968	1	1	1	

Table 18. p-value of the post-hoc test for question S4 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.0001**	1	0.443	0.004**	0.001**	0.378
education	0.0001**		0.908	1	1	0.981	1
IT education	1	0.908		0.768	0.425	0.054	1
STEM education	0.443	1	0.768		1	1	1
other	0.004**	1	0.425	1		1	1
language	0.001**	0.981	0.054	1	1		1
management	0.378	1	1	1	1	1	

Table 19. p-value of the post-hoc test for question S5 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.006*	1	0.440	0.124	0.001**	0.129
education	0.006*		0.137	1	1	0.308	1
IT education	1	0.137		0.127	0.141	0.002**	0.113
STEM education	0.440	1	0.127		1	1	1
other	0.124	1	0.141	1		1	1
language	0.001**	0.308	0.002**	1	1		1
management	0.129	1	0.113	1	1	1	

As you can see actually the most common significant differences in satisfaction levels are between IT and education and IT and language students. Also, we prepared a box plot graph to verify that it is IT students who feel significantly higher satisfaction with IT learning than others (Figures 12-16).

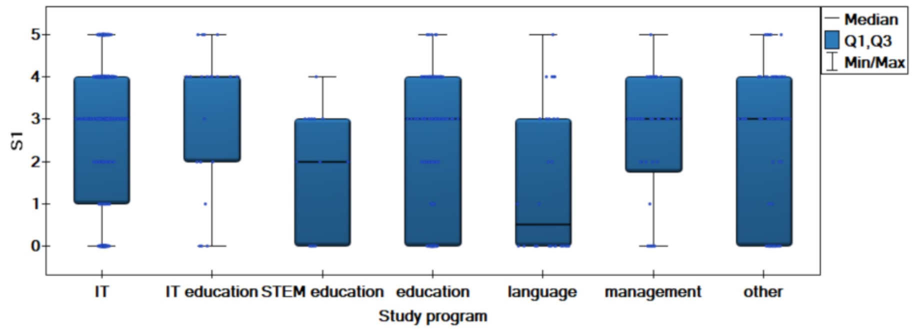

Figure 12. The box plot of responses for questions S1 with respect to study program

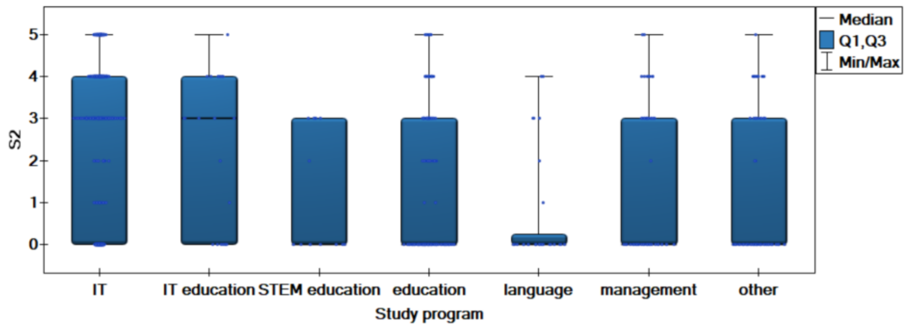

Figure 13. The box plot of responses for questions S2 with respect to study program

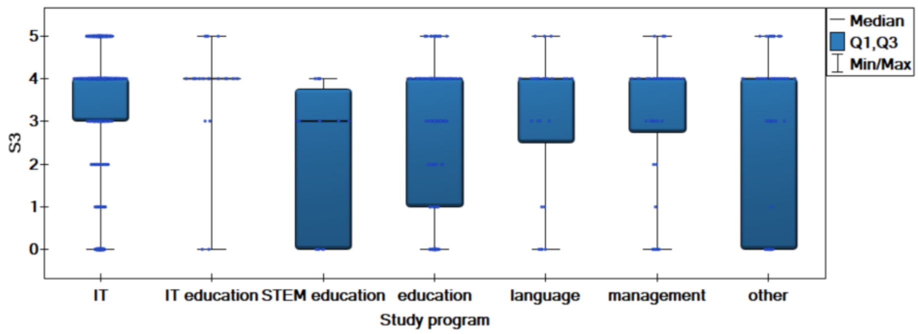

Figure 14. The box plot of responses for questions S3 with respect to study program

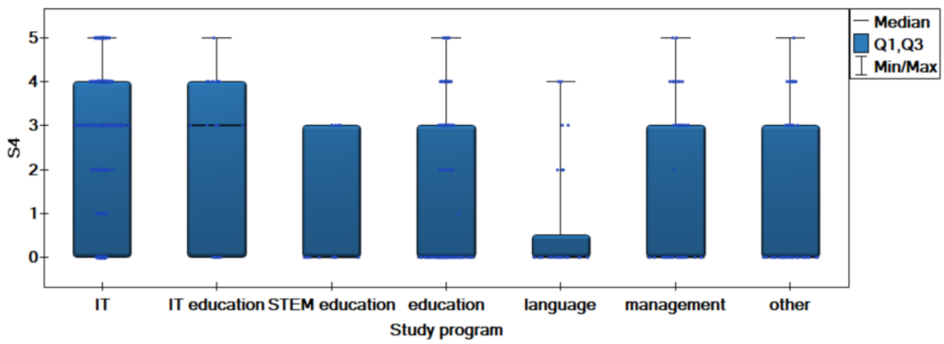

Figure 15. The box plot of responses for questions S4 with respect to study program

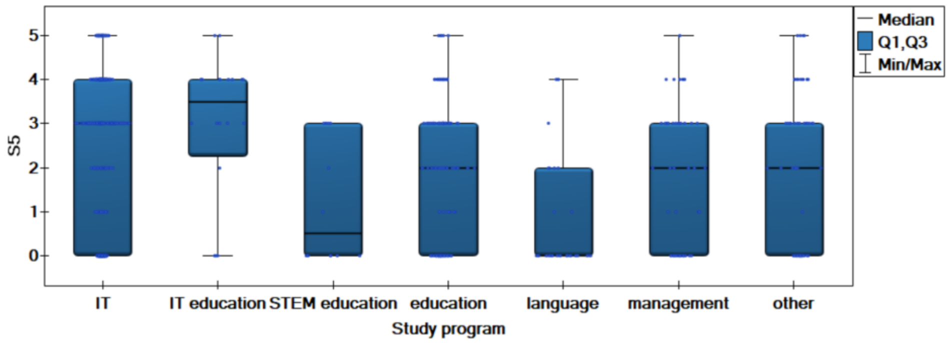

Figure 16. The box plot of responses for questions S5 with respect to study program

It can be noted that actually students of IT, IT in education but also management feel higher satisfaction from learning AI. Thus, the hypothesis was confirmed H3: Study program has a significant impact on satisfaction levels in learning AI.

We will now analyze whether the level of satisfaction with AI learning has changed significantly over the years 2022, 2023 and 2024. Three independent samples were created, each containing responses for a different year. The Kruskal–Wallis test was used to verify the hypothesis of whether there was a statistical difference in satisfaction levels between years. The results obtained, test statistics and the p-value, are given in Table 20.

Table 20. Results for the Kruskal–Wallis test and questions S1-S5, groups defined by years 2022, 2023, 2024

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

Thus, it can be concluded that the year of responses affects satisfaction with learning AI. A post-hoc test (Dunn Bonferroni) was then performed, the results are shown in Tables 21-25. We can see that there is a statistical difference in the level of satisfaction with AI learning between pairs 2022, 2023 and 2023, 2024. Thus, the level varied significantly in 2023 year. Figures 17-21 show the trend of these changes.

Table 21. p-value of the post-hoc Dunn Bonferroni test for question S1 with respect to year of responses

p-value	2022	2023	2024
2022		0.000008**	0.238575
2023	0.000008**		0.000672**
2024	0.238575	0.000672**	

Table 22. p-value of the post-hoc Dunn Bonferroni test for question S2 with respect to year of responses

p-value	2022	2023	2024
2022		<0.000001**	0.619698
2023	<0.000001**		<0.000001**
2024	0.619698	<0.000001**	

Table 23. p-value of the post-hoc Dunn Bonferroni test for question S3 with respect to year of responses

p-value	2022	2023	2024
2022		0.018172*	1
2023	0.018172*		0.063607
2024	1	0.063607	

Table 24. p-value of the post-hoc Dunn Bonferroni test for question S4 with respect to year of responses

p-value	2022	2023	2024
2022		<0.000001**	0.516127
2023	<0.000001**		<0.000001**
2024	0.516127	<0.000001**	

Table 25. p-value of the post-hoc Dunn Bonferroni test for question S5 with respect to year of responses

p-value	2022	2023	2024
2022		<0.000001**	1
2023	<0.000001**		<0.000001**
2024	1	<0.000001**	

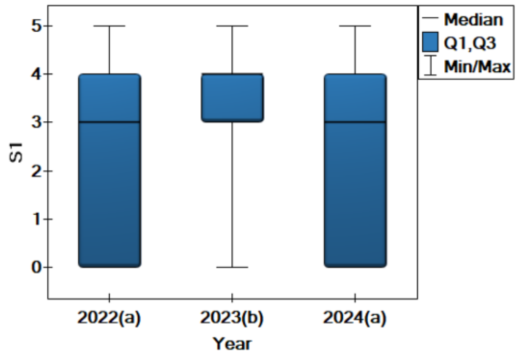

Figure 17. The box plot of responses for questions S1 with respect to year of responses

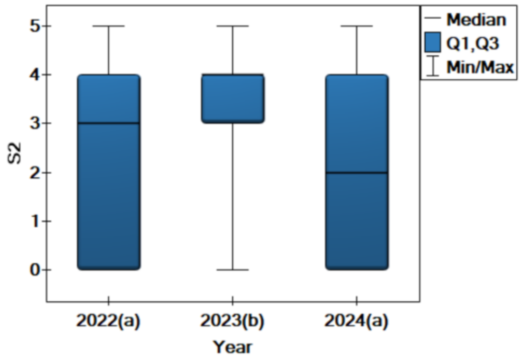

Figure 18. The box plot of responses for questions S2 with respect to year of responses

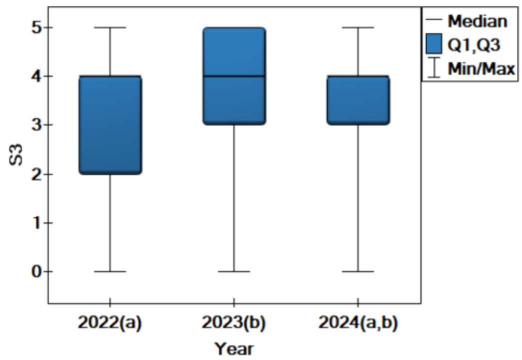

Figure 19. The box plot of responses for questions S3 with respect to year of responses

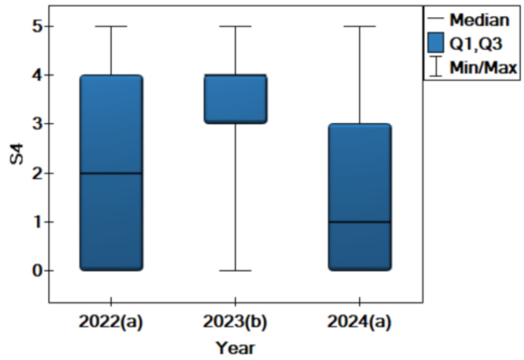

Figure 20. The box plot of responses for questions S4 with respect to year of responses

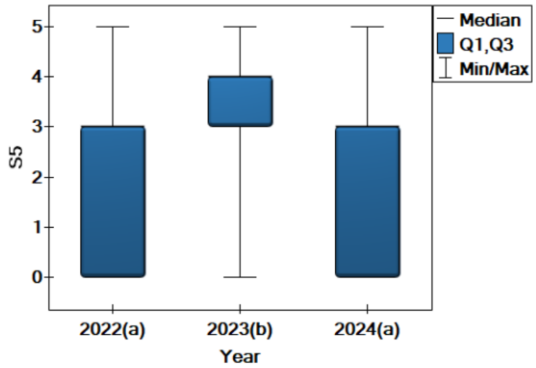

Figure 21. The box plot of responses for questions S5 with respect to year of responses

Thus, it can be seen that the level of satisfaction increased in 2023 while in 2022 and in 2024 it remains at about the same level. Presumably, this may be related to the fact that the first version of ChatGPT was launched by OpenAI in November 2022, based on the GPT-3.5 model. In March 2023, an improved version was made available, based on the GPT-4 model. Perhaps this influenced the increase in satisfaction with AI learning in 2023. Thus, hypothesis H4: Between 2022 and 2024, the level of satisfaction associated with learning AI evolved significantly is confirmed.

AI readiness

We now turn to analysis on AI readiness. The questions addressing this topic were as follows:

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

The box plot of responses to the questions are depicted in Figure 22. Conclusions that can be drawn from these figures indicate that respondents believe that AI technology can help people in their daily lives, and over time it is becoming more and more convenient to use. However, when it comes to simulated thinking and the belief that AI will follow instructions here, one can already see far more uncertainty and lack of conviction among respondents. In further analysis, we will examine potential factors contributing to this.

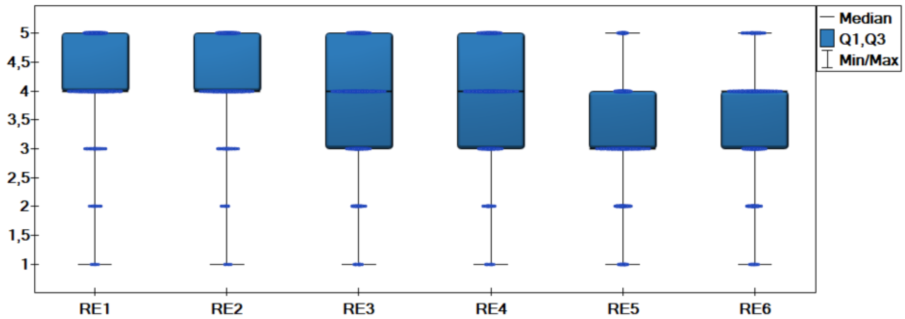

Figure 22. The box plot of responses for questions RE1-RE6

In order to verify whether readiness level are significantly different in the populations for different genders of respondents, the dataset was divided into two independent samples. The Mann-Whitney test was used to verify the null hypothesis that there are no significant differences in readiness levels for men and women. The results obtained, test statistics and the p-value, are given in Table 26. As can be seen in all aspects of readiness, the attitudes of men and women differ significantly. Figures 23-28 show the box plots in a group of men and women. The graphs clearly indicate that women generally show less AI readiness than men. Only for questions about whether AI can help people and whether AI is becoming more convenient does the difference in responses between women and men narrow, although it remains statistically significant, as confirmed by the tests.

Table 26. Mann-Whitney test results for responses to questions RE1-RE6, grouped by gender

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

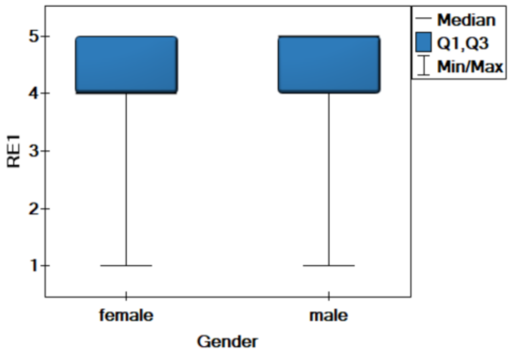

Figure 23. The box plot of responses for questions RE1 with respect to gender

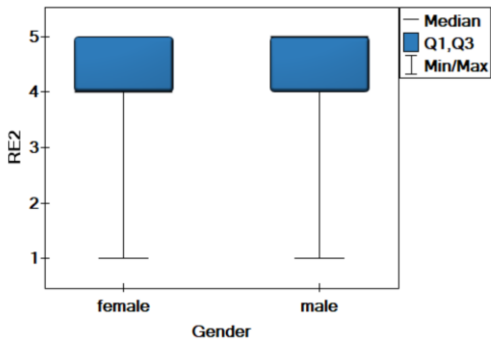

Figure 24. The box plot of responses for questions RE2 with respect to gender

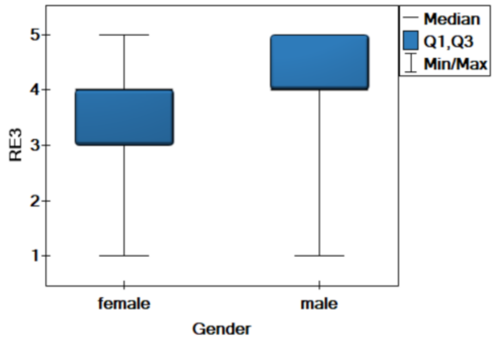

Figure 25. The box plot of responses for questions RE3 with respect to gender

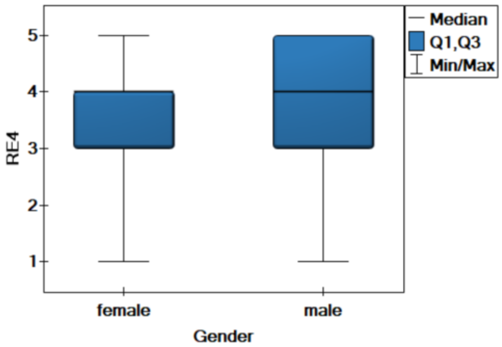

Figure 26. The box plot of responses for questions RE4 with respect to gender

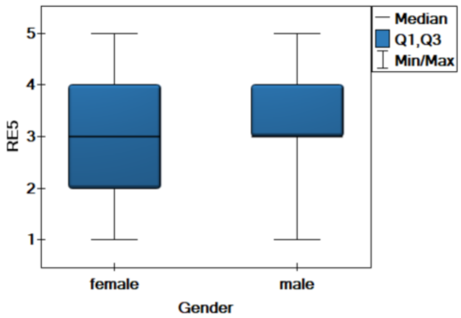

Figure 27. The box plot of responses for questions RE5 with respect to gender

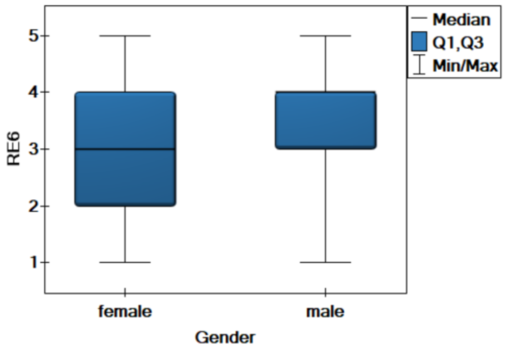

Figure 28. The box plot of responses for questions RE6 with respect to gender

The results suggest that while both genders recognize certain practical benefits of AI, there is a notable disparity in overall readiness and acceptance levels. These findings highlight the need for targeted approaches to address gender-specific attitudes and concerns regarding AI, potentially enhancing AI readiness across diverse populations. Thus, hypothesis H5 ,,Men tend to demonstrate higher levels of AI readiness compared to women'' was confirmed.

Now we proceed to consider whether the study program matters in AI readiness. We created seven independent groups, each for a different study program and used the Kruskal–Wallis test to verify the hypothesis that there are statistical differences in AI readiness grouped by study program. The results obtained, test statistics and the p-value, are given in Table 27.

Table 27. Results for the Kruskal–Wallis test and questions RE1-RE6, groups defined by study program

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

Tests confirm that study program has an impact on readiness of AI. In order to verify between which groups there is a statistical difference in AI readiness, post-hoc tests were performed. The results are shown in Tables 28-35. Based on the results, we can conclude that the most distinctive group of respondents are IT students, who display a significantly higher level of AI readiness compared to students from other fields. This readiness is particularly evident in their responses to questions such as, "The technology can help me adjust things to my needs" and "The new AI technology will stimulate my thinking". Another notable conclusion is that IT students demonstrate a stronger belief in AI's potential to enhance problem-solving and creativity. This suggests that their familiarity with technology has fostered a more optimistic outlook on AI's ability to contribute meaningfully to their academic and personal growth. With that, the H6 hypothesis was confirmed.

Table 28. p-value of the post-hoc test for question RE1 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.001**	0.194	0.004**	0.002**	0.011*	0.514
education	0.001**		1	1	1	1	0.319
IT education	0.194	1		1	1	1	1
STEM education	0.004**	1	1		1	1	0.461
other	0.002**	1	1	1		1	1
language	0.011*	1	1	1	1		1
management	0.514	0.319	1	0.461	1	1	

Table 29. p-value of the post-hoc test for question RE2 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.001**	1	1	1	0.070	1
education	0.001**		1	1	0.829	1	0.566
IT education	1	1		1	1	1	1
STEM education	1	1	1		1	1	1
other	1	0.829	1	1		1	1
language	0.070	1	1	1	1		1
management	1	0.566	1	1	1	1	

Table 30. p-value of the post-hoc test for question RE3 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.001**	1	0.005*	0.004**	0.001**	0.528
education	0.001**		1	1	1	1	1
IT education	1	1		0.320	1	0.521	1
STEM education	0.005*	1	0.320		1	1	0.537
other	0.004**	1	1	1		1	1
language	0.001**	1	0.521	1	1		0.835
management	0.528	1	1	0.537	1	0.835	

Table 31. p-value of the post-hoc test for question RE4 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.001**	1	0.065	0.131	0.046*	0.630
education	0.001**		1	1	1	1	1
IT education	1	1		1	1	1	1
STEM education	0.065	1	1		1	1	1
other	0.131	1	1	1		1	1
language	0.046*	1	1	1	1		1
management	0.630	1	1	1	1	1	

Table 32. p-value of the post-hoc test for question RE5 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.001**	1	0.483	1	0.025*	1
education	0.001**		0.263	1	1	1	1
IT education	1	0.263		0.324	1	0.069	1
STEM education	0.483	1	0.324		1	1	1
other	1	1	1	1		1	1
language	0.025*	1	0.069	1	1		0.874
management	1	1	1	1	1	0.874	

Table 33. p-value of the post-hoc test for question RE6 with respect to study program

p-value	IT	education	IT education	STEM education	other	language	management
IT		0.004**	1	0.078	1	0.008*	1
education	0.004**		1	1	1	1	1
IT education	1	1		0.261	1	0.174	1
STEM education	0.078	1	0.261		1	1	0.607
other	1	1	1	1		0.756	1
language	0.008*	1	0.174	1	0.756		0.374
management	1	1	1	0.607	1	0.374	

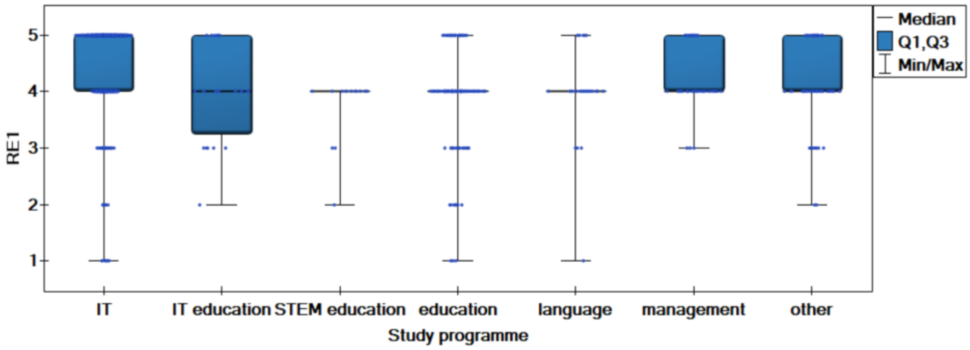

Figure 29. The box plot of responses for questions RE1 with respect to study program

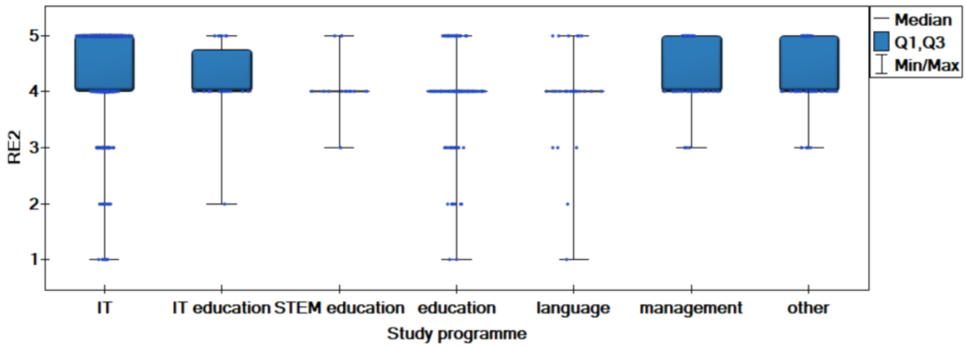

Figure 30. The box plot of responses for questions RE2 with respect to study program

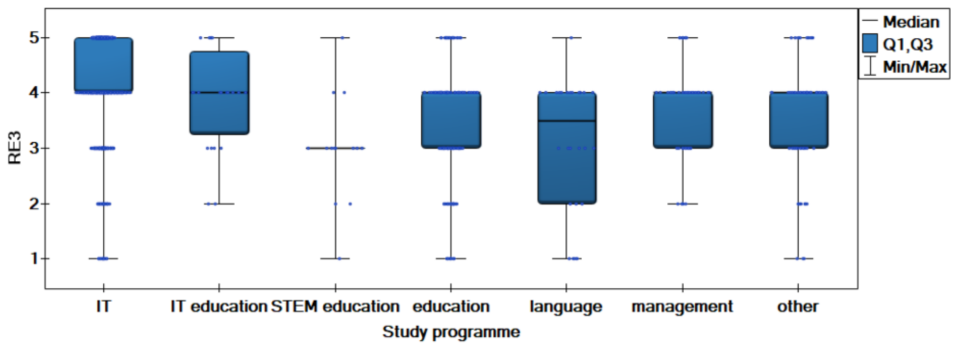

Figure 31. The box plot of responses for questions RE3 with respect to study program

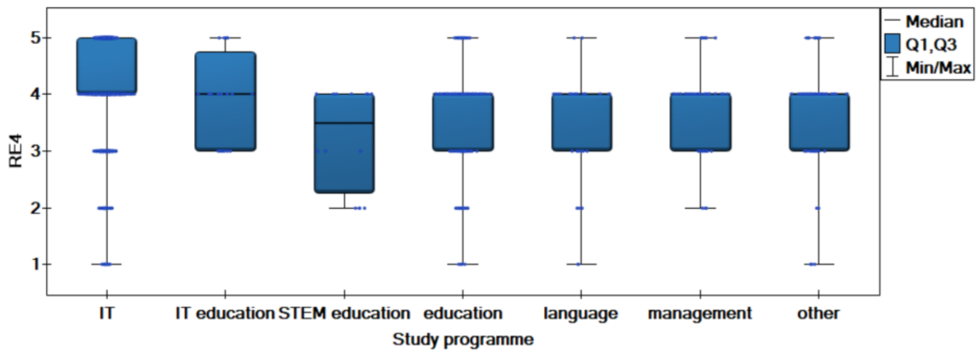

Figure 32. The box plot of responses for questions RE4 with respect to study program

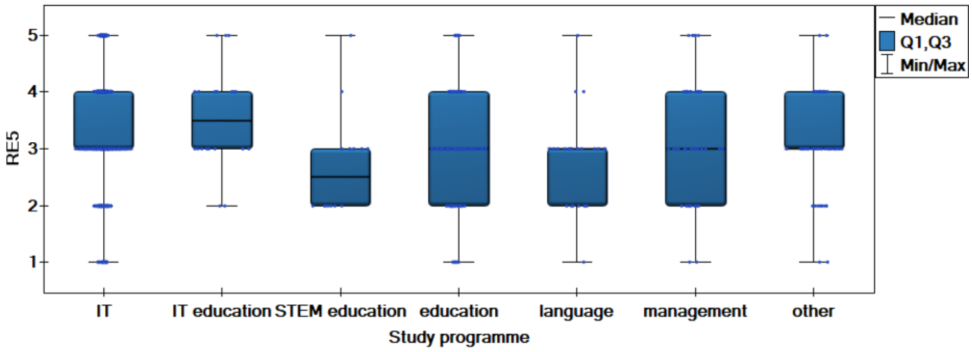

Figure 33. The box plot of responses for questions RE5 with respect to study program

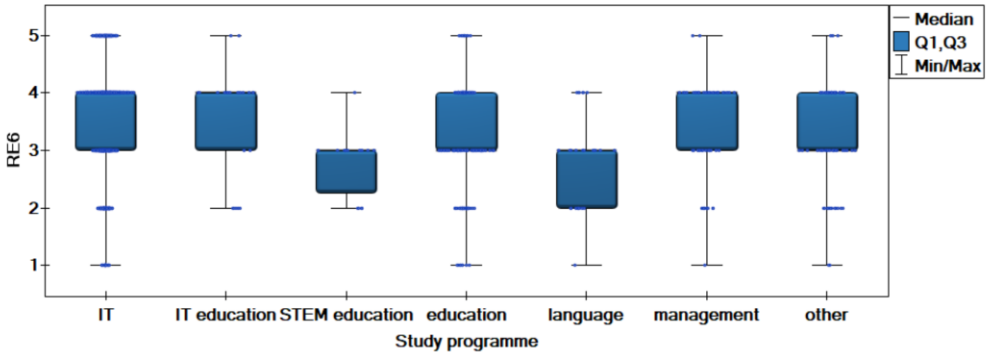

Figure 34. The box plot of responses for questions RE6 with respect to study program

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

AI relevance

We now turn to analysis on the relevance of AI. The questions addressing this topic were as follows:

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

The box plot of responses to the questions are depicted in Figure 35. The plot suggests that respondents generally acknowledge the broader significance of AI (R1) and find value in learning about it (R2). However, there is more uncertainty or less enthusiasm when it comes to personal relevance (R4, R5) and connecting it to everyday life (R6). This could point to a gap in how AI education is perceived in terms of practical, relatable applications.

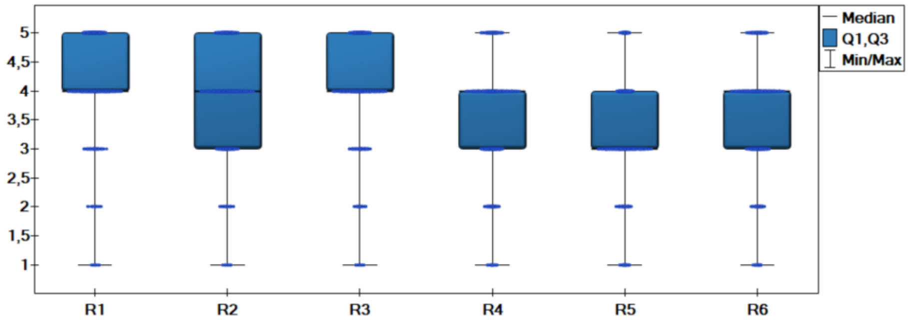

Figure 35. The box plot of responses for questions R1-R6

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

On the other hand, it was observed that the AI relevance level is significantly different in the populations for different genders of respondents. The Mann-Whitney test was used to verify the null hypothesis that there are no significant differences in relevance AI levels for men and women. The results obtained, test statistics and the p-value, are given in Table 34. As can be seen all questions demonstrate statistically significant gender differences in responses, with the strongest differences in questions R1, R2, R3, and R5. This suggests that gender may influence attitudes toward AI’s impact, relevance, and personal interest, with varying degrees of intensity. Figures 35-40 show the box plots in a group of men and women. The boxplot analysis reveals that women generally perceive AI as less relevant compared to men across multiple aspects. This is evidenced by lower median responses from women on questions related to AI's usefulness, impact on future careers, and connection to everyday life. These differences suggest that women may feel less engaged with or interested in AI topics, potentially indicating a gender gap in perceived relevance and enthusiasm toward AI. Addressing this gap could be important in designing more inclusive AI education strategies.

Table 34. Mann-Whitney test results for responses to questions R1-R6, grouped by gender

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

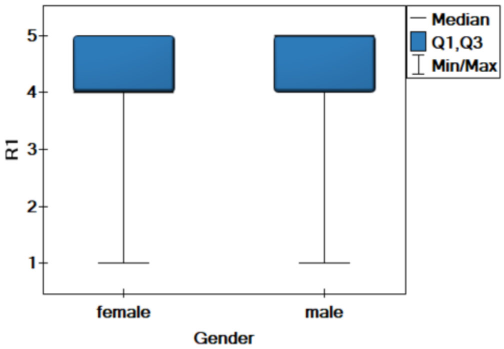

Figure 35. The box plot of responses for questions R1 with respect to gender

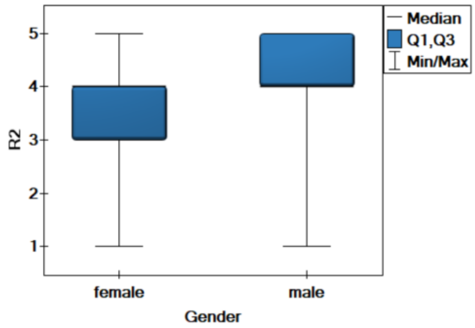

Figure 36. The box plot of responses for questions R2 with respect to gender

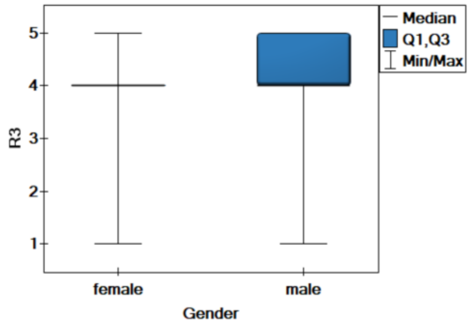

Figure 37. The box plot of responses for questions R3 with respect to gender

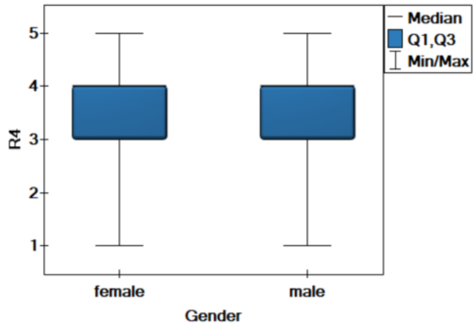

Figure 38. The box plot of responses for questions R4 with respect to gender

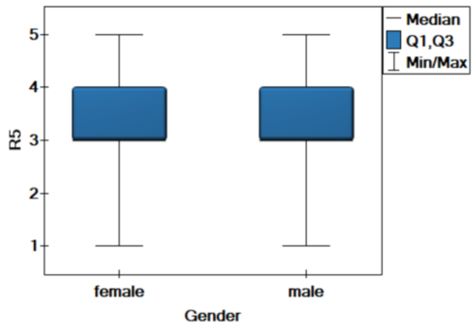

Figure 39. The box plot of responses for questions R5 with respect to gender

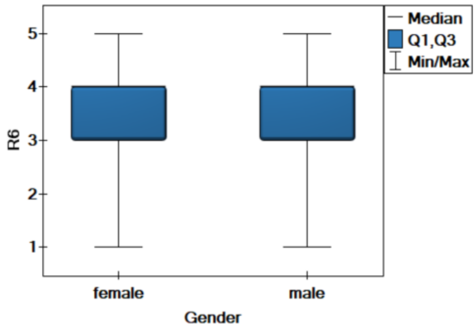

Figure 40. The box plot of responses for questions R6 with respect to gender

4.3.3 Correlation Analysis

Analysis of dependencies and correlations between AI satisfaction, AI readiness and AI relevance

To analyze the relationship between the three components of AI satisfaction, AI readiness, and AI relevance, the following approach was applied. First, the average response for each respondent was calculated separately for each group of questions:

- S1,…,S5 denoted as AVG S,
- RE1,…,RE6 denoted as AVG RE
- R1,…, R6 denoted as AVG R

Next, Spearman's rank correlation was used to assess the relationships between the newly created variables. The results are summarized in Table 35, with the correlations visualized graphically in Figure 41.

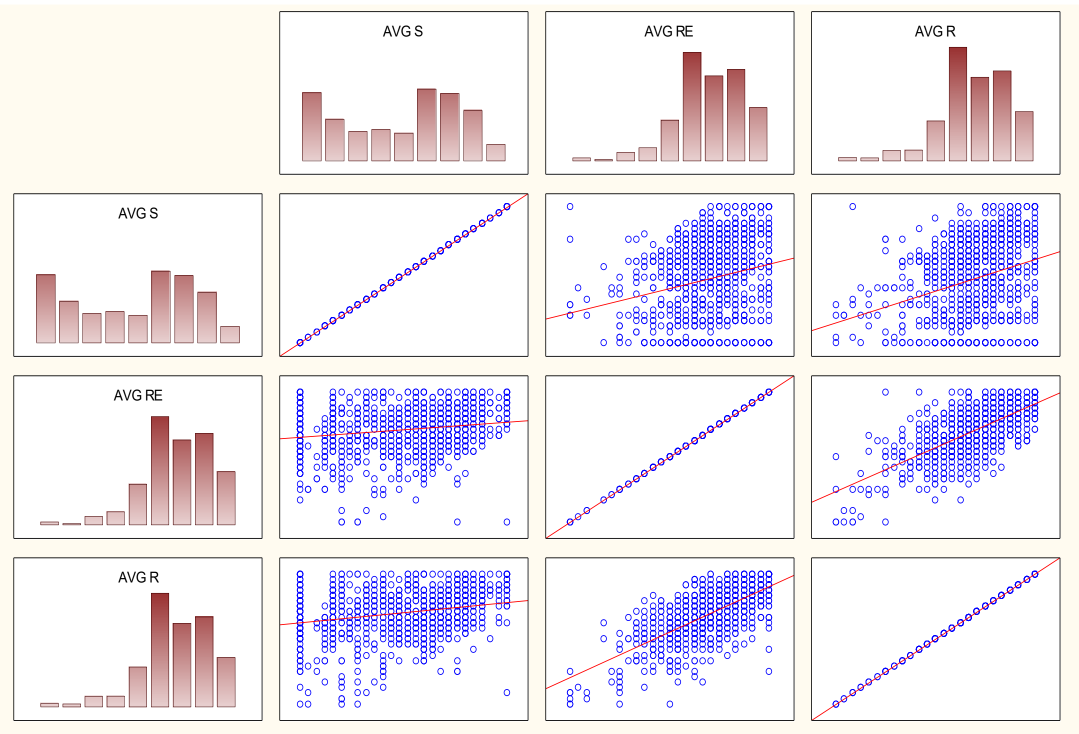

Figure 41. The correlations between the groups of questions AVG S, AVG RE, AVG R visualized graphically

Table 35. Spearman's rank correlate between the groups of questions AVG S, AVG RE, AVG R. Marked correlation coefficients are significant with p <0.05

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

The results show that AI satisfaction is weakly correlated with both AI readiness (0.224) and AI relevance (0.291), suggesting a limited but positive association. This implies that individuals who find AI more relevant or feel more prepared for its use tend to report slightly higher satisfaction levels, though other factors may also influence satisfaction. A stronger relationship emerges between AI readiness and AI relevance (0.643), indicating that individuals or organizations who feel more prepared for AI adoption also perceive it as more relevant. This highlights the close connection between being equipped to work with AI and recognizing its importance in various contexts. These findings underscore readiness as a key factor in shaping the perceived value of AI.

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

Next, Spearman's rank correlation only for IT students are summarized in Table 36, with the correlations visualized graphically in Figure 42.

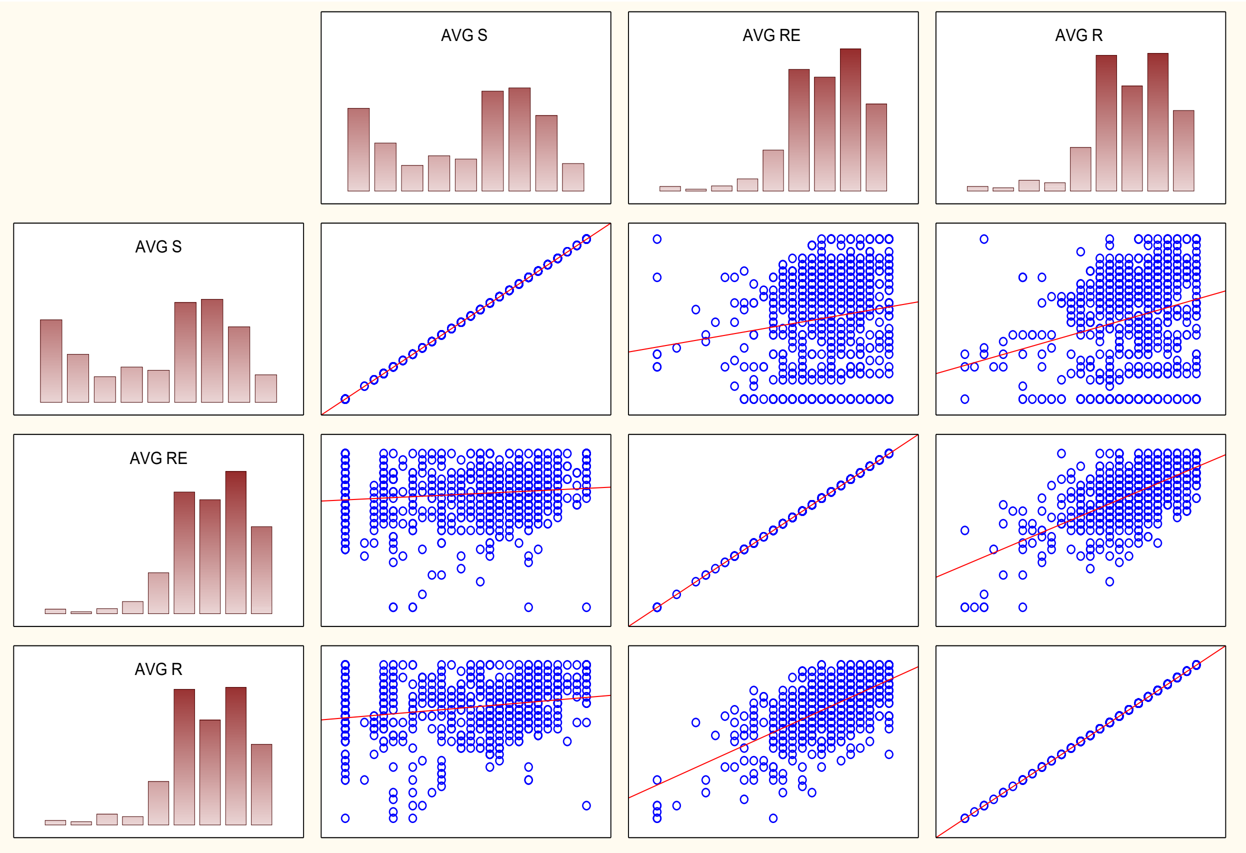

Figure 42. The correlations between the groups of questions AVG S, AVG RE, AVG R visualized graphically for IT students

Table 36. Spearman's rank correlate between the groups of questions AVG S, AVG RE, AVG R for IT students. Marked correlation coefficients are significant with p <0.05

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

The results for IT students reveal variations in the strength of relationships among AI satisfaction (AVG S), AI readiness (AVG RE), and AI relevance (AVG R). These insights help identify how perceptions of AI differ within the IT student group. For IT students, the correlation between AI satisfaction (AVG S) and AI readiness (AVG RE) is weak (0.150), indicating a minimal relationship between satisfaction and readiness in this group. The correlation between AI satisfaction (AVG S) and AI relevance (AVG R) is slightly stronger (0.261), suggesting that students who find AI more relevant tend to report slightly higher satisfaction levels. However, the strongest relationship is between AI readiness (AVG RE) and AI relevance (AVG R) (0.610), highlighting a significant link between readiness to adopt AI and recognizing its importance. Figure 42 visually emphasizes the stronger association between readiness and relevance, while relationships involving satisfaction remain weaker. These findings suggest that while IT students recognize the importance of preparation for AI, their satisfaction with AI may depend on additional factors beyond readiness and relevance.

Analogous results for non-IT students are shown in Table 37 and Figure 43.

Table 37. Spearman's rank correlate between the groups of questions AVG S, AVG RE, AVG R for IT non-students. Marked correlation coefficients are significant with $p < 0.05$

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

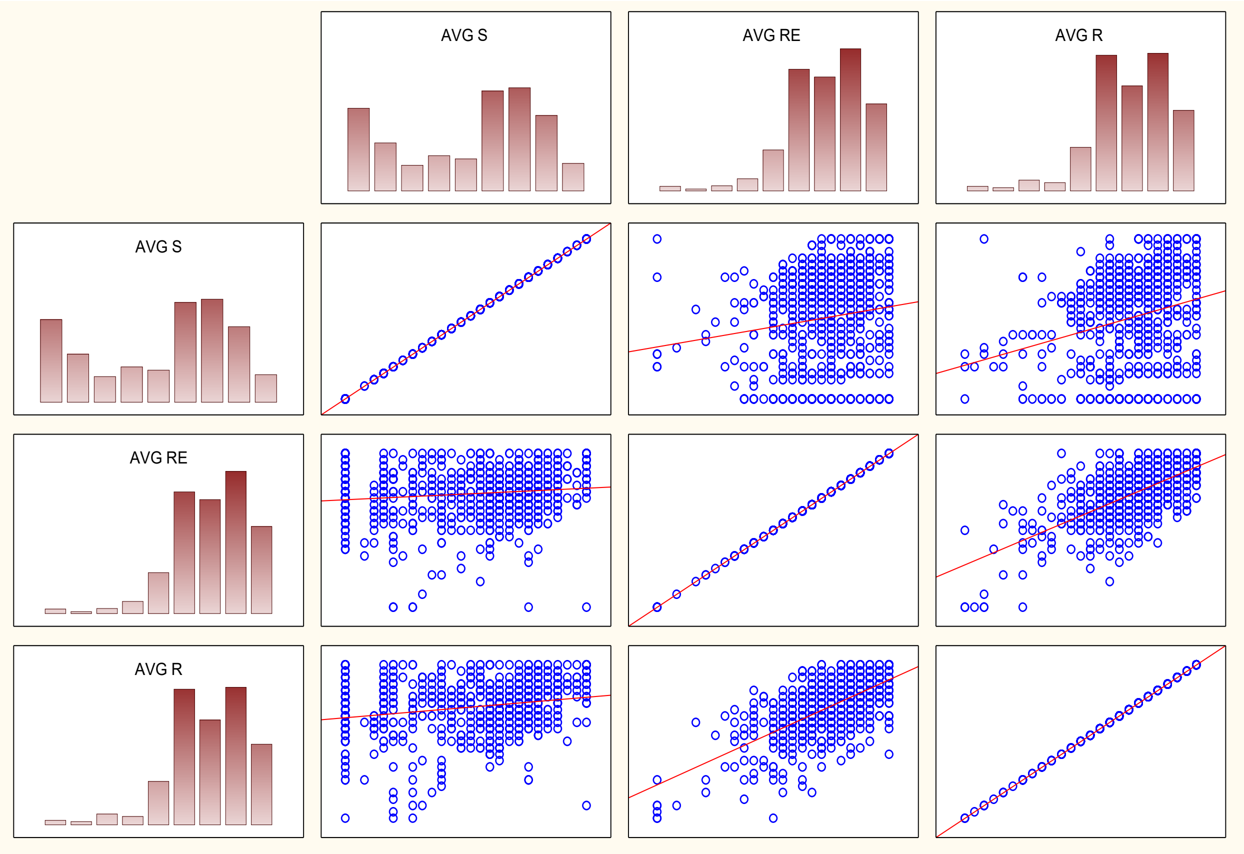

Figure 43. The correlations between the groups of questions AVG S, AVG RE, AVG R visualized graphically for non-IT students.

Both groups exhibit similar patterns, with the strongest correlations consistently observed between AI readiness and AI relevance. However, the strength of the relationships varies slightly between the two groups. For non-IT students, the correlation between AI satisfaction (AVG S) and AI readiness (AVG RE) is 0.238, stronger than the equivalent value for IT students (0.150). Similarly, the correlation between AI satisfaction (AVG S) and AI relevance (AVG R) is almost identical for both groups (0.262 for non-IT students versus 0.261 for IT students). These results indicate that non-IT students have a slightly stronger connection between their satisfaction with AI and their readiness for its use compared to IT students, though the association remains weak overall. The correlation between AI readiness (AVG RE) and AI relevance (AVG R) is high for both groups but slightly stronger for non-IT students (0.640) than IT students (0.610). This suggests that non-IT students who feel more prepared for AI adoption tend to perceive it as relevant even more strongly than their IT counterparts. The graphical visualizations (Figures 42 and 43) likely emphasize these differences in correlation strength across the groups, particularly in readiness and relevance.

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

We also analyzed the correlation for the division concerning gender, as this was another important factor shown to have a significant impact in the studies discussed in previous sections. Spearman's rank correlation for male are summarized in Table 38, with the correlations visualized graphically in Figure 44.

Table 38. Spearman's rank correlate between the groups of questions AVG S, AVG RE, AVG R for male. Marked correlation coefficients are significant with $p < 0.05$

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

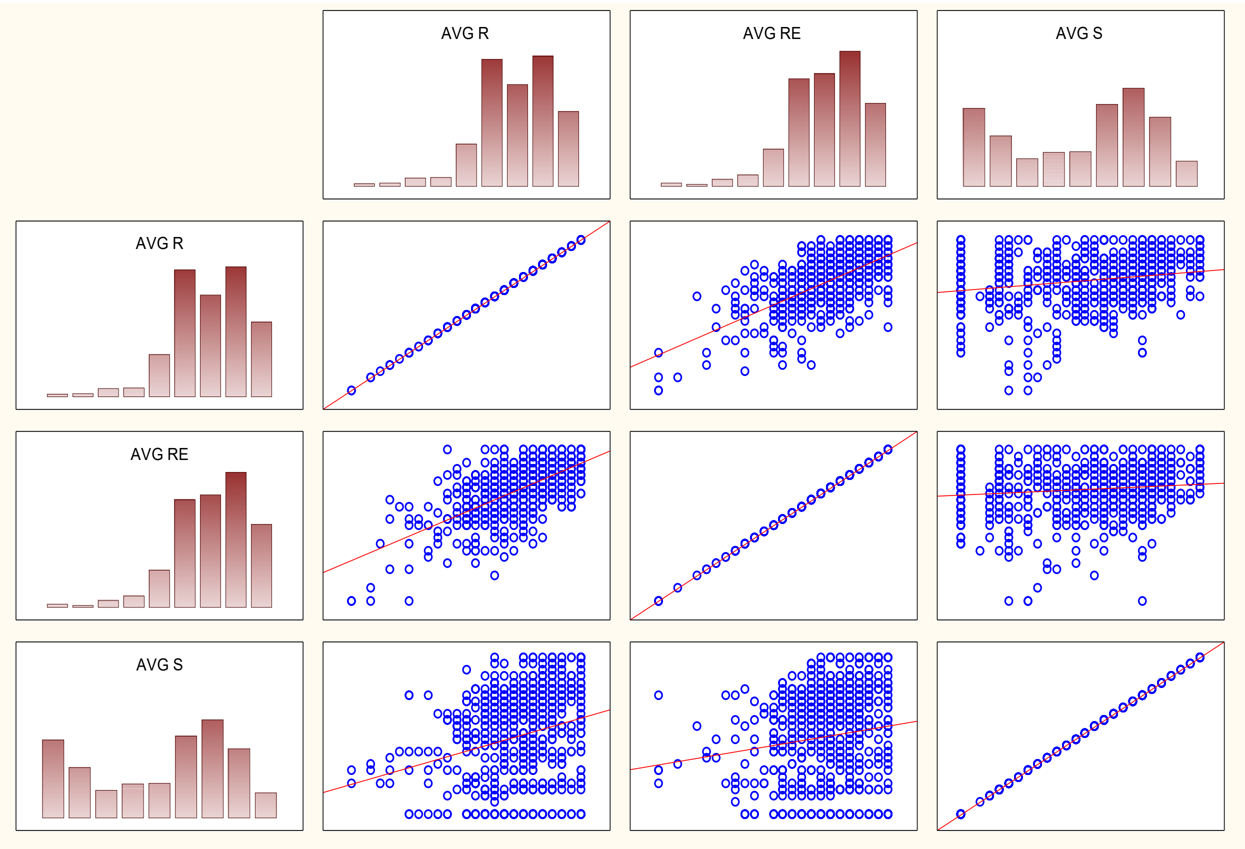

Figure 44. The correlations between the groups of questions AVG S, AVG RE, AVG R visualized graphically for male

The analysis examines the relationships between AI satisfaction (AVG S), AI readiness (AVG RE), and AI relevance (AVG R) among male respondents. For male respondents, the correlation between AI satisfaction (AVG S) and AI readiness (AVG RE) is strong (0.618), significantly higher than in previous analyses for other groups. This suggests that males who feel more prepared for AI tend to report much higher satisfaction levels. Similarly, AI satisfaction (AVG S) and AI relevance (AVG R) exhibit a weak to moderate positive correlation (0.254), indicating that the perceived relevance of AI has a smaller but still positive association with satisfaction.

Interestingly, the correlation between AI readiness (AVG RE) and AI relevance (AVG R) is very weak (0.139), unlike the strong correlations typically observed between these two variables in other groups. This suggests that for male respondents, readiness and relevance are not strongly linked, which may indicate a different underlying perception or experience with AI compared to broader samples.

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

Spearman's rank correlation for male are summarized in Table 39, with the correlations visualized graphically in Figure 45.

Table 39. Spearman's rank correlate between the groups of questions AVG S, AVG RE, AVG R for female. Marked correlation coefficients are significant with $p < 0.05$

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

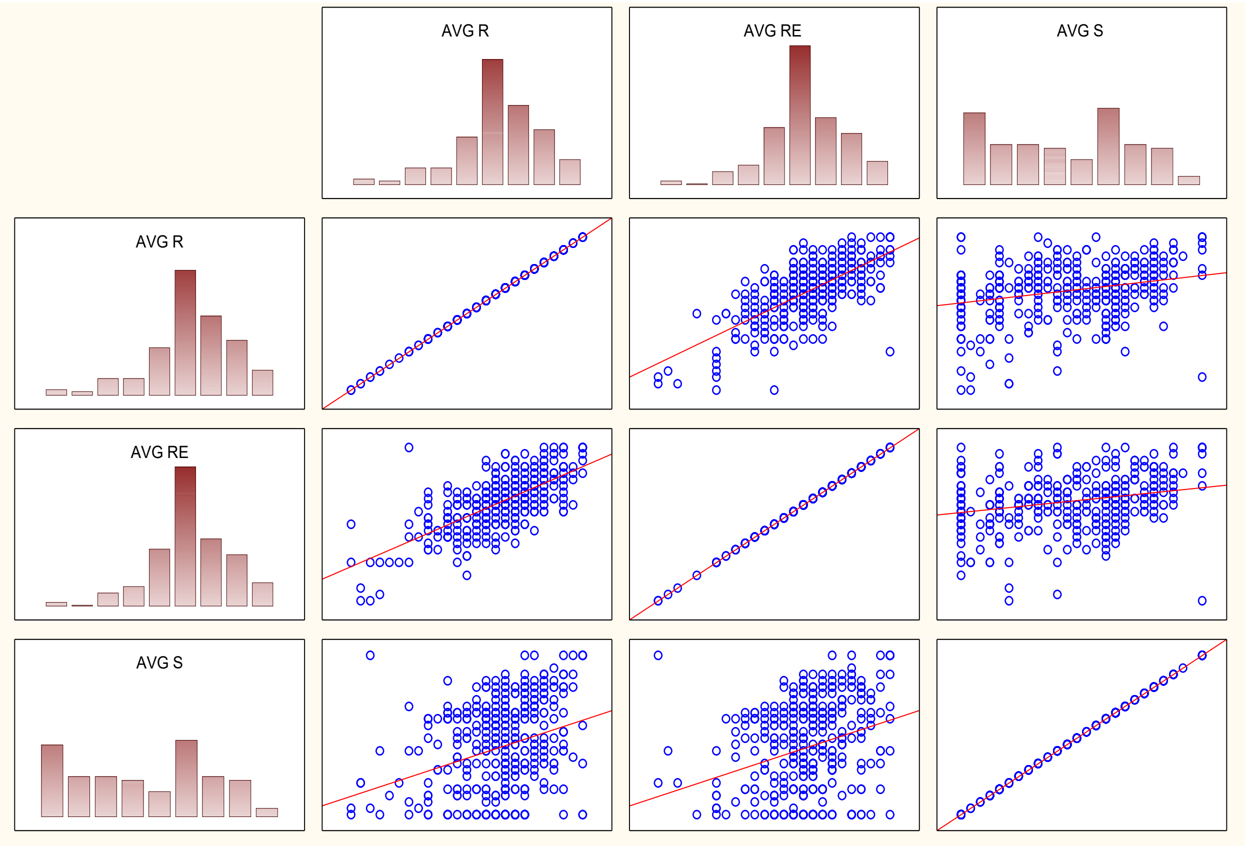

Figure 45. The correlations between the groups of questions AVG S, AVG RE, AVG R visualized graphically for female

The correlation between AI satisfaction (AVG S) and AI readiness (AVG RE) is strong (0.625), similar to the male group (0.618). This indicates that for both genders, individuals who feel more prepared for AI are significantly more likely to report higher satisfaction levels. However, the correlation between AI satisfaction (AVG S) and AI relevance (AVG R) is slightly higher for females (0.300) compared to males (0.254), suggesting that relevance plays a slightly larger role in shaping satisfaction for females.

The correlation between AI readiness (AVG RE) and AI relevance (AVG R) is moderate for females (0.302), in contrast to the very weak correlation observed for males (0.139). This implies that females who feel more prepared for AI are more likely to perceive it as relevant, showing a stronger connection between these two constructs compared to males.

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

The analysis of Spearman's rank correlations across various divisions – IT vs. non-IT students and male vs. female respondents – provides valuable insights into how different groups perceive AI satisfaction, AI readiness, and AI relevance. Across all groups, AI readiness consistently plays a central role, either directly influencing satisfaction or connecting with relevance. However, the strength and nature of these relationships vary significantly depending on the group.

For IT and non-IT students, AI readiness and AI relevance are strongly correlated, suggesting that preparation for AI adoption is closely tied to its perceived importance. In contrast, gender-based differences reveal unique patterns. Among males, readiness has a pronounced impact on satisfaction, while the link between readiness and relevance is weak. Among females, readiness and relevance are more balanced, with moderate correlations between relevance and both satisfaction and readiness.

These findings highlight the diversified ways different groups experience and evaluate AI. Efforts to enhance AI satisfaction, readiness, and relevance should consider these variations. For example, tailored interventions may be necessary: fostering readiness may be key for males, while improving the perception of relevance alongside readiness could be more impactful for females. Additionally, strategies for non-IT students might focus on increasing awareness of AI's practical significance, while for IT students, addressing external factors influencing satisfaction could be more effective.

4.4 Results

The study found several significant differences in perception and attitudes toward AI based on gender, field of study and year of study.

Men demonstrated higher levels of AI readiness and satisfaction with AI learning than women. Men were also more likely to perceive AI as relevant to their future careers. This finding may suggest a need for initiatives to promote women’s engagement and interest in AI.

Students in IT-related fields exhibited significantly higher levels of AI readiness and satisfaction with learning AI compared to students in other fields. This difference might stem from the inherent alignment of IT studies with AI concepts, leading to a more informed and prepared outlook.

Interestingly, satisfaction with learning AI did not necessarily increase with the year of study. The study showed mixed results with some questions indicating higher satisfaction in early years while others showed a slight decrease in later years. This challenges the assumption that continuous exposure to AI necessarily leads to greater satisfaction and hints at the complexities of student perception toward AI throughout their education.

The study also found that the year in which the survey was taken influenced student satisfaction levels, potentially due to major developments in AI technology. A notable increase in satisfaction was observed in 2023, coinciding with the release of advanced AI models, suggesting that technological advancements and their visibility play a role in shaping student perceptions.

These findings highlight the need for tailored educational approaches that consider individual backgrounds and evolving technological landscapes. Promoting AI literacy and readiness among diverse groups requires an understanding of these nuanced differences

The study considers the following answers to individual hypotheses:

H1: Years of study are associated with greater perceived satisfaction in learning AI.

To test this hypothesis, the study looked at how students in different years of study rated their satisfaction with learning AI. The researchers used a statistical test called the Kruskal-Wallis test to determine if there were significant differences in satisfaction levels between the different year groups.

The results of the Kruskal-Wallis test confirmed that there is a statistically significant difference in satisfaction levels based on the year of study. However, the post-hoc tests, which were conducted to determine exactly which year groups differed from each other, showed mixed results.

- Some questions suggested higher satisfaction in earlier years of study, while others showed a slight decrease in satisfaction in later years.
- Visual analysis of the data using box plots (Figures 2-6) supported this finding, demonstrating that satisfaction levels did not consistently increase with the year of study.

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

This finding is important because it challenges the assumption that continuous exposure to AI through education automatically leads to greater satisfaction. The relationship between experience with AI and satisfaction appears to be more complex, potentially influenced by factors beyond the scope of this study, such as the specific content of AI courses, teaching methods, or changes in students' career goals and interests over time.

H2: Men tend to experience greater satisfaction in learning AI that women.

To test this hypothesis, the research compared satisfaction levels between male and female students using the Mann-Whitney test, a statistical test designed to detect differences between two groups. The test was performed on responses to five questions (S1-S5) related to satisfaction with AI learning.

The results of the Mann-Whitney test showed a statistically significant difference in satisfaction levels between men and women for all five questions (S1-S5). Further analysis using box plots (Figures 7-11 in the sources) visually confirmed that men consistently reported higher satisfaction with learning AI compared to women.

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

This finding aligns with other observations in the study, such as men generally demonstrating higher levels of AI readiness and perceiving AI as more relevant to their future careers. The reasons behind this gender difference in satisfaction are not explicitly explored in this study. However, it points to a potential gender gap in engagement and interest in AI, suggesting a need for further research and targeted interventions to promote equal enthusiasm and positive experiences with AI learning for both men and women.

H3: Study program has a significant impact on satisfaction levels in learning AI.

To test this hypothesis, the study investigated how satisfaction with AI learning varied across different study programs. Seven distinct study programs were considered: IT, education, IT education, STEM education, languages, management, and other. The research used the Kruskal-Wallis test to assess whether there were significant differences in satisfaction levels between these groups.

The results of the Kruskal-Wallis test confirmed that there is a statistically significant difference in satisfaction levels based on the study program. This means that students in some study programs reported significantly different levels of satisfaction with AI learning compared to students in other programs.

To pinpoint which specific study programs showed significant differences, we conducted post-hoc tests. These tests revealed that the most significant differences in satisfaction levels were observed between:

- IT students and education students

- IT students and language students

Further visual analysis using box plots (Figures 12-16) reinforced this finding, demonstrating that:

- IT students generally reported the highest levels of satisfaction with AI learning.
- IT education and management students also showed relatively high satisfaction levels.

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

H4: Between 2022 and 2024, the level of satisfaction associated with learning AI evolved significantly.

To test this hypothesis, we examined data collected over three years (2022, 2023, and 2024) and used the Kruskal-Wallis test to assess whether there were significant differences in satisfaction levels across these years. The Kruskal-Wallis test confirmed that the **year of data collection did indeed have a significant effect on reported satisfaction with learning AI**. This finding implies that satisfaction levels were not static over time and that something changed between those years that affected how students perceived their AI learning experience.

To identify specific shifts in satisfaction levels, post-hoc tests (Dunn Bonferroni) were performed. These tests revealed statistically significant differences in satisfaction levels between the following pairs of years:

- 2022 and 2023
- 2023 and 2024

Visual analysis of the data using box plots (Figures 17-21) helped to clarify the trend: **Satisfaction levels appeared to increase notably in 2023 but then returned to roughly the same level in 2024 as observed in 2022**.

We can speculate that this fluctuation in satisfaction might be linked to the release and improvement of ChatGPT:

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

The substantial improvement in ChatGPT's capabilities in 2023 could explain the heightened satisfaction observed that year. Students may have found the enhanced tool more engaging, useful, or relevant to their learning, leading to a more positive perception of AI learning overall. However, as the novelty of the improved ChatGPT wore off and became more integrated into everyday life, satisfaction levels may have stabilized, returning to levels similar to those before its major update.

Therefore, the study supports the statement that **satisfaction associated with learning AI did evolve significantly between 2022-2023 and 2023-2024**. The observed fluctuation in satisfaction, potentially influenced by advancements in AI technology like ChatGPT, underscores the dynamic nature of the field and how perceptions of AI learning can shift in response to new developments.

H5: Men tend to demonstrate higher levels of AI readiness compared to women.

To test this hypothesis, we analyzed responses to six questions (RE1-RE6) related to AI readiness, examining whether significant differences existed between male and female students. We used the Mann-Whitney test, a statistical test suited for comparing two groups.

The Mann-Whitney test revealed a statistically significant difference in AI readiness levels between men and women for all six questions (RE1-RE6). This result strongly indicates that a genuine difference in perceived AI readiness exists between the genders.

Visual analysis using box plots (Figures 23-28) further confirmed this finding, clearly showing that:

- Across all aspects of AI readiness measured, men consistently reported higher levels of readiness compared to women.
- The most pronounced differences were observed in questions related to the perceived usefulness of AI, its ability to stimulate thinking, and confidence in AI's ability to follow instructions.

Therefore, the study provides substantial support for the statement that men tend to demonstrate higher levels of AI readiness compared to women.

We do not delve into the specific reasons behind this gender disparity in AI readiness. However, this finding is consistent with other observations in the study, such as men exhibiting:

- Higher levels of satisfaction with learning AI
- A stronger perception of AI's relevance to their future careers

This pattern suggests a potential gender gap in attitudes and comfort with AI technology, which could stem from various factors like:

- Differences in prior exposure to technology
- Variations in educational experiences related to STEM fields
- Societal influences and stereotypes surrounding technology and gender roles

Further investigation is needed to understand the underlying causes of this gender difference and to develop strategies that promote equal levels of AI readiness among all students, regardless of gender.

H6: IT student demonstrate higher levels of AI readiness compared to other study programs.

To test this hypothesis, we analyzed how AI readiness levels differed across various academic disciplines. They compared responses from seven study program categories:

- IT
- Education
- IT Education
- STEM Education
- Languages
- Management
- Other

The Kruskal-Wallis test, a statistical test used to compare multiple groups, was applied to the data. The results of the Kruskal-Wallis test confirmed a statistically significant difference in AI readiness levels based on the study program. This finding suggests that certain study programs are associated with significantly different levels of AI readiness compared to others.

To determine precisely which study programs differed from one another in terms of AI readiness, post-hoc tests were performed. These tests revealed a consistent pattern: **IT students demonstrated significantly higher levels of AI readiness than students in other study program categories**. This difference was particularly noticeable in responses to questions about:

- AI's ability to help individuals adjust things to their needs
- AI's potential to stimulate thinking

Visual analysis using box plots (Figures 29-34) further supported these findings. The box plots illustrated that IT students consistently expressed higher levels of agreement with statements related to AI readiness compared to their peers in other fields.

Therefore, the study strongly supports the statement that **IT students demonstrate higher levels of AI readiness compared to other study programs**.

This finding aligns with the overall trend observed in the study that students in fields more closely related to AI tend to show greater engagement and comfort with AI technology. This higher level of readiness among IT students might be attributed to factors such as:

- Increased exposure to AI concepts and technologies through their coursework
- Greater familiarity with the practical applications of AI
- Career aspirations that are more likely to be directly impacted by AI advancements

H7: Men tend to demonstrate higher levels of AI relevance compared to women.

To test this hypothesis, we investigated whether there were significant differences in how male and female students perceived the relevance of AI. They analyzed responses to six questions (R1-R6), each addressing a different aspect of AI relevance, using the Mann-Whitney test.

The Mann-Whitney test results showed a statistically significant difference between male and female respondents for all six questions (R1-R6) relating to AI relevance. This finding strongly suggests that gender does play a role in shaping perceptions of how relevant AI is to individuals.

Further analysis using box plots (Figures 35-40 in the sources) provided a visual representation of these differences:

- Across all six aspects of AI relevance, men consistently rated AI as more relevant compared to women.
- The most pronounced differences were observed in questions addressing AI's impact on the world, the usefulness of learning about AI, the importance of learning AI basics, and the connection of AI content to personal interests.

Therefore, the study supports the statement that **men tend to demonstrate higher levels of AI relevance compared to women**.

This finding is consistent with the overall trend in the study that men generally exhibit:

- Higher levels of satisfaction with learning AI
- Greater readiness to engage with AI technologies

We don't offer specific explanations for this gender difference in perceived AI relevance. However, it suggests a potential gap in how men and women connect AI to their personal lives, academic pursuits, and future careers. Possible factors contributing to this gap could include:

- Differences in exposure to AI-related fields or career paths
- Variations in encouragement or support for pursuing AI-related interests
- Societal influences and stereotypes that shape perceptions of technology and gender roles

Further research is needed to explore the underlying reasons for this gender difference and to develop strategies that foster an equal sense of AI relevance and encourage participation in the field for all students, regardless of gender.

5 AI Tools in Higher Education

Artificial intelligence is increasingly being integrated into higher education to enhance teaching, learning, and administrative processes. As technology advances, universities and educational institutions are exploring ways to incorporate AI tools to improve educational outcomes, streamline assessment procedures, and provide personalized learning experiences.

This review synthesizes research findings on the use of AI in HE, AI literacy education, the application of AI tools in general academic settings, and the specific impact of AI on disciplines like engineering and medical education. It also explores the ethical implications and challenges associated with AI integration, as well as best practices for educators and institutions to harness the transformative power of AI responsibly.

5.1.1 AI literacy and competences

Yim and Su [263] investigate pedagogical strategies, instructional tools, and assessment methods in teaching AI literacy in a K-12 context. The study suggests incorporating intelligent agents such as:

- Google's Teachable Machine,
- Learning ML,
- Machine Learning for Kids into AI literacy instruction.

Another strategy is to use programming in:

- Scratch,
- Python,
- C++
- and other programming platforms and languages to teach AI basics.

Hardware-focused devices such as robots are also incorporated into the learning process. Finally, unplugged learning is positioned as an approach to learning AI fundamentals.

In terms of methodology, authentic/constructive pedagogy, reflective pedagogy, didactic pedagogy, and unplugged learning are considered in the context of AI literacy education.

5.1.2 Applications of AI in General Educational Settings

Limna et al. [264] discuss the implementation of AI tools and technologies in general education settings. The study highlights the use of AI as digital assistants, adaptive learning platforms, and automated grading systems, focusing on how these applications enhance personalized learning and provide individualized support based on student needs.

AI tools are also being used for distance learning, providing virtual classrooms and interactive learning environments. The study notes the positive impact of AI on educational efficiency and effectiveness, but also addresses challenges such as privacy and data security issues.

It concludes that while AI has transformative potential for education, addressing ethical and technological challenges is critical to maximize the benefits.

5.1.3 AI in academia

Pinzolits [265] studies AI tools in academic environment. The study indicates the following applications of AI tools in academic environment: literature search, analysing research articles, academic writing and editing. The list of tools for literature search includes:

- Consensus,

- Elicit,
- Inciteful,
- Laser AI,
- Litmaps,
- Research Rabbit,
- System Pro,
- Scite, Semantic
- Scholar.

List of tools for analyzing research papers includes:

- Chat Pdf,
- Explain Paper,
- Lateral AI,
- Open Read,
- Scholarcy,
- SciSpace Copilot,
- Unriddle.

List of tools for writing and editing research papers includes:

- Jenni.ai,
- Paper Pal,
- Quillbot,
- Trinka,
- Wisio,
- Writeful.

5.1.4 AI-assistance in Higher Education

Crompton and Burke [114] report on tools and applications for AI-assisted assistance including:

- virtual, intelligent and learning agents,
- virtual bots
- chatbots.

Assistance is aimed at:

- productivity,
- effort management,
- prompting,
- escorting,
- guidance,
- after-hours support
- working with students.

Another application is student learning management, which includes:

- learning analytics,
- identifying learning patterns,
- curriculum sequencing,
- instructional design,
- learning effects analysis,
- academic detail design,
- student management,

- instructional systems design,
- student clustering,
- and personality profiling.

Jauregui-Correa and Sen [40] explore the integration of AI tools in higher education engineering programs. The study proposes a flexible curriculum model that incorporates AI for developing competencies, knowledge acquisition, and engineering skills. The study emphasizes the use of AI in:

- laboratory activities,
- project-based learning,
- certification processes,

offering a shift from traditional rigid course structures to a node-based system where students progress based on individual learning paces and needs. AI applications include using intelligent tools for assessment, laboratory simulations, and optimizing student learning paths. The paper underscores the role of AI in supporting self-directed learning and enhancing practical, hands-on experiences to prepare students for real-world engineering challenges

Sapci and Sapci [266] discuss the current state of AI tools and education in medical and health informatics programs. The review highlights the use of AI tools such as machine learning algorithms, natural language processing applications, and virtual reality simulators to enhance medical education. These tools are applied in various ways, including:

- real-time analytics for clinical training,
- personalized e-learning systems,
- simulation-based learning environments.

The authors emphasize the importance of integrating AI competencies, such as data analytics and ML programming, into medical curricula to prepare students for the evolving demands of healthcare. The study concludes with a call for standardized AI training frameworks in medical and health informatics education to ensure consistent and effective skill development across programs.

5.1.5 Generative AI and ChatGPT in HE

Grassini [130] discusses the perspectives of using generative AI in HE settings. The study highlights the use of AI technologies such as ChatGPT for:

- automating grading processes,
- facilitating individualized tutoring,
- enhancing adaptive learning environments.

AI tools are employed to support:

- essay grading,
- short-answer evaluations,
- translation of educational materials into multiple languages.

The study also discusses the potential of generative AI models like ChatGPT to assist in creating comprehensive lesson plans, quizzes, and interactive classroom activities, allowing educators to focus on more personalized instruction and professional development. However, concerns are raised about the limitations, biases, and ethical implications of relying on AI for these purposes, particularly in maintaining academic integrity and ensuring unbiased assessments interaction.

Adiguzel [267] discusses various applications of AI tools in higher education. The study highlights AI's ability to:

- facilitate personalized learning,
- automate administrative tasks,
- provide instant feedback through intelligent tutoring systems and chatbots.

ChatGPT is specifically noted for its role in enhancing student engagement and supporting individualized instruction by creating interactive, human-like dialogue. The paper also emphasizes AI's potential to automate grading, manage learning management systems, and offer tailored learning experiences based on student needs and performance data. Despite these advantages, the authors raise concerns about ethical implications, including bias in algorithms and the impact on academic integrity. The study calls for the responsible integration of AI tools in HE to optimize learning outcomes while ensuring ethical considerations are addressed.

Sain et al. [268] explore the integration of AI tools, specifically ChatGPT, in higher education to improve pedagogical practices. The study highlights AI's ability to personalize learning experiences, automate grading and assessment processes, and facilitate language translation and content development. The study also emphasizes how ChatGPT can support educators by creating interactive lesson plans, providing immediate feedback, and acting as a virtual assistant for administrative tasks. The authors also discuss the ethical implications and challenges associated with AI, including the need for critical evaluation and the potential for bias. The paper concludes that while AI offers transformative opportunities, effective implementation requires proper training and ethical guidelines to maximize its educational benefits.

Boubker [269] investigates the impact of AI tools, specifically ChatGPT, on enhancing student learning in higher education institutions in Morocco. The study employs an empirical approach using partial least squares structural equation modeling (PLS-SEM) to evaluate how factors such as output quality, perceived ease of use, and social influence affect the perceived usefulness, usage, and satisfaction associated with ChatGPT. The study also reveals that the perceived quality of output from ChatGPT significantly influences its perceived usefulness, encouraging students to use it more frequently. It highlights that **when students find the AI tool easy to use, they are more likely to perceive it as beneficial, which directly impacts their satisfaction levels**. The research also underscores the importance of social influence, noting that the encouragement from peers and educators positively affects students' willingness to engage with the technology. Furthermore, the study discusses the implications of these findings, suggesting that integrating AI tools like ChatGPT into higher education settings can enhance personalized learning experiences and support academic success. It emphasizes the need for higher education institutions to adapt their policies and curricula to leverage AI's potential while ensuring ethical usage and preventing over-reliance that may hinder the development of critical thinking and problem-solving skills. The research concludes that while AI tools can positively influence student learning outcomes, their effective integration requires thoughtful consideration of user satisfaction and institutional support to maximize educational benefits.

Moorhouse et al. [270] explore how higher education institutions are adapting assessment guidelines in response to the rise of generative AI (GAI) technologies like ChatGPT. The study reviews guidelines from the world's 50 top-ranking universities, revealing that nearly half have developed publicly accessible guidelines addressing GAI usage in assessments. These guidelines focus on three primary areas: maintaining academic integrity, providing advice on assessment design, and improving communication with students regarding GAI use.

HEIs emphasize the need for instructors to rethink traditional assessment tasks, recommending that teachers test their assignments using GAI tools to understand how these technologies might be used by students. Some guidelines also propose integrating GAI into the assessment process itself, such as by having students use these tools as part of their work, while still critically engaging with the output. This shift highlights a growing acceptance of GAI tools, suggesting that rather than banning their use, institutions are aiming to incorporate them responsibly within educational frameworks. The paper also discusses the implications of using GAI tools in assessments, particularly around plagiarism and academic misconduct.

Many universities provide detailed advice on how students should acknowledge their use of GAI, including proper citation practices and documentation of how the tools were utilized. Despite the concerns, the study advocates for a balanced approach where GAI becomes a component of modern education, preparing students for real-world applications while maintaining ethical standards.

Atlas [271] explores the transformative role of AI, particularly ChatGPT, in enhancing teaching, learning, and professional development within higher education. The study emphasizes the various applications of ChatGPT, such as assisting with writing, generating lesson plans, creating interactive learning experiences, and automating administrative tasks. ChatGPT is also presented as a tool for enhancing student engagement through personalized learning and instant feedback. The guide highlights how ChatGPT supports professional communication, including drafting reports, improving presentations, and managing correspondence efficiently. It underscores the tool's capacity for generating tailored responses, offering educators and professionals opportunities to engage with technology innovatively. Additionally, the guide addresses the ethical considerations of using ChatGPT, emphasizing responsible use to avoid biases and maintain academic integrity. By providing step-by-step instructions, the guide equips educators and professionals with strategies to integrate AI effectively into their practices

Gill et al. [272] discuss how ChatGPT and other AI chatbots are reshaping education, focusing on online and blended learning environments. The study highlights the integration of ChatGPT in educational platforms for personalized learning, assessment automation, and language learning support. ChatGPT is shown to assist educators in creating instructional content, enhancing classroom discussions, and offering tailored support to students. The research emphasizes the potential for AI to facilitate language learning, improve critical thinking skills, and support remote learning through integration with IoT devices. However, the paper also identifies significant challenges associated with the use of ChatGPT in education. These include concerns about the reliability and accuracy of the information provided by the AI, the potential for academic misconduct, and the risk of exacerbating digital inequalities. ChatGPT's limitations, such as biases in its responses and outdated knowledge, pose risks that must be addressed to maintain academic integrity and credibility. The authors propose measures for educators and institutions, such as updating assessment practices to account for AI-generated content and providing training for both educators and students on the ethical and responsible use of AI tools. The study concludes that while AI has transformative potential, its effective integration requires proactive measures to ensure fair and equitable educational opportunities.

5.1.6 Conclusions

The findings on AI tools in higher education from the literature reveal several key areas that illustrate diverse applications and challenges associated with AI integration.

1. AI-driven personalization and engagement – AI tools in HE are heavily oriented toward enhancing personalization in learning environments. Intelligent tutoring systems, adaptive learning platforms, and chatbots are leveraged to create customized educational pathways that respond to individual student needs. This trend reflects a move toward flexible learning systems that maximize student engagement and cater to diverse learning styles.
2. Automation and efficiency enhancement – a prominent theme is the use of AI for automating repetitive tasks, including grading, administrative support, and learning management. The implementation of AI in these areas is aimed at increasing efficiency and allowing educators to focus more on instructional and interactive aspects of education. The emphasis is on leveraging AI to optimize operational efficiency, freeing up institutional resources for more strategic and pedagogical efforts.
3. Generative AI integration and classroom innovation – generative AI tools, such as ChatGPT, are recognized for their transformative impact on classroom dynamics. These tools support educators by generating lesson content, quizzes, and interactive activities, facilitating innovative teaching approaches. However, the integration of generative AI also demands new pedagogical strategies to ensure its use enhances rather than undermines learning processes. This includes developing frameworks for critical engagement with AI-generated content and exploring innovative methods for embedding these tools within curricula.

4. Sector-specific applications in engineering and medical education – the literature highlights specific applications of AI in medical and engineering fields, focusing on laboratory simulations, clinical training, and project-based learning environments. AI supports hands-on, practical education, allowing students to gain experience in simulated environments that mirror real-world conditions. These applications aim to bridge the gap between theoretical knowledge and practical skills, preparing students for professional challenges.
5. Ethical and institutional considerations - ethical concerns are a recurring theme, with a focus on the responsible use of AI tools to maintain academic integrity and manage biases inherent in AI systems. Institutions are urged to establish comprehensive guidelines to manage the use of AI tools, particularly in assessment and student support services. Addressing privacy issues, algorithmic fairness, and the impact of AI on traditional educational values remains central to the responsible deployment of AI technologies.
6. Policy development and teacher training – the need for policy adaptation and professional development for educators is another key trend. As AI becomes integral to HE environments, institutions must update policies to align with technological capabilities and provide training to educators on how to implement AI tools effectively. This ensures that AI is used as an enhancement to, rather than a replacement for, traditional teaching methods, supporting teachers in their evolving roles.

Summarising, the future of AI tools in higher education is in their diverse applications and transformative potential. AI tools are primarily used to enhance personalized learning experiences through adaptive learning platforms, intelligent tutoring systems, and chatbots that tailor educational content to individual student needs. These tools also support efficiency by automating administrative tasks such as grading, scheduling, and managing learning management systems.

Generative AI technologies like ChatGPT facilitate innovative teaching methods by creating lesson content, interactive activities, and assessments.

In specialized fields such as medical and engineering education, AI tools are used to provide hands-on, simulated training environments that prepare students for real-world professional scenarios.

However, ethical and institutional considerations, including the management of privacy concerns, academic integrity, and biases in AI algorithms, remain critical. There is a need for policy development, comprehensive guidelines, and educator training to maximize the effective and responsible integration of AI tools in HE.

6 Bibliography

[1] K. Bayly-Castaneda, M. S. Ramirez-Montoya, and A. Morita-Alexander, ‘Crafting personalized learning paths with AI for lifelong learning: a systematic literature review’, in *Frontiers in Education*, 2024, vol. 9, p. 1424386.

[2] M. Bond *et al.*, ‘A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour’, *International Journal of Educational Technology in Higher Education*, vol. 21, no. 1. 2024, doi: 10.1186/s41239-023-00436-z.

[3] X. Chen, D. Zou, G. Cheng, and H. Xie, ‘Artificial intelligence-assisted personalized language learning: Systematic review and co-citation analysis’, 2021, doi: 10.1109/ICALT52272.2021.00079.

[4] M. E. Dogan, T. Goru Dogan, and A. Bozkurt, ‘The Use of Artificial Intelligence (AI) in Online Learning and Distance Education Processes: A Systematic Review of Empirical Studies’, *Applied Sciences (Switzerland)*, vol. 13, no. 5, 2023, doi: 10.3390/app13053056.

[5] W.-L. Chang and J. C.-Y. Sun, ‘Evaluating AI’s impact on self-regulated language learning: A systematic review’, *System*, vol. 126, p. 103484, 2024.

[6] J. Southworth *et al.*, ‘Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy’, *Computers and Education: Artificial Intelligence*, vol. 4, p. 100127, 2023, doi: 10.1016/j.caeai.2023.100127.

[7] S. G. Essa, T. Celik, and N. E. Human-Hendricks, ‘Personalized Adaptive Learning Technologies Based on Machine Learning Techniques to Identify Learning Styles: A Systematic Literature Review’, *IEEE Access*, vol. 11, 2023, doi: 10.1109/ACCESS.2023.3276439.

[8] F. Naseer, M. U. Khalid, N. Ayub, A. Rasool, T. Abbas, and M. W. Afzal, ‘Automated Assessment and Feedback in Higher Education Using Generative AI’, 2024.

[9] S. Dutta, S. Ranjan, S. Mishra, V. Sharma, P. Hewage, and C. Iwendi, ‘Enhancing educational adaptability: A review and analysis of AI-driven adaptive learning platforms’, in *2024 4th International Conference on Innovative Practices in Technology and Management (ICIPTM)*, 2024, pp. 1–5.

[10] M. L. Bernacki, ‘Development, sustainment, and scaling of self-regulated learning analytics: Prediction modeling and digital student success initiatives in university contexts’, in *Supporting Self-Regulated Learning and Student Success in Online Courses*, 2023.

[11] S. S. Jamsandekar, P. G. Naik, and R. S. Kamath, ‘Unveiling New Horizons in Machine Learning, NLP-Driven Framework for Student Learning Behavior’, in *International Conference on Multi-Strategy Learning Environment*, 2024, pp. 167–176.

[12] C. Troussas, F. Giannakas, C. Sgouropoulou, and I. Voyiatzis, ‘Collaborative activities recommendation based on students’ collaborative learning styles using ANN and WSM’, *Interactive Learning Environments*, vol. 31, no. 1, 2023, doi: 10.1080/10494820.2020.1761835.

[13] R. J. Singh, ‘Transforming higher education: The power of artificial intelligence’, *International Journal of Multidisciplinary Research in Arts, Science and Technology*, vol. 1, no. 3, pp. 13–18, 2023.

[14] H. A. A. Alshadoodee, M. S. G. Mansoor, H. K. Kuba, and H. M. Gheni, ‘The role of artificial intelligence in enhancing administrative decision support systems by depend on knowledge management’, *Bulletin of Electrical Engineering and Informatics*, vol. 11, no. 6, 2022, doi: 10.11591/eei.v11i6.4243.

[15] H. T. Hien, P. N. Cuong, L. N. H. Nam, H. L. T. K. Nhung, and L. D. Thang, ‘Intelligent assistants in higher-education environments: The FIT-EBOt, a chatbot for administrative and learning support’, 2018, doi: 10.1145/3287921.3287937.

[16] N. Sandu and E. Gide, ‘Adoption of AI-chatbots to enhance student learning experience in higher education in india’, *2019 18th International Conference on Information Technology Based Higher Education and Training, ITHET 2019*, Sep. 2019, doi: 10.1109/ITHET46829.2019.8937382.

[17] T. Fritsch, ‘Chatbots: An Overview of Current Issues and Challenges’, in *Future of Information and Communication Conference*, 2024, pp. 84–104.

[18] A. J. Lu, T. R. DIllahunt, G. Marcu, and M. S. Ackerman, ‘Data Work in Education: Enacting and Negotiating Care and Control in Teachers’ Use of Data-Driven Classroom Surveillance Technology’, *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW2, 2021, doi: 10.1145/3479596.

[19] C. S. Silangan, R. M. Mocsir, R. M. Regner, and E. D. Peteros, ‘Predictive Analysis on Students’ Academic Performance in Mathematics’, *Global Journal of Educational Studies*, vol. 9, no. 1, 2023, doi: 10.5296/gjes.v9i1.21040.

[20] L. Tetzlaff, F. Schmiedek, and G. Brod, ‘Developing Personalized Education: A Dynamic Framework’, *Educational Psychology Review*, vol. 33, no. 3. 2021, doi: 10.1007/s10648-020-09570-w.

[21] T. K. F. Chiu, H. Meng, C. S. Chai, I. King, S. Wong, and Y. Yam, ‘Creation and Evaluation of a Pretertiary Artificial Intelligence (AI) Curriculum’, *IEEE Transactions on Education*, vol. 65, no. 1, 2022, doi: 10.1109/TE.2021.3085878.

[22] J. Skalka, ‘Microlearning and Automated Assessment -- A Framework Implementation of Dissimilar Elements to Achieve Better Educational Outcomes’, in *Microlearning: New Approaches To A More Effective Higher Education*, E. Smyrnova-Trybulska, P. Kommers, M. Drlík, and J. Skalka, Eds. Cham: Springer International Publishing, 2022, pp. 1–26.

[23] J. C. Rodríguez-del-Pino, Z. J. Hernández-Figueroa, J. D. G. Domínguez, and J. Skalka, ‘Virtual Programming Lab for Moodle: Automatic Program Assessment in a First-year University Course BT - Microlearning: New Approaches To A More Effective Higher Education’, E. Smyrnova-Trybulska, P. Kommers, M. Drlík, and J. Skalka, Eds. Cham: Springer International Publishing, 2022, pp. 195–206.
[24] S. Rakap, ‘Chatting with GPT: Enhancing Individualized Education Program Goal Development for Novice Special Education Teachers’, *Journal of Special Education Technology*, vol. 39, no. 3, 2024, doi: 10.1177/01626434231211295.
[25] Z. F. Khan and S. R. Alotaibi, ‘Applications of Artificial Intelligence and Big Data Analytics in m-Health: A Healthcare System Perspective’, *Journal of Healthcare Engineering*, vol. 2020. 2020, doi: 10.1155/2020/8894694.
[26] B. Kuriakose, R. Shrestha, and F. E. Sandnes, ‘Tools and Technologies for Blind and Visually Impaired Navigation Support: A Review’, *IETE Technical Review (Institution of Electronics and Telecommunication Engineers, India)*, vol. 39, no. 1. 2022, doi: 10.1080/02564602.2020.1819893.
[27] Z. Roozbahani, J. Rezaeenour, A. Katanforoush, and A. Jalaly Bidgoly, ‘Personalization of the collaborator recommendation system in multi-layer scientific social networks: A case study of ResearchGate’, *Expert Systems*, vol. 39, no. 5, 2022, doi: 10.1111/exsy.12932.
[28] L. Chen, P. Chen, and Z. Lin, ‘Artificial Intelligence in Education: A Review’, *IEEE Access*, vol. 8, 2020, doi: 10.1109/ACCESS.2020.2988510.
[29] P. D. Barua *et al.*, ‘Artificial Intelligence Enabled Personalised Assistive Tools to Enhance Education of Children with Neurodevelopmental Disorders—A Review’, *International Journal of Environmental Research and Public Health*, vol. 19, no. 3. 2022, doi: 10.3390/ijerph19031192.
[30] P. Smith and L. Smith, ‘Artificial intelligence and disability: too much promise, yet too little substance?’, *AI and Ethics*, vol. 1, no. 1, 2021, doi: 10.1007/s43681-020-00004-5.
[31] N. Annuš, ‘Education in the Age of Artificial Intelligence’, *TEM Journal*, vol. 13, no. 1, pp. 404–413, 2024.
[32] F. J. Cantú-Ortiz, N. Galeano Sánchez, L. Garrido, H. Terashima-Marin, and R. F. Brena, ‘An artificial intelligence educational strategy for the digital transformation’, *International Journal on Interactive Design and Manufacturing*, vol. 14, no. 4, pp. 1195–1209, 2020, doi: 10.1007/s12008-020-00702-8.
[33] J. Borenstein and A. Howard, ‘Emerging challenges in AI and the need for AI ethics education’, *AI and Ethics*, vol. 1, no. 1, pp. 61–65, 2021, doi: 10.1007/s43681-020-00002-7.
[34] A. Padovano and M. Cardamone, ‘Towards human-AI collaboration in the competency-based curriculum development process: The case of industrial engineering and management education’, *Computers and Education: Artificial Intelligence*, vol. 7, p. 100256, 2024, doi: 10.1016/j.caeai.2024.100256.
[35] D. T. K. Ng, J. K. L. Leung, J. Su, R. C. W. Ng, and S. K. W. Chu, ‘Teachers’ AI digital competencies and twenty-first century skills in the post-pandemic world’, *Educational Technology Research and Development*, vol. 71, no. 1, pp. 137–161, 2023, doi: 10.1007/s11423-023-10203-6.
[36] F. Bellas, S. Guerreiro-Santalla, M. Naya, and R. J. Duro, ‘AI Curriculum for European High Schools: An Embedded Intelligence Approach’, *International Journal of Artificial Intelligence in Education*, vol. 33, no. 2, pp. 399–426, 2023, doi: 10.1007/s40593-022-00315-0.
[37] S. N. Akinwalere and V. Ivanov, ‘Artificial intelligence in higher education: challenges and opportunities’, *Border Crossing*, vol. 12, no. 1, pp. 1–15, 2022.
[38] T. K. F. Chiu, ‘A Holistic Approach to the Design of Artificial Intelligence (AI) Education for K-12 Schools’, *TechTrends*, vol. 65, no. 5, pp. 796–807, 2021, doi: 10.1007/s11528-021-00637-1.
[39] J. L. M. Núñez and A. D. Lantada, ‘Guest Editorial: Artificial Intelligence Aided Engineering Education’, *International Journal of Engineering Education*, vol. 36, no. 6. TEMPUS PUBLICATIONS IJEE, ROSSMORE,, DURRUS, BANTRY, COUNTY CORK 00000, IRELAND, p. 1739, 2020.
[40] J. C. Jauregui-Correa and M. Sen, ‘Revolutionizing Engineering Education: Adapting Curricula to Address Artificial Intelligence Challenges and Opportunities’, *Asean Journal of Engineering Education*, vol. 8, no. 1, pp. 64–69, 2024.
[41] M.-L. How and W. L. D. Hung, ‘Educing AI-thinking in science, technology, engineering, arts, and mathematics (STEAM) education’, *Education Sciences*, vol. 9, no. 3, p. 184, 2019.
[42] J. Crowder, *AI chatbots: The good, the bad, and the ugly*. Springer Nature, 2023.
[43] J. Su and W. Yang, ‘Unlocking the Power of ChatGPT: A Framework for Applying Generative AI in Education’, *ECNU Review of Education*, vol. 6, no. 3, pp. 355–366, 2023, doi: 10.1177/20965311231168423.
[44] F. Naseer, M. N. Khan, M. Tahir, A. Addas, and S. M. H. Aejaz, ‘Integrating deep learning techniques for personalized learning pathways in higher education’, *Heliyon*, vol. 10, no. 11, p. e32628, 2024, doi: https://doi.org/10.1016/j.heliyon.2024.e32628.
[45] H. X. Zhong, J. H. Chang, C. F. Lai, P. W. Chen, S. H. Ku, and S. Y. Chen, ‘Information undergraduate and non-information undergraduate on an artificial intelligence learning platform: an artificial intelligence assessment model using PLS-SEM analysis’, *Education and Information Technologies*, vol. 29, no. 4, 2024, doi: 10.1007/s10639-023-11961-9.
[46] Y. K. Dwivedi *et al.*, ‘Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy’, *International Journal of Information Management*, vol. 57, 2021, doi: 10.1016/j.ijinfomgt.2019.08.002.
[47] L. Alvarez, I. Gransbury, V. Cateté, T. Barnes, Á. Lédeczi, and S. Grover, ‘A Socially Relevant Focused AI Curriculum Designed for Female High School Students’, in *Proceedings of the 36th AAAI Conference on Artificial Intelligence,*

AAAI 2022, 2022, vol. 36, doi: 10.1609/aaai.v36i11.21546.
[48] S. Rizvi, J. Waite, and S. Sentance, ‘Artificial Intelligence teaching and learning in K-12 from 2019 to 2022: A systematic literature review’, *Computers and Education: Artificial Intelligence*, vol. 4, 2023, doi: 10.1016/j.caeai.2023.100145.
[49] L. Chen, ‘Current and Future Artificial Intelligence (AI) Curriculum in Business School: A Text Mining Analysis’, *Journal of Information Systems Education*, vol. 33, no. 4, 2022.
[50] B. Sakulkueakulsuk *et al.*, ‘Kids making AI: Integrating Machine Learning, Gamification, and Social Context in STEM Education’, 2018, doi: 10.1109/TALE.2018.8615249.
[51] J. Schleiss, M. I. Bieber, A. Manukjan, L. Kellner, and S. Stober, ‘AN INTERDISCIPLINARY COMPETENCE PROFILE FOR AI IN ENGINEERING’, 2022, doi: 10.5821/conference-9788412322262.1288.
[52] D. Wu, M. Chen, X. Chen, and X. Liu, ‘Analyzing K-12 AI education: A large language model study of classroom instruction on learning theories, pedagogy, tools, and AI literacy’, *Computers and Education: Artificial Intelligence*, vol. 7, p. 100295, 2024.
[53] T. Hagendorff, ‘The Ethics of AI Ethics: An Evaluation of Guidelines’, *Minds and Machines*, vol. 30, no. 1, 2020, doi: 10.1007/s11023-020-09517-8.
[54] E. Kazim and A. S. Koshiyama, ‘A high-level overview of AI ethics’, *Patterns*, vol. 2, no. 9. 2021, doi: 10.1016/j.patter.2021.100314.
[55] V. Kavitha and R. Lohani, ‘A critical study on the use of artificial intelligence, e-Learning technology and tools to enhance the learners experience’, *Cluster Computing*, vol. 22, 2019, doi: 10.1007/s10586-018-2017-2.
[56] V. S. Barletta, D. Caivano, D. Gigante, and A. Ragone, ‘A Rapid Review of Responsible AI frameworks: How to guide the development of ethical AI’, 2023, doi: 10.1145/3593434.3593478.
[57] R. Gianni, S. Lehtinen, and M. Nieminen, ‘Governance of Responsible AI: From Ethical Guidelines to Cooperative Policies’, *Frontiers in Computer Science*, vol. 4, 2022, doi: 10.3389/fcomp.2022.873437.
[58] S. Kim *et al.*, ‘Analyzing Teacher Competency with TPACK for K-12 AI Education’, *KI - Kunstliche Intelligenz*, vol. 35, no. 2, 2021, doi: 10.1007/s13218-021-00731-9.
[59] W. Xiao and T. Song, ‘Current situation of artificial intelligence education in primary and secondary schools in China’, 2021, doi: 10.1145/3465631.3465980.
[60] A. Birhane *et al.*, ‘Power to the People? Opportunities and Challenges for Participatory AI’, 2022, doi: 10.1145/3551624.3555290.
[61] R. Williams, ‘How to Train Your Robot: Project-Based AI and Ethics Education for Middle School Classrooms’, 2021.
[62] H. Hamid, K. Zulkifli, F. Naimat, N. L. Che Yaacob, and K. W. Ng, ‘Exploratory study on student perception on the use of chat AI in process-driven problem-based learning’, *Currents in Pharmacy Teaching and Learning*, vol. 15, no. 12, 2023, doi: 10.1016/j.cptl.2023.10.001.
[63] S. C. Tan, A. V. Y. Lee, and M. Lee, ‘A systematic review of artificial intelligence techniques for collaborative learning over the past two decades’, *Computers and Education: Artificial Intelligence*, vol. 3. 2022, doi: 10.1016/j.caeai.2022.100097.
[64] Y. S. Chang, Y. Y. Wang, and Y. Te Ku, ‘Influence of online STEAM hands-on learning on AI learning, creativity, and creative emotions’, *Interactive Learning Environments*, 2023, doi: 10.1080/10494820.2023.2205898.
[65] R. Fojtik, ‘USING HARDWARE TO SUPPORT ARTIFICIAL INTELLIGENCE IN EDUCATION’, in *INTED2024 Proceedings*, 2024, vol. 1, doi: 10.21125/inted.2024.1170.
[66] J. Qadir, ‘Engineering Education in the Era of ChatGPT: Promise and Pitfalls of Generative AI for Education’, in *IEEE Global Engineering Education Conference, EDUCON*, 2023, vol. 2023-May, doi: 10.1109/EDUCON54358.2023.10125121.
[67] A. Abulibdeh, E. Zaidan, and R. Abulibdeh, ‘Navigating the confluence of artificial intelligence and education for sustainable development in the era of industry 4.0: Challenges, opportunities, and ethical dimensions’, *Journal of Cleaner Production*, vol. 437, 2024, doi: 10.1016/j.jclepro.2023.140527.
[68] R. Zviel-Girshin, ‘The Good and Bad of AI Tools in Novice Programming Education’, *Education Sciences*, vol. 14, no. 10, p. 1089, 2024.
[69] I. Lutticken, A. Telahun, and N. Ruzycki, ‘Developing Teacher Professional Development Model for the teaching of Artificial Intelligence within and across Career and Technical Education Courses-EQuIPD-AI’, in *Society for Information Technology \& Teacher Education International Conference*, 2023, pp. 2168–2177.
[70] D. T. K. Ng, M. Lee, R. J. Y. Tan, X. Hu, J. S. Downie, and S. K. W. Chu, ‘A review of AI teaching and learning from 2000 to 2020’, *Education and Information Technologies*, vol. 28, no. 7, 2023, doi: 10.1007/s10639-022-11491-w.
[71] G. J. Hwang, H. Xie, B. W. Wah, and D. Gašević, ‘Vision, challenges, roles and research issues of Artificial Intelligence in Education’, *Computers and Education: Artificial Intelligence*, vol. 1, Jan. 2020, doi: 10.1016/j.caeai.2020.100001.
[72] S. Gartner and M. Krasna, ‘Artificial Intelligence in Education - Ethical framework’, 2023, doi: 10.1109/MECO58584.2023.10155012.
[73] W. Holmes *et al.*, ‘Ethics of AI in Education: Towards a Community-Wide Framework’, *International Journal of Artificial Intelligence in Education*, vol. 32, no. 3, 2022, doi: 10.1007/s40593-021-00239-1.
[74] J. Kim, ‘Leading teachers’ perspective on teacher-AI collaboration in education’, *Education and Information Technologies*, vol. 29, no. 7, 2024, doi: 10.1007/s10639-023-12109-5.
[75] W. Holmes and I. Tuomi, ‘State of the art and practice in AI in education’, *European Journal of Education*, vol. 57,

no. 4, 2022, doi: 10.1111/ejed.12533.
[76] G. P. B. Castro, A. Chiappe, D. F. B. Rodr\'\iguez, and F. G. Sepulveda, 'Harnessing AI for Education 4.0: Drivers of Personalized Learning', *Electronic Journal of e-Learning*, vol. 22, no. 5, pp. 1–14, 2024.
[77] K. Karakaya and A. Bozkurt, 'Mobile-assisted language learning (MALL) research trends and patterns through bibliometric analysis: Empowering language learners through ubiquitous educational technologies', *System*, vol. 110, 2022, doi: 10.1016/j.system.2022.102925.
[78] R. Baltezarević and I. Baltezarević, 'Students' Attitudes on The Role of Artificial Intelligence (Ai) In Personalized Learning', *International Journal of Cognitive Research in Science, Engineering and Education*, vol. 12, no. 2, pp. 387–397, 2024.
[79] N. Humble and P. Mozelius, 'Artificial Intelligence in Education - a Promise, a Threat or a Hype?', *European Conference on the Impact of Artificial Intelligence and Robotics*, no. October, 2019.
[80] S. H. Jin, K. Im, M. Yoo, I. Roll, and K. Seo, 'Supporting students' self-regulated learning in online learning using artificial intelligence applications', *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, 2023, doi: 10.1186/s41239-023-00406-5.
[81] H. U. Rahiman and R. Kodikal, 'Revolutionizing education: Artificial intelligence empowered learning in higher education', *Cogent Education*, vol. 11, no. 1, 2024, doi: 10.1080/2331186X.2023.2293431.
[82] S. Feng, A. J. Magana, and D. Kao, 'A Systematic Review of Literature on the Effectiveness of Intelligent Tutoring Systems in STEM', in *Proceedings - Frontiers in Education Conference, FIE*, 2021, vol. 2021-October, doi: 10.1109/FIE49875.2021.9637240.
[83] R. N. Albdrani and A. A. Al-Shargabi, 'Investigating the Effectiveness of ChatGPT for Providing Personalized Learning Experience: A Case Study', *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 11, 2023, doi: 10.14569/IJACSA.2023.01411122.
[84] J. Kannan and P. Munday, 'New trends in second language learning and teaching through the lens of ICT, networked learning, and artificial intelligence', *Circulo de Linguistica Aplicada a la Comunicacion*, vol. 76, 2018, doi: 10.5209/CLAC.62495.
[85] J. M. Golding, A. Lippert, J. S. Neuschatz, I. Salomon, and K. Burke, 'Generative AI and College Students: Use and Perceptions', *Teaching of Psychology*, 2024, doi: 10.1177/00986283241280350.
[86] M. Guettala, S. Bourekkache, O. Kazar, S. Harous, and others, 'Generative artificial intelligence in education: Advancing adaptive and personalized learning', *Acta Informatica Pragensia*, vol. 13, no. 3, pp. 460–489, 2024.
[87] C. Halkiopoulos and E. Gkintoni, 'Leveraging AI in e-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis', *Electronics*, vol. 13, no. 18, p. 3762, 2024.
[88] J. M. Lodge, P. de Barba, and J. Broadbent, 'Learning with Generative Artificial Intelligence Within a Network of Co-Regulation', *Journal of University Teaching and Learning Practice*, vol. 20, no. 7, 2023, doi: 10.53761/1.20.7.02.
[89] L. Guan, S. Li, and M. M. Gu, 'AI in informal digital English learning: A meta-analysis of its effectiveness on proficiency, motivation, and self-regulation', *Computers and Education: Artificial Intelligence*, vol. 7, p. 100323, 2024.
[90] A. Pack and J. Maloney, 'Using Generative Artificial Intelligence for Language Education Research: Insights from Using OpenAI's ChatGPT', *TESOL Quarterly*, vol. 57, no. 4, 2023, doi: 10.1002/tesq.3253.
[91] K. Mahboob, R. Asif, and L. Umme, 'Leveraging generative AI for cross-cultural knowledge exchange in higher education', in *Facilitating Global Collaboration and Knowledge Sharing in Higher Education With Generative AI*, 2023.
[92] F. Ouyang, L. Zheng, and P. Jiao, 'Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020', *Education and Information Technologies*, vol. 27, no. 6, 2022, doi: 10.1007/s10639-022-10925-9.
[93] M. I. Baig and E. Yadegaridehkordi, 'ChatGPT in the higher education: A systematic literature review and research challenges', *International Journal of Educational Research*, vol. 127, p. 102411, 2024.
[94] A. Alam and A. Mohanty, 'Foundation for the Future of Higher Education or "Misplaced Optimism"? Being Human in the Age of Artificial Intelligence', in *Communications in Computer and Information Science*, 2022, vol. 1737 CCIS, doi: 10.1007/978-3-031-23233-6_2.
[95] B. Klímová and P. M. Ibna Seraj, 'The use of chatbots in university EFL settings: Research trends and pedagogical implications', *Frontiers in Psychology*, vol. 14. 2023, doi: 10.3389/fpsyg.2023.1131506.
[96] C. Fichten *et al.*, 'Current State of the Research on Artificial Intelligence Based Apps for Post-Secondary Students with Disabilities', *Exceptionality Education International*, vol. 31, no. 1, 2021, doi: 10.5206/EEI.V31I1.14089.
[97] C. Chaka, 'Fourth industrial revolution—a review of applications, prospects, and challenges for artificial intelligence, robotics and blockchain in higher education', *Research and Practice in Technology Enhanced Learning*, vol. 18, 2023, doi: 10.58459/rptel.2023.18002.
[98] G. Currie, C. Singh, T. Nelson, C. Nabasenja, Y. Al-Hayek, and K. Spuur, 'ChatGPT in medical imaging higher education', *Radiography*, vol. 29, no. 4, 2023, doi: 10.1016/j.radi.2023.05.011.
[99] R. B. Toma and I. Yánez-Pérez, 'Effects of ChatGPT use on undergraduate students' creativity: a threat to creative thinking?', *Discover Artificial Intelligence*, vol. 4, no. 1, p. 74, 2024.
[100] S. K. Banihashem, M. Farrokhnia, M. Badali, and O. Noroozi, 'The impacts of constructivist learning design and learning analytics on students' engagement and self-regulation', *Innovations in Education and Teaching International*, vol. 59, no. 4, 2022, doi: 10.1080/14703297.2021.1890634.

[101] Y. F. Tu and C. L. Lai, 'Roles, Strategies, and Research Issues of Generative AI in the Mobile Learning Era', *International Journal of Mobile Learning and Organisation*, vol. 1, no. 1, 2025, doi: 10.1504/ijmlo.2025.10059769.

[102] J. Rudolph, S. Tan, and S. Tan, 'ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?', *Journal of Applied Learning and Teaching*, vol. 6, no. 1, pp. 342–363, Jan. 2023, doi: 10.37074/JALT.2023.6.1.9.

[103] M. Al-Emran, N. Al-Qaysi, M. A. Al-Sharafi, M. Khoshkam, B. Foroughi, and M. Ghobakhloo, 'Role of perceived threats and knowledge management in shaping generative AI use in education and its impact on social sustainability', *The International Journal of Management Education*, vol. 23, no. 1, p. 101105, 2025, doi: https://doi.org/10.1016/j.ijme.2024.101105.

[104] H. Yu, 'The application and challenges of ChatGPT in educational transformation: New demands for teachers' roles', *Heliyon*, vol. 10, no. 2. 2024, doi: 10.1016/j.heliyon.2024.e24289.

[105] M. F. Shahzad, S. Xu, W. M. Lim, X. Yang, and Q. R. Khan, 'Artificial intelligence and social media on academic performance and mental well-being: Student perceptions of positive impact in the age of smart learning', *Heliyon*, vol. 10, no. 8, 2024.

[106] L. Li, Z. Ma, L. Fan, S. Lee, H. Yu, and L. Hemphill, 'ChatGPT in education: a discourse analysis of worries and concerns on social media', *Education and Information Technologies*, vol. 29, no. 9, pp. 10729–10762, Jun. 2024, doi: 10.1007/s10639-023-12256-9.

[107] H. Desaire, A. E. Chua, M. Isom, R. Jarosova, and D. Hua, 'Distinguishing academic science writing from humans or ChatGPT with over 99% accuracy using off-the-shelf machine learning tools', *Cell Reports Physical Science*, vol. 4, no. 6, 2023, doi: 10.1016/j.xcrp.2023.101426.

[108] P. Gupta, R. Mahajan, U. Badhera, and P. S. Kushwaha, 'Integrating generative AI in management education: A mixed-methods study using social construction of technology theory', *The International Journal of Management Education*, vol. 22, no. 3, p. 101017, 2024.

[109] A. M. Al-Zahrani, 'Unveiling the shadows: Beyond the hype of AI in education', *Heliyon*, vol. 10, no. 9, 2024.

[110] C. Stöhr, A. W. Ou, and H. Malmström, 'Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study', *Computers and Education: Artificial Intelligence*, vol. 7, p. 100259, Dec. 2024, doi: 10.1016/J.CAEAI.2024.100259.

[111] L. Zhang and J. Xu, 'The paradox of self-efficacy and technological dependence: Unraveling generative AI's impact on university students' task completion', *The Internet and Higher Education*, vol. 65, p. 100978, 2025.

[112] Y. Chen, S. Jensen, L. J. Albert, S. Gupta, and T. Lee, 'Artificial Intelligence (AI) Student Assistants in the Classroom: Designing Chatbots to Support Student Success', *Information Systems Frontiers*, vol. 25, no. 1, pp. 161–182, Feb. 2023, doi: 10.1007/S10796-022-10291-4.

[113] S. Nisar and M. S. Aslam, 'Is ChatGPT a Good Tool for T&CM Students in Studying Pharmacology?', *SSRN Electronic Journal*, 2023, doi: 10.2139/SSRN.4324310.

[114] H. Crompton and D. Burke, 'Artificial intelligence in higher education: the state of the field', *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 22, 2023, doi: 10.1186/s41239-023-00392-8.

[115] H. K. Algabri, K. Kharade, and R. Kamat, 'Promise, threats, and personalization in higher education with artificial intelligence', *Webology*, 2021.

[116] S. Doroudi, 'The Intertwined Histories of Artificial Intelligence and Education', *International Journal of Artificial Intelligence in Education*, vol. 33, no. 4, 2023, doi: 10.1007/s40593-022-00313-2.

[117] O. Zawacki-Richter, B. Cefa, and J. Bai, 'Towards reproducible systematic reviews in Open, Distance, and Digital Education (ODDE)—an umbrella mapping review', 2024.

[118] A. Kirubarajan, D. Young, S. Khan, N. Crasto, M. Sobel, and D. Sussman, 'Artificial Intelligence and Surgical Education: A Systematic Scoping Review of Interventions', *Journal of Surgical Education*, vol. 79, no. 2, 2022, doi: 10.1016/j.jsurg.2021.09.012.

[119] M. A. Saghiri, J. Vakhnovetsky, and N. Nadershahi, 'Scoping review of artificial intelligence and immersive digital tools in dental education', *Journal of Dental Education*, vol. 86, no. 6. 2022, doi: 10.1002/jdd.12856.

[120] Q. Sun, I. Kuzborska, and B. Soden, 'Learning to construct authorial voice through citations: A longitudinal case study of L2 postgraduate novice writers', *System*, vol. 106, 2022, doi: 10.1016/j.system.2022.102765.

[121] X. Wang, H. Pang, M. P. Wallace, Q. Wang, and W. Chen, 'Learners' perceived AI presences in AI-supported language learning: a study of AI as a humanized agent from community of inquiry', *Computer Assisted Language Learning*, vol. 37, no. 4, 2024, doi: 10.1080/09588221.2022.2056203.

[122] R. Pereira, C. Lima, T. Pinto, and A. Reis, 'Virtual Assistants in Industry 4.0: A Systematic Literature Review', *Electronics (Switzerland)*, vol. 12, no. 19. 2023, doi: 10.3390/electronics12194096.

[123] S. Saravanan, J. Vinu Balan, and V. Sankaradass, 'Evaluating Effectiveness of AI-Driven Virtual Assistants in Enhancing Productivity and Well-Being in the Workspace', 2023, doi: 10.1109/ICDSAAI59313.2023.10452579.

[124] J. Kim, K. Merrill, K. Xu, and D. D. Sellnow, 'My Teacher Is a Machine: Understanding Students' Perceptions of AI Teaching Assistants in Online Education', *International Journal of Human-Computer Interaction*, vol. 36, no. 20, 2020, doi: 10.1080/10447318.2020.1801227.

[125] D. Kumar, A. Haque, K. Mishra, F. Islam, B. Kumar Mishra, and S. Ahmad, 'Exploring the Transformative Role of Artificial Intelligence and Metaverse in Education: A Comprehensive Review', *Metaverse Basic and Applied Research*, vol. 2, 2023, doi: 10.56294/mr202355.

[126] G. Ben Brahim, 'Predicting Student Performance from Online Engagement Activities Using Novel Statistical

Features', *Arabian Journal for Science and Engineering*, vol. 47, no. 8, 2022, doi: 10.1007/s13369-021-06548-w.
[127] J. Kabathova and M. Drlik, 'Towards predicting student's dropout in university courses using different machine learning techniques', *Applied Sciences (Switzerland)*, vol. 11, no. 7, 2021, doi: 10.3390/app11073130.
[128] N. Tomasevic, N. Gvozdenovic, and S. Vranes, 'An overview and comparison of supervised data mining techniques for student exam performance prediction', *Computers and Education*, vol. 143, 2020, doi: 10.1016/j.compedu.2019.103676.
[129] T. A. B. Tretow-Fish and M. S. Khalid, 'Methods for Evaluating Learning Analytics and Learning Analytics Dashboards in Adaptive Learning Platforms: A Systematic Review', *Electronic Journal of e-Learning*, vol. 21, no. 5, 2023, doi: 10.34190/ejel.21.5.3088.
[130] S. Grassini, 'Shaping the Future of Education: Exploring the Potential and Consequences of AI and ChatGPT in Educational Settings', *Education Sciences*, vol. 13, no. 7, p. 692, 2023, doi: 10.3390/educsci13070692.
[131] R. J. Sternberg, 'Do not worry that generative AI may compromise human creativity or intelligence in the future: It already has', *Journal of Intelligence*, vol. 12, no. 7, p. 69, 2024.
[132] M. Bearman, J. Ryan, and R. Ajjawi, 'Discourses of artificial intelligence in higher education: a critical literature review', *Higher Education*, vol. 86, no. 2. 2023, doi: 10.1007/s10734-022-00937-2.
[133] N. S. Alotaibi and A. H. Alshehri, 'Prospers and Obstacles in Using Artificial Intelligence in Saudi Arabia Higher Education Institutions—The Potential of AI-Based Learning Outcomes', *Sustainability (Switzerland)*, vol. 15, no. 13. 2023, doi: 10.3390/su151310723.
[134] J. Grunhut, A. T. Wyatt, and O. Marques, 'Educating Future Physicians in Artificial Intelligence (AI): An Integrative Review and Proposed Changes', *Journal of Medical Education and Curricular Development*, vol. 8, 2021, doi: 10.1177/23821205211036836.
[135] N. G. Davy Tsz Kit, W. Luo, H. M. Y. Chan, and S. K. W. Chu, 'Using digital story writing as a pedagogy to develop AI literacy among primary students', *Computers and Education: Artificial Intelligence*, vol. 3, 2022, doi: 10.1016/j.caeai.2022.100054.
[136] A. Brandão, L. Pedro, and N. Zagalo, 'Teacher professional development for a future with generative artificial intelligence--an integrative literature review', *Digital Education Review*, no. 45, pp. 151–157, 2024.
[137] K. Denecke, R. Glauser, and D. Reichenpfader, 'Assessing the Potential and Risks of AI-Based Tools in Higher Education: Results from an eSurvey and SWOT Analysis', *Trends in Higher Education*, vol. 2, no. 4, 2023, doi: 10.3390/higheredu2040039.
[138] J. Jemmy, M. Aina, W. Wahdah, W. Joshua, and S. Sabri, 'Impact of ChatGPT in Higher Education Learning', *Journal International of Lingua and Technology*, vol. 3, no. 1, 2024, doi: 10.55849/jiltech.v3i1.505.
[139] J. Dempere, K. Modugu, A. Hesham, and L. K. Ramasamy, 'The impact of ChatGPT on higher education', *Frontiers in Education*, vol. 8. 2023, doi: 10.3389/feduc.2023.1206936.
[140] S. Maghsudi, A. Lan, J. Xu, and M. Van Der Schaar, 'Personalized Education in the Artificial Intelligence Era: What to Expect Next', *IEEE Signal Processing Magazine*, vol. 38, no. 3, 2021, doi: 10.1109/MSP.2021.3055032.
[141] D. Song and D. Kim, 'Effects of self-regulation scaffolding on online participation and learning outcomes', *Journal of Research on Technology in Education*, vol. 53, no. 3, 2021, doi: 10.1080/15391523.2020.1767525.
[142] B. Rakova, J. Yang, H. Cramer, and R. Chowdhury, 'Where Responsible AI meets Reality: Practitioner Perspectives on Enablers for Shifting Organizational Practices', *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW1. 2021, doi: 10.1145/3449081.
[143] F. Santoni de Sio and G. Mecacci, 'Four Responsibility Gaps with Artificial Intelligence: Why they Matter and How to Address them', *Philosophy and Technology*, vol. 34, no. 4, 2021, doi: 10.1007/s13347-021-00450-x.
[144] A. Aler Tubella, M. Mora-Cantallops, and J. C. Nieves, 'How to teach responsible AI in Higher Education: challenges and opportunities', *Ethics and Information Technology*, vol. 26, no. 1, 2024, doi: 10.1007/s10676-023-09733-7.
[145] D. Domínguez Figaredo and J. Stoyanovich, 'Responsible AI literacy: A stakeholder-first approach', *Big Data and Society*, vol. 10, no. 2, 2023, doi: 10.1177/20539517231219958.
[146] E. Dimitriadou and A. Lanitis, 'A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms', *Smart Learning Environments*, vol. 10, no. 1. 2023, doi: 10.1186/s40561-023-00231-3.
[147] A. K. Pandey, T. R. Mahesh, V. Christy, M. Shaikh, P. Yadav, and S. Das, 'Preliminary Staff Collaboration and Artificial Intelligence', 2023, doi: 10.1109/ICACITE57410.2023.10182877.
[148] I. A. Adeleke, O. G. A. Abimbola, and A. A. Olalekan, 'Exploring AI Integration in Higher Education: University Lecturers' Perspectives on Engagement, Critical Thinking, and Interdisciplinary Collaboration', *Faculty of Natural and Applied Sciences Journal of Mathematics, and Science Education*, vol. 6, no. 1, pp. 1–10, 2024.
[149] K. Karu and K. Aava, 'Appreciative Development Research to Support the Teaching Culture of the Academic Staff at University', *Journal of Perspectives in Applied Academic Practice*, vol. 11, no. 2, 2023, doi: 10.56433/jpaap.v11i2.544.
[150] J. Liu and H. V. Jagadish, 'Institutional Efforts to Help Academic Researchers Implement Generative AI in Research', *Harvard Data Science Review*, no. Special Issue 5, 2024, doi: 10.1162/99608f92.2c8e7e81.
[151] M. Prince, 'Does active learning work? A review of the research', *Journal of Engineering Education*, vol. 93, no. 3. 2004, doi: 10.1002/j.2168-9830.2004.tb00809.x.
[152] C. C. Bonwell and J. a Eison, 'Active Learning : Creating Excitement in the Classroom', *Learning*, 1991, doi: ED340272.

[153] A. Vorderobermeier, J. Abel, and M. Sailer, 'Theoretical foundations and approaches in research on educational escape rooms: A systematic review', *Educational Research Review*, p. 100625, 2024.

[154] M. P. C. Lin and D. Chang, 'CHAT-ACTS: A pedagogical framework for personalized chatbot to enhance active learning and self-regulated learning', *Computers and Education: Artificial Intelligence*, vol. 5, 2023, doi: 10.1016/j.caeai.2023.100167.

[155] S. Y. Wu and K. K. Yang, 'The Effectiveness of Teacher Support for Students' Learning of Artificial Intelligence Popular Science Activities', *Frontiers in Psychology*, vol. 13, 2022, doi: 10.3389/fpsyg.2022.868623.

[156] J. Kay, 'Foundations for Human-AI teaming for self-regulated learning with explainable AI (XAI)', *Computers in Human Behavior*, vol. 147. 2023, doi: 10.1016/j.chb.2023.107848.

[157] S. C. Kong and Y. Q. Wang, 'The impact of school support for professional development on teachers' adoption of student-centered pedagogy, students' cognitive learning and abilities: A three-level analysis', *Computers and Education*, vol. 215, 2024, doi: 10.1016/j.compedu.2024.105016.

[158] J. J. Merelo *et al.*, 'Chatbots and messaging platforms in the classroom: An analysis from the teacher's perspective', *Education and Information Technologies*, vol. 29, no. 2, 2024, doi: 10.1007/s10639-023-11703-x.

[159] H. Shang, C. B. Sivaparthipan, and ThanjaiVadivel, 'Interactive teaching using human-machine interaction for higher education systems', *Computers and Electrical Engineering*, vol. 100, 2022, doi: 10.1016/j.compeleceng.2022.107811.

[160] N. A. Dahri *et al.*, 'Extended TAM based acceptance of AI-Powered ChatGPT for supporting metacognitive self-regulated learning in education: A mixed-methods study', *Heliyon*, vol. 10, no. 8, 2024.

[161] A. N. Wulyani, M. R. M. Sata, D. Rusdin, and others, 'Overcoming challenges: Indonesian EFL teachers' strategies for using moodle in high schools', *Social Sciences \& Humanities Open*, vol. 10, p. 101175, 2024.

[162] K. Freeman, K. Brown, L. Miller, T. Nissly, J. Ricco, and A. Weinmann, 'Knowledge Retention Using "Relay": A Novel Active-Learning Technique', *PRiMER*, vol. 6, 2022, doi: 10.22454/primer.2022.586676.

[163] T. Özgür, 'Active learning improves academic achievement and learning retention in K-12 settings: A meta-analysis', *i-manager's Journal on School Educational Technology*, vol. 18, no. 3, 2023, doi: 10.26634/jsch.18.3.19288.

[164] J. Skalka, M. Drlik, and J. Obonya, 'Automated Assessment in Learning and Teaching Programming Languages using Virtual Learning Environment', *PROCEEDINGS OF IEEE GLOBAL ENGINEERING EDUCATION CONFERENCE (EDUCON2017)*, 2019, doi: 10.1109/EDUCON.2019.8725127.

[165] L. Cheng, A. D. Ritzhaupt, and P. Antonenko, 'Effects of the flipped classroom instructional strategy on students' learning outcomes: a meta-analysis', *Educational Technology Research and Development*, vol. 67, no. 4, 2019, doi: 10.1007/s11423-018-9633-7.

[166] M. Hernández-de-Menéndez, A. Vallejo Guevara, and R. Morales-Menendez, 'Virtual reality laboratories: a review of experiences', *International Journal on Interactive Design and Manufacturing*, vol. 13, no. 3, 2019, doi: 10.1007/s12008-019-00558-7.

[167] T. Al Shloul *et al.*, 'Role of activity-based learning and ChatGPT on students' performance in education', *Computers and Education: Artificial Intelligence*, p. 100219, 2024.

[168] S. Aluvala and S. Pothupogu, 'A Traditional Novel Approach for Skill Enhancement of Teaching - Learning Process in Engineering Education', *Journal of Engineering Education Transformations*, vol. 28, no. 4, 2015, doi: 10.16920/jeet/2015/v28i4/70407.

[169] K. Mehmood, M. Naqeeb, and K. Shaheen, 'Implementation of Activity Based Teaching at Primary Level: A Theoretical Perspective', *Pakistan Journal of Educational Research*, vol. 4, no. 1, 2021.

[170] A. Makri, D. Vlachopoulos, and R. A. Martina, 'Digital escape rooms as innovative pedagogical tools in education: A systematic literature review', *Sustainability (Switzerland)*, vol. 13, no. 8, 2021, doi: 10.3390/su13084587.

[171] R. DiYanni and A. Borst, *The Craft of College Teaching*. 2020.

[172] I. Gligorea, M. Cioca, R. Oancea, A. T. Gorski, H. Gorski, and P. Tudorache, 'Adaptive Learning Using Artificial Intelligence in e-Learning: A Literature Review', *Education Sciences*, vol. 13, no. 12. 2023, doi: 10.3390/educsci13121216.

[173] W. Yan, T. Nakajima, and R. Sawada, 'Benefits and Challenges of Collaboration between Students and Conversational Generative Artificial Intelligence in Programming Learning: An Empirical Case Study', *Education Sciences*, vol. 14, no. 4, p. 433, 2024.

[174] M. Murtaza, Y. Ahmed, J. A. Shamsi, F. Sherwani, and M. Usman, 'AI-Based Personalized E-Learning Systems: Issues, Challenges, and Solutions', *IEEE Access*, vol. 10. 2022, doi: 10.1109/ACCESS.2022.3193938.

[175] O. Tapalova and N. Zhiyenbayeva, 'Artificial Intelligence in Education: AIEd for Personalised Learning Pathways', *Electronic Journal of e-Learning*, vol. 20, no. 5, 2022, doi: 10.34190/ejel.20.5.2597.

[176] M. N. Masrek, T. Susantari, F. Mutia, H. P. Yuwinanto, and R. T. Atmi, 'Enabling Education Everywhere: How artificial intelligence empowers ubiquitous and lifelong learning', *Environment-Behaviour Proceedings Journal*, vol. 9, no. SI18, pp. 57–63, 2024.

[177] M. K. Shahid, T. Zia, L. Bangfan, Z. Iqbal, and F. Ahmad, 'Exploring the relationship of psychological factors and adoption readiness in determining university teachers' attitude on AI-based assessment systems', *International Journal of Management Education*, vol. 22, no. 2, 2024, doi: 10.1016/j.ijme.2024.100967.

[178] M. Drlik, J. Skalka, P. Svec, and J. Kapusta, 'Proposal of Learning Analytics Architecture Integration into University IT Infrastructure', *IEEE International Conference on Application of Information and Communication Technologies*,

2018, doi: 10.1109/ICAICT.2018.8747068.
[179] K. Pahi, S. Hawlader, E. Hicks, A. Zaman, and V. Phan, ‘Enhancing active learning through collaboration between human teachers and generative AI’, *Computers and Education Open*, vol. 6, p. 100183, 2024.
[180] J. L. Hung, M. C. Wang, S. Wang, M. Abdelrasoul, Y. Li, and W. He, ‘Identifying At-Risk Students for Early Interventions - A Time-Series Clustering Approach’, *IEEE Transactions on Emerging Topics in Computing*, vol. 5, no. 1, 2017, doi: 10.1109/TETC.2015.2504239.
[181] S. S. Fatima, N. A. Sheikh, and A. Osama, ‘Authentic assessment in medical education: exploring AI integration and student-as-partners collaboration’, *Postgraduate Medical Journal*, vol. 100, no. 1190, pp. 959–967, 2024.
[182] G. Makransky and L. Lilleholt, ‘A structural equation modeling investigation of the emotional value of immersive virtual reality in education’, *Educational Technology Research and Development*, vol. 66, no. 5, 2018, doi: 10.1007/s11423-018-9581-2.
[183] D. Soto, M. Higashida, S. Shirai, M. Ueda, and Y. Uranishi, ‘Enhancing Learning Dynamics: Integrating Interactive Learning Environments and ChatGPT for Computer Networking Lessons’, *Procedia Computer Science*, vol. 246, pp. 3595–3604, 2024, doi: https://doi.org/10.1016/j.procs.2024.09.198.
[184] J. Skalka and M. Drlik, ‘Automated assessment and microlearning units as predictors of at-risk students and students’ outcomes in the introductory programming courses’, *Applied Sciences (Switzerland)*, vol. 10, no. 13, 2020, doi: 10.3390/app10134566.
[185] K. Børte, S. Lillejord, J. Chan, B. Wasson, and S. Greiff, ‘Prerequisites for teachers’ technology use in formative assessment practices: A systematic review’, *Educational Research Review*, vol. 41. 2023, doi: 10.1016/j.edurev.2023.100568.
[186] D. T. T. Mai, C. Van Da, and N. Van Hanh, ‘The use of ChatGPT in teaching and learning: a systematic review through SWOT analysis approach’, *Frontiers in Education*, vol. 9. 2024, doi: 10.3389/feduc.2024.1328769.
[187] D. Vlachopoulos and A. Makri, ‘A systematic literature review on authentic assessment in higher education: Best practices for the development of 21st century skills, and policy considerations’, *Studies in Educational Evaluation*, vol. 83, p. 101425, 2024, doi: https://doi.org/10.1016/j.stueduc.2024.101425.
[188] M. Chassignol, A. Khoroshavin, A. Klimova, and A. Bilyatdinova, ‘Artificial Intelligence trends in education: A narrative overview’, in *Procedia Computer Science*, 2018, vol. 136, doi: 10.1016/j.procs.2018.08.233.
[189] D. Rico-Bautista, Y. Medina-Cardenas, L. A. Coronel-Rojas, F. Cuesta-Quintero, G. Maestre-Gongora, and C. D. Guerrero, ‘Smart University: Key Factors for an Artificial Intelligence Adoption Model’, in *Advances in Intelligent Systems and Computing*, 2021, vol. 1307 AISC, doi: 10.1007/978-981-33-4565-2_10.
[190] J. J. Xu and T. Babaian, ‘Artificial intelligence in business curriculum: The pedagogy and learning outcomes’, *International Journal of Management Education*, vol. 19, no. 3, 2021, doi: 10.1016/j.ijme.2021.100550.
[191] A. L. Lindqwister, S. Hassanpour, P. J. Lewis, and J. M. Sin, ‘AI-RADS: An Artificial Intelligence Curriculum for Residents’, *Academic Radiology*, vol. 28, no. 12, 2021, doi: 10.1016/j.acra.2020.09.017.
[192] E. Eaton *et al.*, ‘Blue sky ideas in artificial intelligence education from the EAAI 2017 new and future AI educator program’, *AI Matters*, vol. 3, no. 4, 2018, doi: 10.1145/3175502.3175509.
[193] P. Langley, ‘An integrative framework for artificial intelligence education’, 2019, doi: 10.1609/aaai.v33i01.33019670.
[194] S. Russell and P. Norvig, ‘Artificial Intelligence A Modern Approach (4th Edition)’, *Pearson Series*. 2021.
[195] J. Finlay, *An introduction to artificial intelligence*. Crc Press, 2020.
[196] W. Ertel, *Introduction to artificial intelligence*. Springer, 2018.
[197] M. Flasiński, *Introduction to artificial intelligence*. Springer, 2016.
[198] P. C. Jackson, *Introduction to artificial intelligence*. Courier Dover Publications, 2019.
[199] F. Heintz and T. Roos, ‘ELEMENTS OF AI - TEACHING THE BASICS OF AI TO EVERYONE IN SWEDEN’, in *EDULEARN21 Proceedings*, 2021, vol. 1, doi: 10.21125/edulearn.2021.0559.
[200] E. Smyrnova-Trybulska, T. Noskova, T. Pavlova, O. Yakovleva, and N. Morze, ‘New educational strategies in contemporary digital environment’, *International Journal of Continuing Engineering Education and Life-Long Learning*, vol. 26, no. 1, 2016, doi: 10.1504/IJCEELL.2016.075036.
[201] G. S. Latwal, S. K. Sharma, P. Mahajan, and P. Kommers, *Role of ICT in Higher Education: Trends, Problems, and Prospects*. CRC Press, 2020.
[202] M. Capay, J. Skalka, and M. Drlik, ‘Computer science learning activities based on experience’, 2017, doi: 10.1109/EDUCON.2017.7943025.
[203] S. Hartikainen, H. Rintala, L. Pylväs, and P. Nokelainen, ‘The concept of active learning and the measurement of learning outcomes: A review of research in engineering higher education’, *Education Sciences*, vol. 9, no. 4, 2019, doi: 10.3390/educsci9040276.
[204] D. B. Markant, A. Ruggeri, T. M. Gureckis, and F. Xu, ‘Enhanced Memory as a Common Effect of Active Learning’, *Mind, Brain, and Education*, vol. 10, no. 3. 2016, doi: 10.1111/mbe.12117.
[205] M. J. D’Souza and P. Rodrigues, ‘Investigating the effectiveness of the flipped classroom in an introductory programming course’, *New Educational Review*, vol. 40, no. 2, 2015, doi: 10.15804/tner.2015.40.2.11.
[206] H. Özyurt and Ö. Özyurt, ‘Analyzing the effects of adapted flipped classroom approach on computer programming success, attitude toward programming, and programming self-efficacy’, *Computer Applications in Engineering Education*, vol. 26, no. 6, 2018, doi: 10.1002/cae.21973.
[207] M. K. P. Peethambaran, V. G. Renumol, and S. Murthy, ‘Flipped Classroom Strategy to Help Underachievers in Java

Programming', 2018, doi: 10.1109/LaTICE.2018.000-7.
[208] J. W. Carter and C. Youssef-Morgan, 'Psychological capital development effectiveness of face-to-face, online, and Micro-learning interventions', *Education and Information Technologies*, 2022, doi: 10.1007/s10639-021-10824-5.
[209] G. P. Gasca-Hurtado and M. C. Gomez-Alvarez, 'Mobile application based on gamification to promote microlearning in Software Engineering', 2021, doi: 10.23919/CISTI52073.2021.9476569.
[210] J. Skalka *et al.*, 'Conceptual framework for programming skills development based on microlearning and automated source code evaluation in virtual learning environment', *Sustainability (Switzerland)*, vol. 13, no. 6, 2021, doi: 10.3390/su13063293.
[211] J. Skalka and M. Drlik, 'Priscilla - Proposal of System Architecture for Programming Learning and Teaching Environment', *IEEE International Conference on Application of Information and Communication Technologies*, 2018, [Online]. Available: https://publons.com/publon/27387754/.
[212] J. Skalka and M. Drlík, *Conceptual framework of microlearning-based training mobile application for improving programming skills*, vol. 725. 2018.
[213] F. Pérez and B. E. Granger, 'Project Jupyter : Computational Narratives as the Engine of Collaborative Data Science', *UC Berkeley*, no. April, 2015.
[214] J. W. Johnson, 'Benefits and Pitfalls of Jupyter Notebooks in the Classroom', 2020, doi: 10.1145/3368308.3415397.
[215] Project Jupyter, 'Standalone Jupyter server enhancement', 2022. https://jupyter.org/enhancement-proposals/28-jupyter-server/jupyter-server.html (accessed Aug. 30, 2022).
[216] Project Jupyter Team, 'Jupyter Kernel Gateway', 2022. https://jupyter-kernel-gateway.readthedocs.io/en/latest/ (accessed Aug. 30, 2020).
[217] P. Hintjens, *ZeroMQ: messaging for many applications*. ' O'Reilly Media, Inc.', 2013.
[218] J. C. Rodríguez-del-Pino, E. Rubio-Royo, and Z. Hernández-Figueroa, 'A Virtual Programming Lab for Moodle with automatic assessment and anti-plagiarism features', *Conference on e-Learning, e-Business, Entreprise Information Systems, & e-Government*, 2012.
[219] D. T. K. Ng, J. K. L. Leung, K. W. S. Chu, and M. S. Qiao, 'AI Literacy: Definition, Teaching, Evaluation and Ethical Issues', *Proceedings of the Association for Information Science and Technology*, vol. 58, no. 1, pp. 504–509, 2021, doi: 10.1002/pra2.487.
[220] M. Kandlhofer, G. Steinbauer, S. Hirschmugl-Gaisch, and P. Huber, 'Artificial intelligence and computer science in education: From Kindergarten to university', in *Proceedings - Frontiers in Education Conference, FIE*, 2016, vol. 2016-November, doi: 10.1109/FIE.2016.7757570.
[221] H. Burgsteiner, M. Kandlhofer, and G. Steinbauer, 'IRobot: Teaching the basics of artificial intelligence in high schools', 2016, doi: 10.1609/aaai.v30i1.9864.
[222] A. Lindner and M. Berges, 'Can you explain AI to me? Teachers' pre-concepts about Artificial Intelligence', in *Proceedings - Frontiers in Education Conference, FIE*, 2020, vol. 2020-October, doi: 10.1109/FIE44824.2020.9274136.
[223] Z. H. Aung *et al.*, 'Designing a novel teaching platform for AI: A case study in a Thai school context', *Journal of Computer Assisted Learning*, vol. 38, no. 6, 2022, doi: 10.1111/jcal.12706.
[224] M. Hooda, C. Rana, O. Dahiya, A. Rizwan, and M. S. Hossain, 'Artificial Intelligence for Assessment and Feedback to Enhance Student Success in Higher Education', *Mathematical Problems in Engineering*, vol. 2022, 2022, doi: 10.1155/2022/5215722.
[225] C. P. Dai and F. Ke, 'Educational applications of artificial intelligence in simulation-based learning: A systematic mapping review', *Computers and Education: Artificial Intelligence*, vol. 3. 2022, doi: 10.1016/j.caeai.2022.100087.
[226] Y. Omae, T. Furuya, M. Matsushita, K. Mizukoshi, K. Yatsushiro, and H. Takahashi, 'Artificial Intelligence Education in an Elementary School and Its Evaluation by Career Development, Motivation and Rubrics', *Information and Technology in Education and Learning*, vol. 3, no. 1, 2023, doi: 10.12937/itel.3.1.trans.p002.
[227] H. Zhang, I. Lee, S. Ali, D. DiPaola, Y. Cheng, and C. Breazeal, 'Integrating Ethics and Career Futures with Technical Learning to Promote AI Literacy for Middle School Students: An Exploratory Study', *International Journal of Artificial Intelligence in Education*, vol. 33, no. 2, 2023, doi: 10.1007/s40593-022-00293-3.
[228] Y. Y. Yakovenko, M. Y. Bilyk, and Y. V. Oliinyk, 'The Transformative Impact of the Development of Artificial Intelligence on Employment and Work Motivation in Business in the Conditions of the Information Economy', 2022, doi: 10.1109/MEES58014.2022.10005652.
[229] D. Long and B. Magerko, 'What is AI Literacy? Competencies and Design Considerations', 2020, doi: 10.1145/3313831.3376727.
[230] W. Yang, 'Artificial Intelligence education for young children: Why, what, and how in curriculum design and implementation', *Computers and Education: Artificial Intelligence*, vol. 3, 2022, doi: 10.1016/j.caeai.2022.100061.
[231] J. Su, D. T. K. Ng, and S. K. W. Chu, 'Artificial Intelligence (AI) Literacy in Early Childhood Education: The Challenges and Opportunities', *Computers and Education: Artificial Intelligence*, vol. 4. 2023, doi: 10.1016/j.caeai.2023.100124.
[232] I. Tuomi, 'A Framework for Socio-Developmental Ethics in Educational AI', in *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2023, vol. 2023-January.
[233] L. Alzahrani, 'Analyzing students' attitudes and behavior toward artificial intelligence technologies in higher education', *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 11, no. 6, pp. 65–73, 2023.
[234] A. Katsantonis and I. G. Katsantonis, 'University Students' Attitudes toward Artificial Intelligence: An Exploratory

Study of the Cognitive, Emotional, and Behavioural Dimensions of AI Attitudes', *Education Sciences*, vol. 14, no. 9, 2024, doi: 10.3390/educsci14090988.

[235] S. F. Mousavi Baigi, M. Sarbaz, K. Ghaddaripouri, M. Ghaddaripouri, A. S. Mousavi, and K. Kimiafar, 'Attitudes, knowledge, and skills towards artificial intelligence among healthcare students: A systematic review', *Health Science Reports*, vol. 6, no. 3. 2023, doi: 10.1002/hsr2.1138.

[236] J. Kimmerle, J. Timm, T. Festl-Wietek, U. Cress, and A. Herrmann-Werner, 'Medical Students' Attitudes Toward AI in Medicine and their Expectations for Medical Education', *Journal of Medical Education and Curricular Development*, vol. 10, 2023, doi: 10.1177/23821205231219346.

[237] J. Stewart *et al.*, 'Western Australian medical students' attitudes towards artificial intelligence in healthcare', *PLoS ONE*, vol. 18, no. 8 August, 2023, doi: 10.1371/journal.pone.0290642.

[238] J. A. Moldt, T. Festl-Wietek, A. Madany Mamlouk, K. Nieselt, W. Fuhl, and A. Herrmann-Werner, 'Chatbots for future docs: exploring medical students' attitudes and knowledge towards artificial intelligence and medical chatbots', *Medical Education Online*, vol. 28, no. 1, 2023, doi: 10.1080/10872981.2023.2182659.

[239] C. K. Y. Chan and W. Hu, 'Students' voices on generative AI: perceptions, benefits, and challenges in higher education', *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, 2023, doi: 10.1186/s41239-023-00411-8.

[240] C. Stöhr, A. W. Ou, and H. Malmström, 'Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study', *Computers and Education: Artificial Intelligence*, vol. 7, p. 100259, 2024, doi: https://doi.org/10.1016/j.caeai.2024.100259.

[241] A. R. Malik *et al.*, 'Exploring Artificial Intelligence in Academic Essay: Higher Education Student's Perspective', *International Journal of Educational Research Open*, vol. 5, 2023, doi: 10.1016/j.ijedro.2023.100296.

[242] H. Kong, Z. Yin, Y. Baruch, and Y. Yuan, 'The impact of trust in AI on career sustainability: The role of employee–AI collaboration and protean career orientation', *Journal of Vocational Behavior*, vol. 146, 2023, doi: 10.1016/j.jvb.2023.103928.

[243] A. Köchling, M. C. Wehner, and S. A. Ruhle, 'This (AI)n't fair? Employee reactions to artificial intelligence (AI) in career development systems', *Review of Managerial Science*, 2024, doi: 10.1007/s11846-024-00789-3.

[244] B. Marinette and X. Hui, 'The Principal as a Curriculum-instructional Leader: A Strategy for Curriculum Implementation inCameroon Secondary Schools', *International Journal of Education and Research*, vol. 8, no. 4, 2020.

[245] M. Rožman, P. Tominc, and I. Vrečko, 'Building skills for the future of work: Students' perspectives on emerging jobs in the Data and AI Cluster through artificial intelligence in education', *Environment and Social Psychology*, vol. 8, no. 2, 2023, doi: 10.54517/esp.v8i2.1670.

[246] E. Felten, M. Raj, and R. Seamans, 'The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization', *NYU Stern School of Business*, vol. 08544, 2019.

[247] S. Kelly, S. A. Kaye, and O. Oviedo-Trespalacios, 'What factors contribute to the acceptance of artificial intelligence? A systematic review', *Telematics and Informatics*, vol. 77, 2023, doi: 10.1016/j.tele.2022.101925.

[248] Z. Slimi and B. V. Carballido, 'Systematic Review: AI's Impact on Higher Education - Learning, Teaching, and Career Opportunities', *TEM Journal*, vol. 12, no. 3. 2023, doi: 10.18421/TEM123-44.

[249] D. L. Waltz, 'Evolution, sociobiology, and the future off artificial intelligence', *IEEE Intelligent Systems*, vol. 21, no. 3. 2006, doi: 10.1109/MIS.2006.46.

[250] D. G. Johnson and M. Verdicchio, 'AI Anxiety', *Journal of the Association for Information Science and Technology*, vol. 68, no. 9, 2017, doi: 10.1002/asi.23867.

[251] H. H. Haladjian and C. Montemayor, 'Artificial consciousness and the consciousness-attention dissociation', *Consciousness and Cognition*, vol. 45. 2016, doi: 10.1016/j.concog.2016.08.011.

[252] J. M. Beer, A. D. Fisk, and W. A. Rogers, 'Toward a Framework for Levels of Robot Autonomy in Human-Robot Interaction', *Journal of Human-Robot Interaction*, vol. 3, no. 2, 2014, doi: 10.5898/jhri.3.2.beer.

[253] E. Yudkowsky, 'Artificial Intelligence as a positive and negative factor in global risk', in *Global Catastrophic Risks*, 2008.

[254] N. Bostrom, 'Existential Risks: Analyzing Human Extinction Scenarios and Related Hazards', *Journal of Evolution and Technology*, vol. 9, no. 1, 2002.

[255] R. Clarke, 'Why the world wants controls over Artificial Intelligence', *Computer Law and Security Review*, vol. 35, no. 4, 2019, doi: 10.1016/j.clsr.2019.04.006.

[256] A. Holzinger, A. Saranti, C. Molnar, P. Biecek, and W. Samek, 'Explainable AI Methods - A Brief Overview', in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2022, vol. 13200 LNAI, doi: 10.1007/978-3-031-04083-2_2.

[257] V. Sehrawat, 'Autonomous weapon system: Law of armed conflict (LOAC) and other legal challenges', *Computer Law and Security Review*, vol. 33, no. 1, 2017, doi: 10.1016/j.clsr.2016.11.001.

[258] J. Curzon, T. Ann Kosa, R. Akalu, and K. El-Khatib, 'Privacy and Artificial Intelligence', *IEEE Transactions on Artificial Intelligence*, vol. 2, no. 2, 2021, doi: 10.1109/TAI.2021.3088084.

[259] L. Floridi, 'Artificial Intelligence, Deepfakes and a Future of Ectypes', in *Philosophical Studies Series*, vol. 144, 2021.

[260] M. Drlik, M. Munk, and J. Skalka, 'Identification of changes in vle stakeholders' behavior over time using frequent patterns mining', *IEEE Access*, vol. 9, pp. 23795–23813, 2021.

[261] T. K. F. Chiu and C. S. Chai, 'Sustainable curriculum planning for artificial intelligence education: A self-

determination theory perspective', *Sustainability (Switzerland)*, vol. 12, no. 14, 2020, doi: 10.3390/su12145568.

[262] Y. Dai, C. S. Chai, P. Y. Lin, M. S. Y. Jong, Y. Guo, and J. Qin, 'Promoting students'well-being by developing their readiness for the artificial intelligence age', *Sustainability (Switzerland)*, vol. 12, no. 16, 2020, doi: 10.3390/su12166597.

[263] I. H. Y. Yim and J. Su, 'Artificial intelligence (AI) learning tools in K-12 education: A scoping review', *Journal of Computers in Education*, pp. 1–39, 2024, doi: 10.1007/s40692-023-00304-9.

[264] P. Limna, S. Jakwatanatham, S. Siripipattanakul, P. Kaewpuang, and P. Sriboonruang, 'A Review of Artificial Intelligence (AI) in Education during the Digital Era', *Advance Knowledge for Executives*, vol. 1, no. 1, pp. 1–9, 2022.

[265] R. Pinzolits, 'AI in academia: An overview of selected tools and their areas of application', *MAP Education and Humanities*, vol. 4, pp. 37–50, 2024.

[266] A. Hasan Sapci and H. Aylin Sapci, 'Artificial intelligence education and tools for medical and health informatics students: Systematic review', *JMIR Medical Education*, vol. 6, no. 1, p. e19285, 2020, doi: 10.2196/19285.

[267] T. Adiguzel, M. H. Kaya, and F. K. Cansu, 'Revolutionizing education with AI: Exploring the transformative potential of ChatGPT', *Contemporary Educational Technology*, vol. 15, no. 3, 2023, doi: 10.30935/CEDTECH/13152.

[268] Z. H. Sain, H. Baharun, and N. B. Abdullah, 'Enhancing Higher Education Pedagogy with ChatGPT: Leveraging the Power of Generative AI', *Journal Emerging Technologies in Education*, vol. 2, no. 3, pp. 267–281, 2024, doi: 10.70177/jete.v2i3.1189.

[269] O. Boubker, 'From chatting to self-educating: Can AI tools boost student learning outcomes?', *Expert Systems with Applications*, vol. 238, p. 121820, 2024, doi: 10.1016/j.eswa.2023.121820.

[270] B. L. Moorhouse, M. A. Yeo, and Y. Wan, 'Generative AI tools and assessment: Guidelines of the world's top-ranking universities', *Computers and Education Open*, vol. 5, p. 100151, 2023.

[271] S. Atlas, 'ChatGPT for higher education and professional development: A guide to conversational AI', *University of Rhode Island*, 2023.

[272] S. S. Gill *et al.*, 'Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots', *Internet of Things and Cyber-Physical Systems*, vol. 4, pp. 19–23, 2024, doi: 10.1016/j.iotcps.2023.06.002.

7 Appendix

7.1 Questionnaire items

Source: https://www.mdpi.com/2071-1050/12/16/6597

Basic personal information

- Q1 Gender:
- Q2 Grade (year of study):
- Q3 Age (just fill in a whole number):
- Q4 Study programme:
- Q5 How many hours of AI-related courses have you taken (from 0 to many, not per week, summary in your study):

AI Literacy

- L1 I know that AI can be used for image recognition and search.
- L2 I know that AI can be used for speech recognition and search.
- L3 I (will) use AI-assisted online translation.
- L4 I (will) communicate with the AI voice assistant (such as Siri, Baidu voice search).
- L5 I know that AI technology can predict some things (such as popular music and books).

AI readiness

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

The relevance of AI

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

Career motivation

- CM1 I think learning AI is helpful to my future.
- CM2 I think learning AI can help me find a good job.
- CM3 Working in AI-related work is an interesting way to earn a living for me.
- CM4 I will learn AI related knowledge for my future interests.

Social Goods

- SG1 I hope to use my AI knowledge to serve others.
- SG2 I hope to use AI to help people who are weak and in difficulties.

- SG3 I hope to use AI to bring benefits to all mankind.
- SG4 The combination of AI and design thinking can enhance my ability to help others.
- SG5 It should be consider the interests of the majority when using AI.

AI anxiety

- A1 I am worried that AI will bring trouble to my future.
- A2 Considering AI, I am not sure what my future will become.
- A3 I am worried that my future will fail because of AI.
- A4 When I think about AI, I feel uneasy.
- A5 I feel very pressured to hear about the advancement of AI technology.

Confidence

- C1 I am confident of getting good grades in AI classes.
- C2 I believe that I can learn the AI course well as long as I work hard.
- C3 I believe I can understand the most difficult content in AI classes.
- C4 I believe I can learn the basic concepts in AI class well.
- C5 I believe I can understand the most complex content explained by the teacher in the AI class.

Satisfaction

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

Intrinsic motivation

- IM1 I prefer AI topics that arouse my curiosity, even if they are difficult to understand.
- IM2 I like the challenging AI courses so that I can learn new things.
- IM3 What I am most satisfied with is to understand the content of AI courses as thoroughly as possible.
- IM4 I like the content of passed AI courses.

Behavioural intention

- BI1 I will continue to learn about AI.
- BI2 I want to pay active attention to the application of AI.
- BI3 I will continue to stay tuned for AI-related information.
- BI4 I plan to use AI tools to help me learn.
- BI5 I intend to use AI to help me solve problems.

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