

Why and what do students want to learn about AI? Investigating motivations and learning interests among undergraduates across disciplines

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Abstract. Artificial Intelligence (AI) systems are now widely applied across different domains. As AI systems increasingly shape professional and academic domains, there is a growing need to prepare future professionals to work with these technologies responsibly and effectively. Accordingly, an increasing number of studies advocate AI education for undergraduates across disciplines. However, there is limited qualitative research on these students' motivations for learning about AI and on what they are interested in learning, despite the importance of such understanding for designing motivating, engaging, and effective learning experiences. Therefore, the objective of this research is to answer the following two research questions: (1) What motivates undergraduates across disciplines to learn about AI? (2) What are undergraduates across disciplines interested in learning about AI? To answer the research questions, we conducted a survey with 128 students who voluntarily enrolled in an elective introductory AI course over three semesters. The findings indicate that these students are motivated to learn about AI not only for career-related utility but also due to its perceived societal relevance and ethical implications. Regarding learning interests, students most frequently expressed interest in learning how AI systems work, how these systems impact society positively and negatively, and how to use them effectively and responsibly. In the discussion section, we provide guidance on how these results can inform the design or adaptation of AI curricula, course invitations, and learning experiences to foster sustained engagement and meaningful learning among these students.

Key words: AI education; Higher education; Students' perspectives; Curriculum design.

1. Introduction

According to the EU AI Act, an AI system is a "machine-based system that is designed to operate with varying levels of autonomy, and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how

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to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments" (European Union, 2024). In recent years, with advancements in the deep learning field, improvements in computing power, and the availability of a large amount of data, AI systems have achieved exceptional results on a variety of complex tasks in numerous disciplines (Taye, 2023; Sarker, 2021; Maslej *et al.*, 2025). For example, in medicine, AI systems have demonstrated the potential to help identify outbreaks of infectious diseases, identify patients' rare and common conditions, and support hospital business operations (Haug and Drazen, 2023; Krishnan *et al.*, 2023). Similarly, the marketing field has adopted AI systems to support the creation of marketing content that enhances user engagement, improves real-time customer assistance, and personalizes promotions, discounts, and recommendations (Kshetri *et al.*, 2024; Kumar *et al.*, 2024). In journalism, AI systems have also been increasingly used in the news industry to support the gathering of information, production of content, customization, and dissemination of news (Shi and Sun, 2024; de Lima-Santos and Ceron, 2022).

With the rising integration of AI systems across these and various other disciplines (Sarker, 2022), the literature increasingly points out the need to equip future professionals with core AI competencies to use these AI systems effectively and critically in their workplaces, and the critical role of universities in preparing these students who will become professionals in the near future (Tenório and Romeike, 2024; Laupichler *et al.*, 2022; Al-Zahrani and Alasmari, 2024; UNESCO IESALC and Mendigutxia, 2024; Liu *et al.*, 2023). In addition, the importance of interdisciplinary courses at universities is also pointed out, where students from different disciplines can learn from each other to diminish differences between disciplines and enable all students to develop a critical understanding of AI (Hornberger *et al.*, 2025). However, the design of an effective AI curriculum and course for undergraduates across domains, aimed at equipping them with essential AI competencies, presents various challenges. First, AI is a broad, multidisciplinary field with diverse technical approaches and methods ranging from knowledge-based AI to machine learning (ML) and deep learning (Russell and Norvig, 2021; Bringsjord and Govindarajulu, 2024), and with a wide range of applications across domains, such as finance, science, health, and the public sector, and with diverse social, ethical, and legal implications for society, economy, and global governance (Maslej *et al.*, 2025). Additionally, AI is a rapidly evolving field. According to recent reports (Maslej *et al.*, 2025), notable developments in AI models have occurred over the past years, resulting in significant improvements in AI capabilities. Consequently, it is challenging to identify fundamental concepts of AI to design an AI curriculum in such a rapidly evolving area that will remain current, relevant, and engaging in the years to come (Eaton and Epstein, 2024; Steinbauer *et al.*, 2021; Long and Magerko, 2020).

Moreover, since the target audience is undergraduates across disciplines, this heterogeneity may pose a substantial pedagogical challenge, as students may have different interests, experiences, and varying prior knowledge of computer science basics or AI (Hornberger *et al.*, 2023). Hence, it is challenging to design an AI curriculum that motivates this audience and addresses their different learning needs and expectations. Therefore, it is important that educational researchers, professors, or curriculum developers follow

educational models that support the effective development of curricula in fields where there is a lack of consensus on needed core content, such as fields in the Computer Science (CS) area (Diethelm et al., 2012), as AI. An example of an educational model that can be adopted for this task is the Model of Educational Reconstruction (MER) for Computer Science Education (CSE). According to MER for CSE, for the development of CS curricula, lessons, or learning environments, it is necessary to clarify the science content structure, analyze social demands, and investigate teachers' and students' perspectives (Diethelm et al., 2012; Grillenberger et al., 2016). Regarding students' perspectives, more specifically, MER for CSE highlights the relevance of investigating learners' cognitive and affective perspectives, such as interests, attitudes, and motivation (Duit et al., 2012; Diethelm et al., 2012; Grillenberger et al., 2016). All these components of MER for CSE contribute to the development of an effective curriculum that aligns science subject matter with students' learning interests, needs, and capabilities (Duit et al., 2012; Diethelm et al., 2012; Grillenberger et al., 2016). Although MER for CSE was developed for the school context, it may also be applicable in the multidisciplinary undergraduate education context since both involve novice learners aiming to learn about computer science topics.

In alignment with the MER for CSE, in the AI education field for undergraduates across disciplines, previous research has qualitatively investigated perspectives of different audiences, such as professionals with working experience at the intersection of AI and other domains for understanding the social demands (Tenório and Romeike, 2024) and higher education lecturers from different domains (Tenório et al., 2025), with the objective of collecting the reasons for AI education for this audience and AI competencies that are relevant to non-computer science undergraduate students according to their perspectives. Other research has quantitatively investigated university students' cognitive and affective perspectives, including their knowledge of AI, AI self-efficacy, interest in AI, and attitudes towards AI (Hornberger et al., 2023, 2025). Although the results of quantitative assessments are highly relevant for providing an overview of the current state of students' cognitive and affective variables, they are limited in informing the design of curricula and learning environments. Therefore, qualitative approaches can be valuable for extending these results and clarifying concrete actions and topics that translate students' affective perspectives directly into curriculum and course structure and design. For example, although the quantitative research indicated that university students are interested in AI and in learning new things about AI (Hornberger et al., 2023, 2025), there is a lack of understanding of what perspectives, topics, methods, and concepts they are interested in learning, which is valuable knowledge for professors, AI education researchers, and curriculum developers who are designing curricula and learning environments to be motivating for this audience.

Understanding what motivates students and incorporating what interests them may prove to be a highly beneficial pedagogical strategy (Hagay and Baram-Tsabari, 2011). Studies in the literature demonstrate that students' motivation is a significant predictor of academic achievement, persistence, and self-regulation in learning (Robbins et al., 2004; Schunk et al., 2014). Learning motivation refers to the extent to which a student consistently applies effort in learning (Law et al., 2010), which can be influenced by different

factors (Law et al., 2010; Zuckerman et al., 2024). An understanding of motivational factors can elucidate why and how undergraduates across disciplines initiate their learning trajectories, and how motivated participation in an AI undergraduate course for this audience can be enabled (Zuckerman et al., 2024). Moreover, positive relationships have been reported between interests and a wide range of learning indicators (Hagay and Baram-Tsabari, 2011; Pintrich and Schunk, 2002). Interest constitutes a form of intrinsic motivation, referring to "doing something because it is inherently interesting or enjoyable" (Ryan and Deci, 2000). When students are learning a topic they are interested in, they participate more, stay involved for longer periods, exhibit creative practices, process information effectively, and ultimately perform better (Harackiewicz et al., 2016; Schiefele et al., 1992; Seiler, 2013). Therefore, professors and curriculum developers also need to be encouraged to understand students' interests, along with the science content structure, social demands, and teachers' perspectives. Christidou (2006) argues that curricula should engage students by incorporating topics and experiences that are both interesting and relevant to them.

Based on this, this article aims to investigate the following two research questions:

RQ1: What motivates undergraduates across disciplines to learn about AI?

RQ2: What are undergraduates across disciplines interested in learning about AI?

To answer these research questions, we conducted a questionnaire survey with open-ended questions with undergraduates across disciplines enrolled in an introductory AI course to understand their motivation for learning about AI and what they are interested in learning. Consequently, this study contributes to the growing body of research on AI literacy for undergraduates across domains. While existing AI literacy works in this field specify what learners should know, they are largely expert-derived (Tenório and Romeike, 2024; Tenório et al., 2025). Following MER for CSE, this study adds the complementary learner perspective: what motivates undergraduates across disciplines to learn about AI, and what they want to know.

2. Theoretical background

2.1. *Model of Educational Reconstruction for Science Education*

The Model of Educational Reconstruction (MER) was introduced by Kattmann et al. (1997) as a framework for research and development in science education. Grounded in the German Didaktik tradition (Duit et al., 2012), the model emphasizes that both science subject matter and student learning needs and capabilities are equally important for the successful design of science teaching and learning sequences (Duit et al., 2012). Duit et al. (2012) argue that progress in students' understanding and learning may be achieved only if there is a balance between the scientific and student perspectives. Therefore, the MER consists of three closely interrelated components: (1) clarification and analysis of science content, which encompasses subject-matter clarification and analysis of educational significance; (2) research on teaching and learning, which encompasses research on learners' cognitive and affective perspectives, such as interests, attitudes, and motivation (Kattmann

et al., 1997), and teachers' views and conceptions (Duit et al., 2012); and (3) design and evaluation of teaching and learning environments (Duit et al., 2012), where the research findings on students' and teachers' perspectives and the results of the subject-matter clarification are the main resources for the design of the activities. As shown in Figure 1, the three components interact in a cyclical (recursive) process.

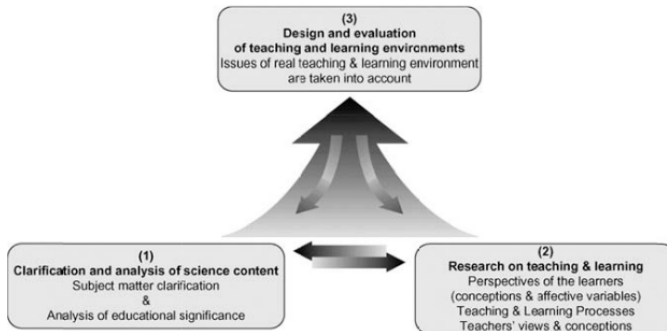


Figure 1. Three components of the Model of Educational Reconstruction for Science Education. Source: Duit et al. (2012)

2.2. Model of Educational Reconstruction for Computer Science Education

Drawing on the Model of Educational Reconstruction for science education, Diethelm et al. (2012) introduced a detailed framework for designing and developing lessons in computer science education (CSE). Diethelm et al. (2012) argue that adopting educational models from other disciplines in CS education may be problematic, since CS differs from other traditional subjects. For example, there is a strong consensus about the core content of the curriculum of traditional subjects such as biology, chemistry, and physics. In addition, teachers in these subjects are educated based on long traditions and curricula that are similar across countries (Diethelm et al., 2012). Therefore, in Diethelm et al. (2012), a specific framework for CSE was derived based on MER for science education.

In this framework, *Selection of CS Phenomena* is placed in the center (Figure 2), reflecting the broad agreement within CSE that teaching units should start from a "real-world" context or phenomenon, aiming to motivate students to connect prior knowledge. According to Humbert and Puhlmann (2004), phenomena in CSE are "occurrences of informatics in everyday life and society". Connected to the *Selection of CS Phenomena*, the framework includes the components derived from the Model of Educational Reconstruction for science education: the *Clarification of Science Content Structure*, which reveals how a phenomenon can be explained scientifically and thus which CS concepts must be taught; the *Investigation of Students' Perspectives*, which clarifies learners' experiences with the chosen phenomena and whether these are attractive, accessible, and important

to them; and the *Investigation of Teachers' Perspectives*, which accounts for variation in teachers' subject-domain, pedagogical, and pedagogical content knowledge. Moreover, the framework also places the process *Analysis of Social Demands* since it is a very important step to assess the educational significance of a certain topic. These components inform the "Design and Arrangement of CS Lessons and Courses" component (Diethelm et al., 2012).

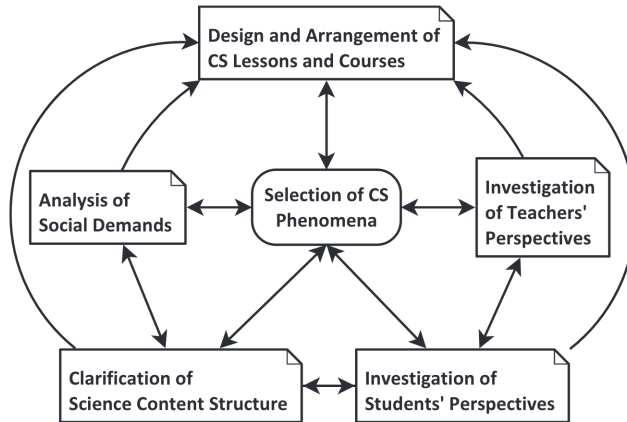


Figure 2. Components of the Educational Reconstruction Framework for Computer Science Education. Source: Diethelm et al. (2012)

In Grillenberger et al. (2016), the Educational Reconstruction Framework for CSE was proposed as a research framework. The authors rearranged and slightly adapted the components of the Educational Reconstruction Framework for CSE, and in this way transferred it to a process perspective, as can be seen in Figure 3. In the research framework proposed in Grillenberger et al. (2016), the results of the investigation of *students' and teachers' perspectives*, *the investigation of social demands*, and *the analysis of science content structure* are used to derive contents, contexts, and phenomena suitable for CS teaching and general design principles. All these components should be processed at least once in order to design and arrange CS lessons. As discussed and proposed in Kattmann et al. (1997) and Diethelm et al. (2012), Grillenberger et al. (2016) also highlighted that students' cognitive and affective perspectives should be pervasive in all steps. Consequently, the students' interests, perspectives, and conceptions support the appropriate selection of contexts and the appropriate adaptation of lessons and courses to their needs and interests (Grillenberger et al., 2016). Moreover, Grillenberger et al. (2016) propose that the selection of CS phenomena be derived in relation to concepts and context relevant for students.

Within this framework, the present study contributes to the *Investigation of Students' Perspectives* component by examining the affective variables of motivation and learning interest regarding AI among undergraduates across disciplines. The results may inform the selection of relevant contexts and phenomena for designing AI courses and learning experiences for this audience (Grillenberger et al., 2016).

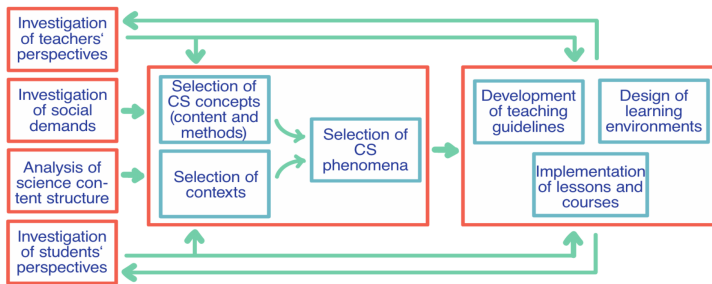


Figure 3. Application of the Educational Reconstruction Framework for Computer Science Education. Source: Grillenberger et al. (2016)

3. Related work

This section aims to provide a review of a targeted selection of studies that, in line with MER, investigated students' perspectives to inform the practice and development of course environments that motivate students and promote their interests, thereby increasing the chance of positive learning outcomes. In Zuckerman et al. (2024), focus group interviews were conducted with life science majors who registered for an introductory programming course in biology. The objective of the study was to understand students' motivation to take a new introductory coding class in biology, as well as their expectations for the course. The overall objective was to gain insights that would inform how to recruit and retain non-CS students in the computational area of biology by identifying their characteristics. The authors frame their analysis using Social Cognitive Career Theory (SCCT). The results indicated that students' motivation varied from social and career-related motivations to the ability to be creative or analyze biological datasets. Through these results, the authors could draw recommendations for practice, such as highlighting in the curriculum how coding plays a role in creative and social applications, more specifically, through project-based work that addresses issues relevant to students' career goals and values. Furthermore, it was recommended that departments and universities enhance student awareness of the benefits of coding, increase the accessibility of non-computer science coding education, and promote positive role models to inspire students to pursue these opportunities. Another recommendation was to make efforts to dismantle students' perceptions about the linkage between coding and mathematics, since it may gatekeep non-CS students from pursuing opportunities to learn programming.

In Liben-Nowell and Rafferty (2022), researchers surveyed students from a liberal arts college who registered for a CS1 course on the first day of the CS1 offering. The objective of the study was to investigate students' motivations and goals for CS1 in order to gain a collective understanding of them, enabling instructors to tailor courses to better serve the entire student population. The authors use qualitative and quantitative methods to identify clusters of students that encompass the majority of students taking CS1. The results point out that there are mainly three subpopulations: (1) "The Planners" enter the course with significant intention to further study CS in their student career; (2) "The Explorers"

seem to be taking the course hoping to have a fun experience, engage with a different way of thinking, and better understand what computer science actually is; and (3) "The Utilitarians" enter the course with a more instrumental view of CS, seeking to gain skills which they perceive as useful for their future careers or for their study of some topic other than CS. These results offer practical insights, such as the importance of social support for learning among students with no pre-CS1 programming experience.

In Alshahrani *et al.* (2018), semi-structured interviews were conducted with students who were studying CS at three Scottish universities. The purpose of this study was to explore the factors that motivate students to pursue CS at university. The authors used SCCT, which focuses on students' prior experience, social support, self-efficacy, and outcome expectations. The primary objective was to identify motivational factors that could inform policy interventions aimed at enhancing pre-university experiences for all students, with particular attention to female students. The findings indicate that a range of factors, including social support from family, teachers, friends, and mentors, as well as the career opportunities associated with a computer science degree and exposure to problem-solving, programming, online self-learning, and internships, influence students' decisions. Based on these results, the authors recommend that policymakers improve computer science education in schools by making it compulsory, introducing it at an earlier stage, incorporating more programming and problem-solving activities, and increasing the visibility of female role models and exemplars.

In Monteiro *et al.* (2022), a questionnaire survey was conducted with students from electrical engineering programs at a polytechnic higher education institution. The overall objective was to understand the motivations and expectations of students in order to contribute to institutions promoting actions to attract people to this area of knowledge, and adapt their programs to students' expectations and thus reduce academic dropouts or failure. Using content analysis, the results point out that students were motivated to pursue electrical engineering programs due to the fact that it is a broad area, with high employability and a wide variety of potential professional activities, and also due to their perception that the role of engineering reflects a generalized view that its objective is to improve the living conditions of humanity. Considering these results, the authors propose some actions to enhance the attractiveness of electrical engineering, including disseminating several examples of the practical applicability of electrical engineering with a strong impact on society and everyday people's lives, through concrete examples, and also making it more evident throughout the curricula in the various sub-areas, so that students develop an interest in any of these areas.

In Hagay and Baram-Tsabari (2011), a questionnaire survey was conducted to investigate high school students' interest in biology topics. The overall objective was to include students' voices in the curriculum and then enable researchers and practitioners to use these results to develop a curriculum that is more aligned with students' interests. Through qualitative analysis, the results indicate that half of the questions that students are interested in regarding genetics, the cardiovascular system, and the reproductive system are not covered by the national curriculum. This demonstrates that students' interests are a neglected factor, and the results from the article may serve as a tool to better link the curriculum to their interests and informational needs.

In AI education, some studies have quantitatively analyzed students' affective perspectives through surveys. For example, Hornberger et al. (2023, 2025) conducted quantitative surveys to investigate students' AI literacy, AI self-efficacy, interest in AI, attitudes towards AI, AI use, and students' prior learning experiences. In Hornberger et al. (2023), the overall objective was to develop and validate an instrument that can be used by professors, curriculum developers, and researchers to assess students. In Hornberger et al. (2025), the validated instrument was used among students in Germany, the UK, and the US. From a curriculum perspective, the studies offer recommendations for educators and policymakers on how to create effective learning opportunities based on students' affective perspectives, such as attitudes towards AI. Some of the recommendations provided in the studies include: investing in interdisciplinary courses where students can learn from each other, enabling all students to develop a critical understanding of AI, and providing hands-on experiences to develop practical experience and interest in AI, leading to AI literacy.

Chai et al. (2024) developed and validated a scale called the Artificial Intelligence Learning Intention Scale (AILIS), which supports the investigation of the factors influencing university students' behavioral intentions to learn about AI and their AI learning. The survey was distributed online among Chinese university students from various disciplines who reported a preliminary understanding of AI and was developed from the perspective of the theory of planned behavior. Of the seventeen hypothesized relationships among the factors, sixteen were supported. For example, supportive social norms, programming efficacy, design for social good, optimism, and personal relevance were positively associated with students' behavioral intention to learn AI. Based on these results, the authors made some recommendations for AI courses, such as designing tasks aimed at social good, including programming experience, and paying attention to the personal relevance of AI for students.

In Li et al. (2025b), researchers conducted a survey with undergraduate students using the validated AI motivation scale (Li et al., 2025a). The survey followed self-determination theory (SDT) as a theoretical framework. The authors used a network analysis approach to explore the motivational system of university students, as well as to identify the most central factor in students' AI motivation and its association with social context. Results showed that introjected regulation, i.e., engagement in learning to maintain self-esteem and avoid being perceived as incapable, was the primary driver of students' AI learning. However, according to SDT, intrinsic motivation and identified regulation are the optimal forms of motivation. Some of the implications of these results include that educators are encouraged to promote strategies to nurture students' intrinsic motivation, such as the need for clear goals and standards and the development of students' competence in using AI tools.

Therefore, this study complements previous contributions by investigating undergraduates' motivations to learn about AI and their learning interests in AI through qualitative research, specifically by applying an open-ended survey in a university introductory AI course. The investigation of these two affective perspectives can provide concrete actions and topics for the development of effective curriculum and learning experiences for

this audience, according to the MER for CSE. We interpret our results through situated expectancy-value theory and the Dagstuhl triangle.

4. Method

As previously pointed out, this work is motivated by the MER, which highlights the need to consider students' perspectives for the design of learning experiences (Kattmann et al., 1997; Duit, 2007; Diethelm et al., 2012; Grillenberger et al., 2016). These studies highlight that different methods can be used to investigate students' perspectives, including interviews, surveys, and written tasks (Grillenberger et al., 2016; Duit et al., 2012). Based on this, we adopted the questionnaire survey with open-ended questions as a method in this work to investigate students' affective perspectives on AI education, specifically their motivation and learning interests in the field.

4.1. Participants

This study took place during the first meetings of an introductory AI course, called "AI Across Domains", offered in the winter semester of 2024/2025, the summer semester of 2025, and the winter semester of 2025/2026 at Freie Universität Berlin, Germany. No pre-requisites were required to enroll, and enrollment in the course was voluntary and elective. During the first meeting, 19 students from the winter semester 2024/2025, 49 from the summer semester, and 60 from the winter semester 2025/2026 participated in the survey, resulting in a total sample size of $N = 128$. The domains of the students that participated in the survey can be seen in Table 1. Due to the major–minor structure of the study programs, some students were enrolled in more than one academic domain. All reported domains were documented, so the total number of domain entries exceeds the number of participants ($N = 128$). The objective of the course is to enable undergraduates across disciplines to explore the fundamental concepts of AI, its applications, and its social, ethical, and legal aspects, and to equip them with the necessary knowledge and relevant skills to use AI technologies in an effective and responsible way in their own domains.

Table 1: Participants' study domains by semester

Domain	S1	S2	S3	Total
Business Administration	4	11	12	27
Media and Communication Studies	5	5	4	14
Political Science	1	1	5	7
Economics	3	2	1	6
Language and Society	1	1	4	6
Film Studies	1	1	4	6

Continued on next page

Table 1: Participants' study domains by semester (Continued)

Computer Science	1	2	3	6
Geological Sciences	3	0	2	5
Geographical Sciences	0	3	2	5
Psychology	1	4	0	5
History	0	1	4	5
Chemistry	0	3	2	5
German Philology	2	2	1	5
Chinese Studies	0	2	2	4
Korean Studies	0	2	2	4
Philosophy	0	2	2	4
Art History	0	0	4	4
Educational Science	0	1	2	3
Biochemistry	1	2	0	3
Physics	0	0	2	2
Japanese Studies	0	1	1	2
English Philology	0	0	2	2
Social and Cultural Anthropology	0	0	2	2
North American Studies	0	1	0	1
Islamic Studies	0	1	0	1
Mathematics	0	0	1	1
Bioinformatics	0	0	1	1
Chinese Language and Society	0	0	1	1
International Relations	0	0	1	1
Theater Studies	0	0	1	1
Equine Science	0	0	1	1
Meteorology	0	0	1	1
Unspecified	0	1	1	2

Note: S1 = winter semester 2024/2025 ($n = 19$); S2 = summer semester 2025 ($n = 49$); S3 = winter semester 2025/2026 ($n = 60$). Unspecified = students who did not report a domain.

4.2. Survey procedure and data collection

The course was delivered online. However, the first and last meetings took place in person at the university. At the beginning of the first meeting, students were asked to complete a questionnaire survey so that the professors could collect information on students' motivations and interests in AI. The professors provided a QR code, and students were redirected to an online survey. The first page of the survey contained an informed consent form that described the survey's objective, the procedure, and information about the

researchers involved. After reading the form and agreeing to participate in the research study, the students began the survey. The survey consisted of three questions: *Q1: What motivates you to learn about AI? Q2: What do you most want to learn about AI? Q3: What is your domain?* The professors did not restrict the time for the students to answer all the questions. Besides the survey, in the first meeting, students had the opportunity to meet the professors and each other, be presented with what they were going to learn during the semester, understand the details about the course, such as requirements, assessments, the final project, and ask questions. Across all three semesters, the survey included the same three questions, and the administration timing, objectives, procedure, and basic course context of the first meeting remained consistent. Participation was voluntary and anonymous and had no influence on course assessment. The data from the three semesters were combined to identify recurring themes among students enrolled in the course, rather than to conduct comparative analyses. We included semester-level counts to ensure transparency. The study was approved by the Central Ethics Committee of the university.

4.3. Data analysis

The qualitative data analysis was conducted using the directed qualitative content analysis method (Hsieh and Shannon, 2005). In this approach, existing theory or prior research informs the initial coding scheme, and additional codes may be developed during the data analysis process (Hsieh and Shannon, 2005). The process of data analysis followed the framework suggested by Elo and Kyngäs (2008), which includes three main phases: (1) preparing the data, (2) organizing the data into categories and subcategories, and (3) reporting the findings. Students originally wrote their responses in German. The responses were then translated into English using Google Translate. The second and third authors, fluent in German and English, verified the accuracy of these translations before coding to ensure the meaning was preserved.

To analyze students' motivation to learn about AI, we employed situated expectancy-value theory (SEVT) (Eccles and Wigfield, 2020) to initiate the categorization process. SEVT is particularly well suited for understanding the dynamic nature of students' motivation, as it identifies students' expectancies for success, task values, and cost as important determinants of their motivation and subsequent academic outcomes (Rosenzweig et al., 2019; Eccles and Wigfield, 2020). To analyze what students are interested in learning about AI, we used the Dagstuhl triangle (Brinda et al., 2016; Michaeli et al., 2023) to initiate the categorization process. The Dagstuhl triangle is a framework that supports the idea that education about digitalization phenomena should be examined through different perspectives to secure a sustainable education for the connected digital world. The three perspectives are the technological perspective (How does it work?), the socio-cultural perspective (What are the effects?), and the user-oriented perspective (How do I use it?).

During the preparation phase, the first author prepared an initial codebook, i.e., a set of codes and definitions to be used as a guide during the qualitative data analysis process (DeCuir-Gunby et al., 2011). The initial codebook consisted of categories derived from the SEVT constructs and the three perspectives of the Dagstuhl triangle. Each category

(i.e., each SEVT construct and Dagstuhl triangle perspective) was followed by a definition extracted from the papers of Eccles and Wigfield (2020) and Michaeli et al. (2023). The second and third authors read the initial codebook and familiarized themselves with the SEVT constructs and the Dagstuhl triangle perspectives. Afterward, the first three authors immersed themselves in the data assigned to them by repeatedly reading students' questionnaire responses to gain a comprehensive understanding (Vaismoradi et al., 2013). The first author read responses from all three semesters (S1-S3), the second author read responses from S1 and S2, and the third author read responses from S2 and S3.

In this phase, the unit of analysis and the coding unit were also selected (Elo and Kyngäs, 2008). Responses to Q1 and Q2 were analyzed separately, and the unit of analysis was the individual student's response to each question. Within individual responses, the coding unit was a part of the text whose content and meaning differed from those of the surrounding text (i.e., a passage or meaning unit) (Lindgren et al., 2020). In our data, a coding unit consisted of a passage expressing one distinct idea, e.g., one motivation to learn about AI or one learning interest. Therefore, a response was divided into more than one passage and could receive more than one code when its content shifted from one meaning to another. For example, the response of the following student for Q2, "I wanted to take this class to learn how to use AI tools more efficiently, but also to understand more about the technical background of it and its risks," was divided into three passages: (1) "to learn how to use AI tools more efficiently," coded as the user-oriented perspective; (2) "to understand more about the technical background", coded as the technological perspective; (3) "its risks," coded as the socio-cultural perspective. Repeated mentions of the same idea within a response were coded once.

In the organizing phase, the first three authors divided the initial coding as follows: the first author coded responses from all three semesters, the second author from S1 and S2, and the third author from S2 and S3. The researchers began coding passages from students' answers into categories based on the initial codebook. To code the subcategories, open coding was then applied. During open coding, students' passages were labeled with codes representing the core idea they conveyed. Passages that could not be assigned to a single SEVT construct, namely concerns about the ethical and societal implications of AI, were grouped into an additional, inductively derived category (Hsieh and Shannon, 2005). After the initial coding, all three authors reviewed, compared, and discussed their coding of both categories and subcategories in consensus meetings to ensure trustworthiness through collaborative debriefing, which provided different perspectives on the interpretation of the data (Creswell and Miller, 2000). Disagreements were resolved through discussion until consensus was reached. In this step, codes were added, renamed, or related codes were grouped. This iterative process of coding and discussion ensured that the final set of codes was robust and reflected the nuances of the data.

Finally, the results are presented in Section 5. The frequencies in Section 5 indicate the number of students whose responses included at least one passage assigned to the subcategory. As a result, individual students may be represented in multiple subcategories, and column totals may exceed the total number of participants. The data analysis process was supported by the qualitative analysis tool MAXQDA (Woolf and Silver, 2017).

5. Results

In this section, we aim to answer the two research questions posed in Section 1:

RQ1: What motivates undergraduates across disciplines to learn about AI?

RQ2: What are undergraduates across disciplines interested in learning about AI?

We divide our findings into two subsections (i.e., one subsection for each research question).

5.1. Motivation

The students who participated in the survey stated different motivations for learning about AI. To initiate the categorization process, we adopted SEVT (Eccles and Wigfield, 2020). Students' responses reflected three SEVT constructs: intrinsic value, utility value, and attainment value, as can be seen in Table 2. Moreover, many students' responses expressed motivation to learn about AI arising from concerns about the ethical and societal implications of AI. Because these concerns were linked to different types of value, we did not assign them to a single SEVT construct. Instead, we report them as an inductively derived category (Hsieh and Shannon, 2005). Below, we present the motivations cited by the students, and Table 2 provides an overview.

5.1.1. Attainment value

Attainment value concerns the extent to which a student finds a task to be personally meaningful or important. More specifically, the relative within-person attainment value derives from the assumed fit of perceived task characteristics with the individual's core self-schema, social and personal identities, and ought selves (Rosenzweig et al., 2019; Eccles and Wigfield, 2020). In our context, the concept refers to the extent to which learning about AI is personally important to students, since feeling competent in AI aligns with their identities as future professionals or students. Sixty-five students reported that they are motivated to learn about AI because they perceive AI as relevant due to its prevalence and importance in many areas of society and across domains, and reported that due to the importance of AI, they would like to be competent so they could "feel confident and have an informed presence in the working world".

5.1.2. Intrinsic value

According to SEVT (Rosenzweig et al., 2019; Eccles and Wigfield, 2020), intrinsic value (sometimes called interest value) refers to the extent to which a student is interested in or enjoys doing a task. In our context, this refers to the extent to which a student is interested in and enjoys learning about AI. For the intrinsic value category, three main subcategories emerged: curiosity/interest ($n = 27$), enjoyment ($n = 5$), and excitement ($n = 5$). Curiosity or interest was the most frequently cited subcategory. Several students expressed curiosity about specific tools. For instance, a student from Korean Studies mentioned an interest in "tools for translation and how advanced they are." Others were curious to understand how AI methods and systems are applied in different domains, such as medicine and psychotherapy. Some students were curious to learn how AI systems work technically.

For example, a psychology student stated an interest in "knowing exactly how AI systems such as ChatGPT work technically." Additionally, some students wanted to learn about AI because they enjoyed using AI tools and wanted to know more about them, as reflected in comments such as "I really enjoy working with ChatGPT and NotebookLM." Finally, a number of students described AI as an exciting field and expressed a wish to "stay up to date with the latest knowledge."

5.1.3. *Utility value*

Utility value refers to the extent to which a student believes a task will be useful for current or future goals (Rosenzweig et al., 2019; Eccles and Wigfield, 2020). In our context, this refers to the extent to which a student believes that learning about AI will be useful for current or future goals. Fifty-three students reported being motivated to learn about AI because they perceive AI competencies as useful for their work or studies. Some students were already working professionally with AI systems and wished to deepen their knowledge (e.g., "I have actually been working professionally on implementing AI in a company for quite some time now, and I look forward to continuing to use and develop my knowledge!"). Others, although not currently using AI systems in their professional activities, recognized its growing relevance across various fields. For example, a student from Business Administration stated that they are motivated because they see "professional advantages, since AI expertise is becoming increasingly important in many jobs." Similarly, a student from Economics reported that they think AI will become more widespread and want to learn more about it so they can use it to their advantage and adapt to the changes ahead, especially for professional purposes.

5.1.4. *Ethical and societal concerns*

Twenty-four students were motivated to learn about AI because they were concerned about its effects on society. For example, a student stated, "AI will play an important role in all areas in the future, and we need to learn/recognize where potential dangers can arise, especially in research." Another student pointed out, "In my opinion, AI has great potential, but also dangers if not used properly. That's why I want to learn more about it and strengthen my skills," and another stated, "I think generally I am fascinated by all moral, anthropological, practical, and psychological questions and issues around AI."

Table 2: Participants' motivation to learn about AI by semester

Category	Motivation	S1	S2	S3	Total
Attainment value	Perceive AI as a highly prevalent and relevant field nowadays, and learning about it is personally important to them as future professionals who want to be competent in the field.	14	24	27	65
Intrinsic value	Curious/interested in the topic of AI	6	9	12	27
	Enjoy using AI systems	1	2	2	5
	Find AI an exciting field	1	1	3	5
Utility value	Find that AI competencies will be useful/helpful for current or future goals in private, work, or study life	9	10	34	53
Ethical and societal concerns	Care about the ethical implications of AI on society, research, and across domains	2	10	12	24

Note: S1 = winter semester 2024/2025 ($n = 19$); S2 = summer semester 2025 ($n = 49$); S3 = winter semester 2025/2026 ($n = 60$).

5.2. Learning interests

Students who participated in the survey stated different learning interests regarding AI. The results will be depicted through three subsections, according to the Dagstuhl triangle perspectives: technological perspective ("What is AI and how do AI methods/systems work?"), socio-cultural perspective ("What are the effects of AI?"), and user-oriented perspective ("How do I use AI systems?"). The overview of the results can be seen in Table 3.

5.2.1. Technological perspective

Within the technological perspective, the most cited learning interest from students is learning how AI methods, algorithms, and models work ($n = 30$). Some examples of responses are "How do the models behind AI systems work?", "How does the self-learning mechanism work?", "How does it work on a technological level?". Students also expressed interest in the technical limitations of AI systems ($n = 22$). Some examples of responses are "Why do AI systems generate inaccurate outputs?", "How reliable is the information provided by AI systems?" and "What are the weak points of AI systems?"

Moreover, ten students were also interested in the topic of the future of AI. For example, student responses included, "What hinders artificial general intelligence (AGI) development?" and another student answered, "What is the next big milestone?", and "What can we expect in the future?". In addition, six students expressed interest in having an overview of the field of AI. For example, one student answered, "I would like to find out more about how it is structured", and another student answered, "What exactly does the term AI cover, and what subcategories are there?"

Students are also interested in learning about data in the context of AI. Five students answered that they would like to learn what data is used for training AI models and where it comes from. Additionally, two students expressed interest in understanding what happens to their data when they use AI systems (e.g., "Where does my data go?"). Finally, one student pointed out an interest in understanding the difference between AI systems and traditional systems.

5.2.2. *Socio-cultural perspective*

Within the socio-cultural perspective, the most frequently stated learning interest among students is to learn about the positive and negative effects of AI systems on society and the environment ($n = 30$). Within this category, for example, some students showed interest in the topic of the replacement of humans in workplaces. A student answered, "Can jobs actually be replaced by AI?" Other students showed interest specifically in learning the impact of AI systems on the environment. For example, one student pointed out, "What impact does AI use have on climate change?".

Moreover, thirteen students were interested in learning about strategies for mitigating negative effects and ensuring that AI serves the good of all people. For example, one student pointed out, "Is there an estimate of how high the energy consumption is for the use of AI systems, and are there ways of limiting it?" and another student pointed out, "How can AI systems make people's lives easier instead of taking work away from them?". Also, other students showed interest in learning how AI systems can be compliant with data protection and copyright requirements. Furthermore, five students also indicated interest in learning about the legal aspects.

Students also expressed interest in having an overview of AI systems that are available and for which tasks they can be applied ($n = 12$). For example, a student answered, "I would like to know more about how AI is used in different areas in general, so no specific question, more of a desire for an overview that will help me find my way around this topic". In addition, students are also interested in having an overview of which areas AI systems are mostly used in and how AI systems are being applied in different areas ($n = 12$). For example, a student answered, "I am also interested in the extent to which AI can support users in creative processes, such as writing songs," and another student answered, "In which professional fields does AI currently have the greatest significance?"

Four students also expressed interest in learning which skills are necessary for the working world and how knowledge about AI will stay relevant while the field itself is changing fast. For example, one student answered, "What skills are necessary for the working world?" Finally, one student expressed interest in learning more about the history of AI, and another in experts' perspectives on AI development.

5.2.3. *User-oriented perspective*

Within the user-oriented perspective, the most cited learning interest was to learn how to use AI systems effectively for study and work ($n = 26$). Furthermore, nine students are also interested in learning how to interact with AI systems to avoid inaccurate outputs. Students answered, for example, "How can I handle AI hallucinations?", "How can AI be

used without receiving partially incorrect information?". Nine students are also interested in learning how to detect AI-generated content. For example, a student answered, "How should videos created using AI be assessed in terms of credibility?". Five students are also interested in learning how to use AI systems in order to protect themselves from risks. Finally, one student was interested in learning how to develop an AI assistant.

Table 3: Participants’ learning interests regarding AI by semester

AI perspective	Learning interests	S1	S2	S3	Total
Technological	Functioning: AI methods, algorithms and models				
	How do the AI methods, algorithms, and models work?	5	7	18	30
	What does the field of AI encompass?	2	1	3	6
	Capabilities and limitations				
	What are the limitations of AI systems?	7	8	7	22
	What does the future development of AI look like?	3	3	4	10
	Data in the context of AI				
	What data is used, and where does the data for training AI come from?	3	1	1	5
	What happens with my data when I use AI systems?	1	1	0	2
	AI systems vs. traditional systems				
	What is the difference between AI systems and traditional systems?	0	1	0	1
Socio-cultural	Societal, ethical, and legal implications				
	What are the positive and negative effects that AI systems bring?	7	10	13	30
	How can we mitigate the negative effects and ensure that artificial intelligence truly serves the good of all people?	5	2	6	13
	What are the legal frameworks?	0	2	3	5
	What do experts think about AI development?	0	0	1	1
	AI in society, student life and work life				
	Which AI systems are there and for which tasks?	2	5	5	12

Continued on next page

Table 3: Participants' learning interests regarding AI by semester (Continued)

User-oriented	Which areas are AI systems being mostly used in?	2	3	7	12
	How are AI systems being applied in different areas?				
	Needed skills				
	What skills are necessary for the working world?	0	1	3	4
	How will knowledge about AI stay relevant while the field itself is changing fast?				
	History of AI				
	Since when do AI systems actually exist?	0	0	1	1
	Effective AI interaction				
	How can I use AI systems effectively for my studies and work?	11	3	12	26
	Safe and responsible AI use				
	How can I use AI systems in a way that avoids errors?	4	3	2	9
	How can I be safe when I use AI systems?	2	3	0	5
	Identifying and evaluating AI outputs				
	How can I detect whether it is AI-generated content and evaluate its credibility?	5	1	3	9
	Building an AI assistant				
	How can I develop an AI assistant?	0	1	0	1

Note: S1 = winter semester 2024/2025 ($n = 19$); S2 = summer semester 2025 ($n = 49$); S3 = winter semester 2025/2026 ($n = 60$).

6. Discussion

Our results provide concrete resources to inform the design of learning experiences on AI for undergraduates across disciplines. Based on the MER for CSE (Diethelm et al., 2012; Grillenberger et al., 2016), these students' perspectives are important to consider for curricula and course design, alongside analyses of content structure, social demands, and teachers' perspectives. In the following, we distinguish between (a) what students reported and interpretations supported by previous literature, and (b) examples of curricular application that we propose as illustrations, based on our findings. It is important to highlight that the latter are not direct findings of the survey, but are illustrations of how our results can be translated into practice.

6.1. *Motivations for learning about AI*

Student-reported findings and interpretation considering previous literature

Students described motivations that encompass attainment, utility, and intrinsic values, as well as ethical and societal concerns, rather than career-related utility alone. Attainment value was the most frequently coded category ($n = 65$). Students whose responses were coded as attainment value considered it personally meaningful to be good professionals in their fields. Because they perceive that AI systems are becoming very relevant in different areas, they want to learn about AI to be competent as professionals, not only because it is a useful skill for their work or studies. They want to feel confident and informed as a journalist, economist, scientist, or citizen, for example.

Utility value was the second most frequently coded category ($n = 53$). These students wanted to learn about AI because it will be useful for current or future goals in their work or studies. We would like to highlight that this interpretation should be treated with caution, since the boundary between attainment and utility value is subtle, as utility value can also connect to personal goals and sense of self (Eccles and Wigfield, 2020), and the coders experienced this difficulty during the analysis (see Section 7).

Intrinsic value was the third most frequently coded category in our study, indicating it was referenced less often than attainment value and utility value. In a study grounded in SDT, Li *et al.* (2025b) analyzed the motivation of undergraduates to learn AI in Greater China, including Mainland China and Hong Kong. They similarly found intrinsic motivation to be less central than other types of motivation, including introjected regulation (i.e., engagement in learning to maintain self-esteem and avoid being perceived as an incapable person) and external regulation (i.e., engagement in learning due to external reasons such as punishments or rewards). However, these results are not directly comparable with ours, because they are grounded in different theories, rely on rating scales rather than spontaneously reported motives, and our participants did not describe introjected or external motives.

Moreover, ethical and societal concerns also emerged as a prominent category. Twenty-four students reported motivation to learn about AI due to its ethical and societal implications and the desire to better understand associated dangers and risks. Some students identified acquiring knowledge of AI ethics as important, while others emphasized the significance of responsible system use as a meaningful competence. Additionally, some students expressed fascination with topics related to AI ethics.

Illustrative curricular application

These findings can inspire future research related to course development and help professors better encourage these students to enroll in introductory AI courses. For example, invitations to AI courses for this audience may highlight that the course aims to provide personally meaningful and socially important skills, acknowledging the increasing prevalence and relevance of AI, the ethical challenges it raises, and its value for students' career paths and educational goals.

6.2. Students' learning interests

Regarding learning interests, students reported interest in learning the technical, practical, and socio-cultural dimensions of AI, i.e., all three perspectives of the Dagstuhl triangle framework, which a comprehensive AI literacy curriculum would ideally cover (Michaeli et al., 2023).

6.2.1. Technological perspective

Student-reported findings and interpretation considering previous literature

Within the technological perspective, the most frequently stated interest was learning how AI methods, algorithms, and models work ($n = 30$). Regarding their interest in how AI works, they normally formulated it at a general level, without naming specific methods or algorithms. Students' interest in learning how AI methods, algorithms, and models work is in alignment with opinions from professionals working at the intersection between AI and other domains, where most participants stated that students need to learn how ML techniques and their main algorithms work (Tenório and Romeike, 2024). Unlike students, professionals were more specific about which AI methods should be learned, mainly pointing out the ML techniques: supervised, unsupervised, and reinforcement learning, and more advanced techniques, such as artificial neural networks and more advanced architectures, such as transformers (Tenório and Romeike, 2024).

Moreover, students reported learning interest in the limitations of AI systems ($n = 22$). Smaller numbers of students showed interest in the future development of AI ($n = 10$), what the field of AI encompasses ($n = 6$), where training data come from ($n = 5$), what happens to their own data when they use AI systems ($n = 2$), and how AI systems differ from traditional systems ($n = 1$).

Illustrative curricular application

Following the MER for CSE (Grillenberger et al., 2016), the AI methods pointed out as relevant in previous works (Tenório and Romeike, 2024; Michaeli et al., 2023), along with context relevant to undergraduate students, can support the derivation of phenomena that can be used to develop learning materials that motivate students during the learning process by connecting them to prior knowledge.

The following examples are not derived from the results, but they illustrate how the reported interests could be addressed. For example, to enable students to learn about unsupervised learning (an AI method), a context related to undergraduates across disciplines can be selected, such as business, and then a phenomenon in the intersection of unsupervised learning and business can be selected, such as customer segmentation (Saxena et al., 2024; Shen, 2021). This phenomenon could further guide the development of lessons that address students' interests. Students can learn about this, for example, through a simulation that demonstrates how an unsupervised learning algorithm, such as k-means, iteratively groups customers into clusters by assigning each customer to the nearest cluster center and updating the centers, and how the resulting segments must then be interpreted by humans. This is in line with work in the field of AI literacy (Long and Magerko, 2020), which recommends using graphical visualizations, simulations, explanations of agent decision-

making processes, or interactive demonstrations to aid non-technical learners' understanding of AI.

Concerning the second learning interest most coded in the technological perspective, students stated they are not only interested in understanding how AI systems work but also in going a step further to understand their limitations arising from their internal mechanisms. For example, students were particularly interested in inaccuracies in the outputs of AI systems (i.e., why do AI systems infer incorrect results?). This could be addressed in learning experiences in different ways. For example, when students are learning about how ML systems work, they can learn that a ML model learns the patterns of the training data and generalizes what it has learned to new, unseen data to infer outputs in real-world contexts (Domingos, 2012; OECD, 2024). However, the model may not work well with unknown, new data (Domingos, 2012). One of the main reasons for this, for example, is that the performance of a model is often related to the quality and quantity of the data used for training, and care must be taken to collect or acquire a large amount of high-quality data that can represent the target population (Sarker, 2021; Gallegos et al., 2024; Anh-Hoang et al., 2025). Therefore, students need to be critical when using outputs from machine-learning-based AI systems, since these systems infer outputs based on what they have learned, and the inferences can be inaccurate.

Besides that, students also stated interest in learning more about training data, where it comes from, and what happens to the data provided when using AI systems, as well as the distinction between AI systems and traditional systems, and what the field of AI encompasses. Some helpful sources to provide science content structure to develop didactic materials about these topics are OECD papers, such as the policy paper that maps the principal mechanisms currently used to source data for training AI systems (OECD, 2025) and the memorandum that contains clarifications to the definition of an AI system (OECD, 2024). Finally, these findings indicate that many students explicitly request explanations of AI's internal mechanisms rather than only usage skills, although their requests remain at a high level of abstraction. They provide educators with concrete objectives for incorporating technical content that responds to these interests.

6.2.2. *Socio-cultural perspective*

Student-reported findings and interpretation considering previous literature

The most cited interest related to the socio-cultural perspective was learning about the positive and negative effects that AI systems bring ($n = 30$), with students referring, for example, to the replacement of human workers and the environmental impact of AI. These findings align with previous studies involving professionals working at the intersection of AI and other domains (Tenório and Romeike, 2024) and university lecturers from different disciplines (Tenório et al., 2025), both of which emphasized the importance of understanding AI-related ethical and societal issues.

Moreover, thirteen students also showed interest in learning how the negative effects can be mitigated and how AI can serve "the good of all people". Students also pointed out interest in learning which AI systems exist and for which tasks ($n = 12$), in which areas AI systems are mostly used and how they are applied ($n = 12$), what legal frameworks

apply ($n = 5$), which skills are needed for the working world ($n = 4$), what experts think about AI development ($n = 1$), and since when AI systems have existed ($n = 1$).

Illustrative curricular application

Some of the negative issues of AI systems are related to their technical functionalities. For example, the negative environmental impact of current AI systems, mainly generative AI systems, is partly due to the way these systems work. The environmental impact of AI systems, raised by students interested in energy consumption and climate effects, can illustrate how such an interest can be educationally reconstructed as a phenomenon serving multiple Dagstuhl perspectives simultaneously. The following examples do not originate from the study's results, but they serve to demonstrate potential approaches for addressing the reported interests. For example, following the MER for CSE (Grillenberger et al., 2016), this interest can be addressed through a teaching sequence anchored in the technological perspective: once students understand what parameters are and how the training of deep neural networks proceeds through repeated computations (LeCun et al., 2015), they can more easily learn why training and inference phases of large models based on deep neural networks, such as large language models (LLMs), in data centers can be energy- and water-intensive (Bourzac, 2024; Mytton, 2021; Crawford, 2024). Building on this technical understanding, the second most cited interest of the socio-cultural perspective (i.e., students also interested in how these negative effects can be mitigated) can then be addressed by examining mitigation strategies proposed for industry, research, and policy (Crawford, 2024). This may include legal frameworks such as the EU AI Act (European Union, 2024), thereby also serving the interests of some students who wished to learn about legal aspects. In this way, a single phenomenon connects students' interest in how AI works with their interest in its societal effects and in mitigating negative impacts, exemplifying the joint didactic processing of technological and socio-cultural perspectives.

6.2.3. User-oriented perspective

Student-reported findings and interpretation considering previous literature

The most frequently cited interest within the user-oriented perspective was learning to use AI systems effectively for their studies and work ($n = 26$). This suggests that students aim not only to develop a conceptual understanding of AI systems and their societal effects, but also practical skills for applying AI in their studies and work. This is in alignment with the Dagstuhl triangle, which posits that only joint didactic processing (socio-cultural, user-oriented, and technological perspectives) can lead to a well-founded and sustainable education in the digitally networked world (Brinda et al., 2016).

Illustrative curricular application

When learning experiences are developed, the effective use of AI systems for students' studies and work can be taught together with the technical understanding of AI systems and their positive and negative effects on society and the environment. The following examples are not derived from the results but illustrate how the reported interests may be addressed. For example, in the case of the phenomenon of language generation, students can first understand what LLMs can do and how they work, then learn about their positive and negative effects, and then learn how to use AI systems based on LLMs to support the

performance of tasks required in studies and work lives, such as learning prompt strategies that increase the quality of LLM outputs and mitigate hallucinations (Lin, 2024; Anh-Hoang *et al.*, 2025; Wang *et al.*, 2024).

Furthermore, students are also interested in learning how to use AI systems responsibly and safely. Nine students expressed interest in learning strategies to detect AI-generated content and evaluate its credibility, and five in protecting themselves from risks. These risks could include, for example, deepfakes (Mustak *et al.*, 2023), misinformation (Park and Nan, 2025), and superficial texts with hallucinations (Huang *et al.*, 2025). This suggests that courses for this audience may benefit from dedicating time to the practical use of AI systems, critical analysis of the possible effects of AI outputs (Pawelec, 2022), the evaluation of the veracity and credibility of content following some guidelines, and the understanding of mitigation strategies such as watermarks in AI-generated content and mandatory labeling of AI outputs in social media (Jones, 2023; Romero Moreno, 2024) in order to be critical users. A course that addresses this may increase its perceived utility. Moreover, such skills may support students in using AI systems responsibly in their academic and professional tasks.

7. Conclusion, limitations and future work

In this study, we presented the results of a survey performed with 128 undergraduates across disciplines during the first meeting of an introductory AI course at a German university. The objective of the survey was to collect undergraduate students' motivations to learn about AI and their learning interests. The results, presented in Section 5, provide curriculum developers with an empirical basis for designing learning experiences aligned with the motivations and interests of students who enroll in such courses. In Section 6, we provide suggestions for leveraging the results to advance AI education for undergraduates across disciplines, including recommendations on how the technological, user-oriented, and socio-cultural perspectives can be jointly taught in meaningful, effective learning experiences.

A first limitation concerns the analysis of the data related to students' motivation to learn AI. The first three authors who participated in the process faced difficulties during the coding process in differentiating between answers that were related to attainment value and utility value. However, this was expected, since the distinction between these constructs is subtle: utility value can also connect to personal goals and sense of self, and so has some ties to attainment value (Eccles and Wigfield, 2020). This was mitigated through a collaborative review process composed of several discussions until a consensus was reached. Moreover, responses to the open-ended question elicited only three SEVT constructs: intrinsic, utility, and attainment value. Other constructs, including expectancies for success and perceived costs, may still influence students' motivation, but were not identified through this question. This outcome is likely a result of the elicitation method, which relied on a single open-ended question on motivation, rather than evidence that expectancy beliefs or perceived costs were absent. Future studies could combine open-ended questions with items that explicitly address expectancy and cost, such as perceived difficulty or concerns regarding mathematical or programming prerequisites.

Furthermore, data were collected between October 2024 and October 2025, a period of rapid change in the capabilities of AI systems, public debate, and regulation (Maslej et al., 2025). Students' motivations and interests are probably shaped by this rapidly evolving AI field. Therefore, the identified themes need to be interpreted as situated in this period and may change as the AI field evolves. Moreover, the sample comprises students who voluntarily enrolled in an elective AI course at one university. Consequently, the reported motivations and interests cannot be generalized to all undergraduates across disciplines and do not address the perspectives of students who choose not to pursue AI education, who may represent a critical audience for AI literacy initiatives. Future research could examine motivations and barriers among non-enrolled students, for instance, by administering surveys outside the context of AI courses, and considering international or cross-institutional perspectives. Finally, researchers in AI education may integrate this study's findings and recommendations with related results from the existing literature to inform the development of AI curricula and learning experiences for undergraduates across diverse disciplines.

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Declarations

- **Ethical Approval** This study was approved by the Central Ethics Committee of Freie Universität Berlin (ZEA26026) in accordance with the recommendations of the relevant scientific societies in Germany.
- **Consent to Participate** Students provided consent to the use of their anonymized data for research purposes before starting the questionnaire. Participants' confidentiality and anonymity were strictly maintained to protect their privacy throughout the study.
- **Availability of supporting data** The data are available from the corresponding author upon request.
- **Competing interests** The authors have no competing interests to declare that are relevant to the content of this article.
- **Authors' contributions** Conceptualization: Kamilla Tenório and Ralf Romeike; Methodology: Kamilla Tenório; Formal analysis and investigation: Kamilla Tenório, Emma Lessmann, Esra Lewin; Writing - original draft preparation: Kamilla Tenório; Writing - review and editing: Kamilla Tenório, Emma Lessmann, Esra Lewin, Ralf Romeike; Funding acquisition: Ralf Romeike; Supervision: Kamilla Tenório and Ralf Romeike. All authors agreed with the content and gave explicit consent to submit.
- **Declaration of generative AI and AI-assisted technologies** German responses were translated into English using Google Translate and checked by the second and third

authors before coding. During the preparation of this work, the authors used Grammarly, Claude (Anthropic), and ChatGPT (OpenAI) to support language refinements and suggest improvements to the article's wording and structure. After using the tools, the authors carefully reviewed and edited the content as necessary, assuming full responsibility for the publication's content.

References

- Al-Zahrani, A. M. and Alasmari, T. M. (2024). Exploring the impact of artificial intelligence on higher education: The dynamics of ethical, social, and educational implications. *Humanities and Social Sciences Communications*, 11(1):912. <https://doi.org/10.1057/s41599-024-03432-4>.
- Alshahrani, A., Ross, I., and Wood, M. I. (2018). Using Social Cognitive Career Theory to Understand Why Students Choose to Study Computer Science. In *Proceedings of the 2018 ACM Conference on International Computing Education Research*, ICER '18, pages 205–214, New York, NY, USA. Association for Computing Machinery. <https://doi.org/10.1145/3230977.3230994>.
- Anh-Hoang, D., Tran, V., and Nguyen, L.-M. (2025). Survey and analysis of hallucinations in large language models: attribution to prompting strategies or model behavior. *Frontiers in Artificial Intelligence*, 8. <https://doi.org/10.3389/frai.2025.1622292>.
- Bourzac, K. (2024). Fixing AI's energy crisis. *Nature*. <https://doi.org/10.1038/d41586-024-03408-z>.
- Brinda, T., Diethelm, I., Gemulla, R., Romeike, R., Schöning, J., and Schulte, C. (2016). Dagstuhl-Erklärung: Bildung in der digitalen vernetzten Welt. Technical report, Gesellschaft für Informatik.
- Bringsjord, S. and Govindarajulu, N. S. (2024). Artificial Intelligence. In Zalta, E. N. and Nodelman, U., editors, *The Stanford Encyclopedia of Philosophy*. Metaphysics Research Lab, Stanford University, fall 2024 edition.
- Chai, C. S., Yu, D., King, R. B., and Zhou, Y. (2024). Development and Validation of the Artificial Intelligence Learning Intention Scale (AILIS) for University Students. *Sage Open*, 14(2):21582440241242188. <https://doi.org/10.1177/21582440241242188>.
- Christidou, V. (2006). Greek Students' Science-related Interests and Experiences: Gender differences and correlations. *International Journal of Science Education*, 28(10):1181–1199. <https://doi.org/10.1080/09500690500439389>.
- Crawford, K. (2024). Generative AI's environmental costs are soaring — and mostly secret. *Nature*, 626(8000):693–693. <https://doi.org/10.1038/d41586-024-00478-x>.
- Creswell, J. W. and Miller, D. L. (2000). Determining Validity in Qualitative Inquiry. *Theory Into Practice*, 39(3):124–130. https://doi.org/10.1207/s15430421tip3903_2.
- de Lima-Santos, M.-F. and Ceron, W. (2022). Artificial Intelligence in News Media: Current Perceptions and Future Outlook. *Journalism and Media*, 3(1):13–26. <https://doi.org/10.3390/journalmedia3010002>.
- DeCuir-Gunby, J. T., Marshall, P. L., and McCulloch, A. W. (2011). Developing and Using a Codebook for the Analysis of Interview Data: An Example from a Professional Development Research Project. *Field Methods*, 23(2):136–155. <https://doi.org/10.1177/1525822X10388468>.
- Diethelm, I., Hubwieser, P., and Klaus, R. (2012). Students, teachers and phenomena: educational reconstruction for computer science education. In *Proceedings of the 12th Koli Calling International Conference on Computing Education Research*, Koli Calling '12, pages 164–173, New York, NY, USA. Association for Computing Machinery. <https://doi.org/10.1145/2401796.2401823>.
- Domingos, P. (2012). A few useful things to know about machine learning. *Communications of the ACM*, 55(10):78–87. <https://doi.org/10.1145/2347736.2347755>.
- Duit, R. (2007). Science Education Research Internationally: Conceptions, Research Methods, Domains of Research. *Eurasia Journal of Mathematics, Science and Technology Education*, 3(1):3–15. <https://doi.org/10.12973/ejmste/75369>.
- Duit, R., Gropengießer, H., Kattmann, U., Komorek, M., and Parchmann, I. (2012). The Model of Educational Reconstruction – a Framework for Improving Teaching and Learning Science. In Jorde, D. and Dillon, J., editors, *Science Education Research and Practice in Europe: Retrospective and Prospective*, pages 13–37. SensePublishers, Rotterdam. https://doi.org/10.1007/978-94-6091-900-8_2.

- Eaton, E. and Epstein, S. L. (2024). Artificial Intelligence in the CS2023 Undergraduate Computer Science Curriculum: Rationale and Challenges. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(21):23078–23083. <https://doi.org/10.1609/aaai.v38i21.30352>.
- Eccles, J. S. and Wigfield, A. (2020). From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, 61:101859. <https://doi.org/10.1016/j.cedpsych.2020.101859>.
- Elo, S. and Kyngäs, H. (2008). The qualitative content analysis process. *Journal of Advanced Nursing*, 62(1):107–115. <https://doi.org/10.1111/j.1365-2648.2007.04569.x>.
- European Union (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act).
- Gallegos, I. O., Rossi, R. A., Barrow, J., Tanjim, M. M., Kim, S., Dernoncourt, F., Yu, T., Zhang, R., and Ahmed, N. K. (2024). Bias and Fairness in Large Language Models: A Survey. *Computational Linguistics*, 50(3):1097–1179. https://doi.org/10.1162/coli_a_00524.
- Grillenberger, A., Przybylla, M., and Romeike, R. (2016). Bringing CS Innovations to the Classroom: a Process Model of Educational Reconstruction. In Brodnik, A. and Tort, F., editors, *Proceedings of 9th International Conference on Informatics in Schools: Situation, Evolution, and Perspectives, ISSEP 2016*, pages 31–39. Münster, DE.
- Hagay, G. and Baram-Tsabari, A. (2011). A Shadow Curriculum: Incorporating Students' Interests into the Formal Biology Curriculum. *Research in Science Education*, 41(5):611–634. <https://doi.org/10.1007/s11165-010-9182-5>.
- Harackiewicz, J. M., Smith, J. L., and Priniski, S. J. (2016). Interest Matters: The Importance of Promoting Interest in Education. *Policy insights from the behavioral and brain sciences*, 3(2):220–227. <https://doi.org/10.1177/2372732216655542>.
- Haug, C. J. and Drazen, J. M. (2023). Artificial Intelligence and Machine Learning in Clinical Medicine, 2023. *New England Journal of Medicine*, 388(13):1201–1208. <https://doi.org/10.1056/NEJMr2302038>.
- Hornberger, M., Bewersdorff, A., and Nerdel, C. (2023). What do university students know about Artificial Intelligence? Development and validation of an AI literacy test. *Computers and Education: Artificial Intelligence*, 5:100165. <https://doi.org/10.1016/j.caeai.2023.100165>.
- Hornberger, M., Bewersdorff, A., Schiff, D. S., and Nerdel, C. (2025). A multinational assessment of AI literacy among university students in Germany, the UK, and the US. *Computers in Human Behavior: Artificial Humans*, 4:100132. <https://doi.org/10.1016/j.chbah.2025.100132>.
- Hsieh, H.-F. and Shannon, S. E. (2005). Three Approaches to Qualitative Content Analysis. *Qualitative Health Research*, 15(9):1277–1288. <https://doi.org/10.1177/1049732305276687>.
- Huang, L., Yu, W., Ma, W., Zhong, W., Feng, Z., Wang, H., Chen, Q., Peng, W., Feng, X., Qin, B., and Liu, T. (2025). A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions. *ACM Trans. Inf. Syst.*, 43(2):42:1–42:55. <https://doi.org/10.1145/3703155>.
- Humbert, L. and Puhlmann, H. (2004). Essential ingredients of literacy in informatics. In Magenheimer, J. and Schubert, S., editors, *Informatics and Student Assessment. Concepts of empirical research and standardisation of measurement in the area of didactics of informatics.*, pages 65–76. GI, Gesellschaft für Informatik, Bonn.
- Jones, N. (2023). How to stop AI deepfakes from sinking society — and science. *Nature*, 621(7980):676–679. <https://doi.org/10.1038/d41586-023-02990-y>.
- Kattmann, U., Duit, R., Gropengießer, H., and Komorek, M. (1997). Das Modell der Didaktischen Rekonstruktion - Ein Rahmen für naturwissenschaftsdidaktische Forschung und Entwicklung. *Zeitschrift für Didaktik der Naturwissenschaften : ZfDN*, 3(3):3–18.
- Krishnan, G., Singh, S., Pathania, M., Gosavi, S., Abhishek, S., Parchani, A., and Dhar, M. (2023). Artificial intelligence in clinical medicine: catalyzing a sustainable global healthcare paradigm. *Frontiers in Artificial Intelligence*, 6. <https://doi.org/10.3389/frai.2023.1227091>.
- Kshetri, N., Dwivedi, Y. K., Davenport, T. H., and Panteli, N. (2024). Generative artificial intelligence in marketing: Applications, opportunities, challenges, and research agenda. *International Journal of Information Management*, 75:102716. <https://doi.org/10.1016/j.ijinfomgt.2023.102716>.
- Kumar, V., Ashraf, A. R., and Nadeem, W. (2024). AI-powered marketing: What, where, and how? *International Journal of Information Management*, 77:102783. <https://doi.org/10.1016/j.ijinfomgt.2024.102783>.
- Laupichler, M. C., Aster, A., Schirch, J., and Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. *Computers and Education: Artificial Intelligence*, 3:100101. <https://doi.org/10.1016/j.caeai.2022.100101>.

- Law, K., Lee, V., and Yu, Y. (2010). Learning motivation in e-learning facilitated computer programming courses. *Computers and Education*, 55(1):218–228. <https://doi.org/10.1016/j.compedu.2010.01.007>.
- LeCun, Y., Bengio, Y., and Hinton, G. (2015). Deep learning. *Nature*, 521(7553):436–444. <https://doi.org/10.1038/nature14539>.
- Li, J., King, R. B., Chai, C. S., Zhai, X., and Lee, V. W. Y. (2025a). The AI Motivation Scale (AIMS): a self-determination theory perspective. *Journal of Research on Technology in Education*, 58(5):961–982. <https://doi.org/10.1080/15391523.2025.2478424>.
- Li, J., Zhang, J., Chai, C. S., Lee, V. W. Y., Zhai, X., Wang, X., and King, R. B. (2025b). Analyzing the network structure of students' motivation to learn AI: a self-determination theory perspective. *npj Science of Learning*, 10(1):48. <https://doi.org/10.1038/s41539-025-00339-w>.
- Liben-Nowell, D. and Rafferty, A. N. (2022). Student Motivations and Goals for CS1: Themes and Variations. In *Proceedings of the 53rd ACM Technical Symposium on Computer Science Education - Volume 1*, volume 1 of *SIGCSE 2022*, pages 237–243, New York, NY, USA. Association for Computing Machinery. <https://doi.org/10.1145/3478431.3499358>.
- Lin, Z. (2024). How to write effective prompts for large language models. *Nature Human Behaviour*, 8(4):611–615. <https://doi.org/10.1038/s41562-024-01847-2>.
- Lindgren, B.-M., Lundman, B., and Graneheim, U. H. (2020). Abstraction and interpretation during the qualitative content analysis process. *International Journal of Nursing Studies*, 108:103632. <https://doi.org/10.1016/j.ijnurstu.2020.103632>.
- Liu, B. L., Morales, D., Chinchilla, J. F. R., Sabzalieva, E., Valentini, A., do Nascimento, D. V., and Yerovi, C. (2023). Harnessing the era of artificial intelligence in higher education: A primer for higher education stakeholders. UNESCO International Institute for Higher Education in Latin America and the Caribbean.
- Long, D. and Magerko, B. (2020). What is AI Literacy? Competencies and Design Considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–16. Association for Computing Machinery, New York, NY, USA.
- Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., Etchemendy, J., Ligett, K., Lyons, T., Manyika, J., Niebles, J. C., Shoham, Y., Wald, R., Walsh, T., Hamrah, A., Santarlasci, L., Lotufo, J. B., Rome, A., Shi, A., and Oak, S. (2025). The AI Index 2025 Annual Report. Technical report, AI Index Steering Committee, Institute for Human-Centered AI, Stanford University, Stanford, CA.
- Michaeli, T., Romeike, R., and Seegerer, S. (2023). What students can learn about artificial intelligence – recommendations for k-12 computing education. In Keane, T., Lewin, C., Brinda, T., and Bottino, R., editors, *Towards a Collaborative Society Through Creative Learning*, volume 685 of *IFIP Advances in Information and Communication Technology*, pages 196–208. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-43393-1_19.
- Monteiro, F., Monteiro Pereira, R. M., Pereira, A. J. C., and Vasconcelos, V. (2022). Motivation and expectations for choosing the field of Electrical Engineering: students' perceptions. In *2022 31st Annual Conference of the European Association for Education in Electrical and Information Engineering (EAEEIE)*, pages 1–5. <https://doi.org/10.1109/EAEEIE54893.2022.9819987>.
- Mustak, M., Salminen, J., Mäntymäki, M., Rahman, A., and Dwivedi, Y. K. (2023). Deep-fakes: Deceptions, mitigations, and opportunities. *Journal of Business Research*, 154:113368. <https://doi.org/10.1016/j.jbusres.2022.113368>.
- Mytton, D. (2021). Data centre water consumption. *npj Clean Water*, 4(1):1–6. <https://doi.org/10.1038/s41545-021-00101-w>.
- OECD (2024). Explanatory memorandum on the updated OECD definition of an AI system. Technical report, OECD, Paris. <https://doi.org/10.1787/623da898-en>.
- OECD (2025). Mapping relevant data collection mechanisms for AI training. OECD Artificial Intelligence Papers. <https://doi.org/10.1787/3264cd4c-en>.
- Park, S. and Nan, X. (2025). Generative AI and misinformation: a scoping review of the role of generative AI in the generation, detection, mitigation, and impact of misinformation. *AI & Society*. <https://doi.org/10.1007/s00146-025-02620-3>.
- Pawelec, M. (2022). Deepfakes and Democracy (Theory): How Synthetic Audio-Visual Media for Disinformation and Hate Speech Threaten Core Democratic Functions. *Digital Society*, 1(2):19. <https://doi.org/10.1007/s44206-022-00010-6>.
- Pintrich, P. R. and Schunk, D. H. (2002). *Motivation in Education: Theory, Research, and Applications*. Merrill.

- Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., and Carlstrom, A. (2004). Do Psychosocial and Study Skill Factors Predict College Outcomes? A Meta-Analysis. *Psychological Bulletin*, 130(2):261–288. <https://doi.org/10.1037/0033-2909.130.2.261>.
- Romero Moreno, F. (2024). Generative AI and deepfakes: a human rights approach to tackling harmful content. *International Review of Law, Computers & Technology*, 38(3):297–326. <https://doi.org/10.1080/13600869.2024.2324540>.
- Rosenzweig, E. Q., Wigfield, A., and Eccles, J. S. (2019). Expectancy-Value Theory and Its Relevance for Student Motivation and Learning. In Renninger, K. A. and Hidi, S. E., editors, *The Cambridge Handbook of Motivation and Learning*, Cambridge Handbooks in Psychology, pages 617–644. Cambridge University Press, Cambridge. <https://doi.org/10.1017/9781316823279.026>.
- Russell, S. and Norvig, P. (2021). *Artificial Intelligence: A Modern Approach (4th ed., Global Edition)*. Pearson Deutschland.
- Ryan, R. M. and Deci, E. L. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, 25(1):54–67. <https://doi.org/10.1006/ceps.1999.1020>.
- Sarker, I. H. (2021). Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. *SN Computer Science*, 2(6):420. <https://doi.org/10.1007/s42979-021-00815-1>.
- Sarker, I. H. (2022). AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science*, 3(2):158. <https://doi.org/10.1007/s42979-022-01043-x>.
- Saxena, A., Agarwal, A., Pandey, B. K., and Pandey, D. (2024). Examination of the Criticality of Customer Segmentation Using Unsupervised Learning Methods. *Circular Economy and Sustainability*, 4(2):1447–1460. <https://doi.org/10.1007/s43615-023-00336-4>.
- Schiefele, U., Krapp, A., and Winteler, A. (1992). Interest as a predictor of academic achievement: A meta-analysis of research. In Renninger, K. A., Hidi, S., and Krapp, A., editors, *The Role of Interest in Learning and Development*, pages 183–196. Erlbaum, 1 edition.
- Schunk, D. H., Meece, J. L., and Pintrich, P. R. (2014). *Motivation in Education: Theory, Research, and Applications*. Pearson.
- Seiler, G. (2013). Reconstructing Science Curricula Through Student Voice and Choice. *Education and Urban Society*, 45(3):362–384. <https://doi.org/10.1177/0013124511408596>.
- Shen, B. (2021). E-commerce Customer Segmentation via Unsupervised Machine Learning. In *The 2nd International Conference on Computing and Data Science*, CONF-CDS 2021, pages 1–7, New York, NY, USA. Association for Computing Machinery. <https://doi.org/10.1145/3448734.3450775>.
- Shi, Y. and Sun, L. (2024). How Generative AI Is Transforming Journalism: Development, Application and Ethics. *Journalism and Media*, 5(2):582–594. <https://doi.org/10.3390/journalmedia5020039>.
- Steinbauer, G., Kandlhofer, M., Chklovski, T., Heintz, F., and Koenig, S. (2021). A Differentiated Discussion About AI Education K-12. *KI - Künstliche Intelligenz*, 35(2):131–137. <https://doi.org/10.1007/s13218-021-00724-8>.
- Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers*, 12(5):91. <https://doi.org/10.3390/computers12050091>.
- Tenório, K., Knauer, R., Wallsberger, R., Rodner, E., and Romeike, R. (2025). Lecturers' Perspectives Regarding AI Competencies for Non-computer Science Students in Undergraduate Education. In Leahy, M. and Refay, C., editors, *Digitally Transformed Education: Are We There Yet?*, pages 28–38, Cham. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-88744-4_3.
- Tenório, K. and Romeike, R. (2024). AI Competencies for non-computer science students in undergraduate education: Towards a competency framework. In *Proceedings of the 23rd Koli Calling International Conference on Computing Education Research*, Koli Calling '23, pages 1–12, New York, NY, USA. Association for Computing Machinery. <https://doi.org/10.1145/3631802.3631829>.
- UNESCO IESALC and Mendigutxia, A. (2024). The role of higher education in national artificial intelligence strategies: a comparative policy review. Technical report, UNESCO International Institute for Higher Education in Latin America and the Caribbean (IESALC).
- Vaismoradi, M., Turunen, H., and Bondas, T. (2013). Content analysis and thematic analysis: Implications for conducting a qualitative descriptive study. *Nursing & Health Sciences*, 15(3):398–405. <https://doi.org/10.1111/nhs.12048>.
- Wang, L., Chen, X., Deng, X., Wen, H., You, M., Liu, W., Li, Q., and Li, J. (2024). Prompt engineering in consistency and reliability with the evidence-based guideline for LLMs. *npj Digital Medicine*, 7(1):41. <https://doi.org/10.1038/s41746-024-01029-4>.

- Woolf, N. H. and Silver, C. (2017). *Qualitative Analysis Using MAXQDA: The Five-Level QDA® Method*. Routledge, 1 edition. <https://doi.org/10.4324/9781315268569>.
- Zuckerman, A. L., Vo, L., and Juavinett, A. L. (2024). Student Motivations and Expectations for an Introductory Programming Course in Biology. In *Proceedings of the 55th ACM Technical Symposium on Computer Science Education V. 1*, pages 1498–1504, Portland OR USA. ACM. <https://doi.org/10.1145/3626252.3630931>.