AI and Ethics (2026) 6:220
https://doi.org/10.1007/s43681-026-01085-4

RESEARCH

Do our students deserve better than distrust? How students show high integrity in their attitudes towards using AI

Gry Ane Vikanes Lavik[1] · Ingunn Johanne Ness[1] · Erik Knudsen[1] · Stefan Sobolowski[1]

Received: 24 October 2025 / Accepted: 10 March 2026 / Published online: 26 March 2026

Abstract

Contrary to growing concerns among university faculty, our study finds that students demonstrate a principled and ethical stance toward the use of generative artificial intelligence (GenAI) in academic work. Drawing on data from an original survey, including a double-blind conjoint experiment, administered to 426 students across multiple faculties at the University of Bergen (UiB), Norway, we explore students' use of AI tools, their attitudes toward academic integrity, and their demand for AI-related training. Our results indicate that practical experience with AI tools, rather than gender, faculty affiliation, or self-reported knowledge, most strongly predicts students' attitudes, concerns, and learning needs. Students overwhelmingly oppose forms of AI use that compromise academic integrity, and express strong support for clear guidelines and institutional training. Moreover, the conjoint experiment indicates that students are cautious about using AI in ways that could be perceived as dishonest, reinforcing their ethical orientation. These findings challenge dominant faculty narratives that frame students as prone to misconduct, and instead position students as active, reflective users of AI who are seeking institutional support. We argue that universities must respond not with increased surveillance or control, but with trust-based pedagogical strategies and curriculum-integrated AI literacy initiatives that prepare students for the realities of an AI-augmented academic and professional future. The disruptive potential of AI in higher education is real, not because of student dishonesty, but because it challenges assumptions about authorship, assessment, and the boundaries of individual work.

Keywords AI in higher education · Student learning · Student AI attitudes · Ethical AI use · Teaching and assessment

1 Introduction

Generative AI (GenAI) may pose risks to students' academic work, but it also has the potential to enhance both academic skills and learning [7, 9, 16]. A growing body of work analyses the effects of AI (mostly generative large language models such as ChatGPT) on student learning and how students themselves perceive its use [8, 9, 22, 39]. Deng et al., [8] performed a meta-analysis of AI use and found predominantly positive effects on motivation, performance, and higher-order thinking. They note a reduction in mental effort and no negative consequences for self-efficacy. Wang and Fan, [39] suggest similarly positive effects in their meta-study. Despite this, we still know too little about students' attitudes toward AI, their use of AI tools, and whether their interest in learning more about them vary based on factors such as gender, AI knowledge, and AI usage patterns [5, 9].

We also note that more subject specific analyses indicate a more nuanced landscape. For example, Lepp and Kaimre (2024) note that computer science students did not make the link between AI use and potential plagiarism issues. They also found a negative correlation between performance and use, suggesting it was weaker students leaning on it as a crutch. However, it must be acknowledged that Chat GPT was only released in 2022 and as such it will take some time before all its effects become clear. There is even debate on

✉ Gry Ane Vikanes Lavik
Gry.Lavik@uib.no

Ingunn Johanne Ness
Ingunn.ness@uib.no

Erik Knudsen
Erik.Knudsen@uib.no

Stefan Sobolowski
stefan.p.sobolowski@uib.no

[1] University of Bergen, Bergen, Norway

how best to analyze AI's effects on learning and this in turn can affect how it is integrated into learning [1].

1.1 Background

GenAI refers to artificial intelligence systems that produce human-like content, such as text, images, audio, or video, based on user prompts [23, 40, 41]. While its rapid rise in public and educational settings is recent, GenAI has evolved over decades, beginning with early AI research in the 1950s and progressing through neural networks, symbolic systems, and learning algorithms [24, 32].

The 2000s saw breakthroughs in deep learning, followed by generative models like GANs (Goodfellow, 2014) and VAEs [17]. These advances culminated in the development of Large Language Models (LLMs), including OpenAI's GPT series, built on transformer architectures [38], which now power highly sophisticated applications across language, image, and scientific domains [2, 29, 30].

Looking ahead, GenAI continues to expand into multimodal and domain-specific uses, raising important ethical and societal questions around bias, misuse, and employment impacts [23, 41]. In education, this trajectory opens up new possibilities, but also new dilemmas, around how GenAI can be responsibly integrated into teaching, learning, and assessment [27].

1.2 Empirical background

Within Norway (i.e., the case for our study), several surveys have been conducted in recent years to gauge both student use of AI and their perceptions. Tekna, [35], a union of scientists, technologists, and students, conducted a survey and found that nearly three quarters of the almost 4000 respondents use AI tools at least weekly. The survey also found that a significant majority felt there was not enough guidance or training in the use of these tools. NOKUT [28], the national organ for quality in education, included AI-related questions in their general survey of student life and learning. This survey includes a broader cross section of Norway's academic population, but the results are similar to those of Tekna's. Namely, the number of students using AI tools is increasing rapidly and a significant majority (2 out of 3) do not feel they are receiving sufficient training in the use of AI tools in their academic lives. The concern around assessment and students' possible misuse of these tools in a way that conflicts with academic integrity has been raised by faculty in the Higher education sector's online news forum [20]. These somewhat anecdotal calls for restrictions show a need for more knowledge about both the real use and attitudes among students. GenAI technology represents a disruptive force, and there is a need to bridge the two frameworks: academic standards and the industries' need for AI-competent alumni [31].

1.3 Research questions

Our aim is to explore the following research questions:

1. **RQ1**: How does students' use of AI tools vary by gender and AI familiarity?
2. **RQ2**: How does students' interest in learning more about AI differ based on gender, AI familiarity, and AI usage patterns?
3. **RQ3**: How do students' attitudes toward AI differ based on gender, AI familiarity, and AI usage patterns?
4. **RQ4**: What do students consider acceptable and unacceptable uses of AI in an academic exam/assignment setting?

1.4 Methods

To answer RQ1-3, we created a range of survey items with *Likert scales* (e.g., "agree/disagree") and multiple-choice questions. We randomized the order of each item to prevent order effects. To answer RQ4, we embedded a double-blind randomized survey experiment—specifically, a conjoint experiment [13, 19] within the survey. Data collection was carried out "in-class" but was also disseminated to our faculties (Sciences and Technology, Humanities and Social Sciences), displayed survey QR codes on flyers posted in common areas and sent links via student email lists and posted on learning management system (LMS). Data collection occurred during the boreal spring semester of 2025. We note, however, that the survey was also open to all and as such we had several respondents from other faculties and departments. The university of Bergen is a medium-sized Norwegian university with approximately 20,000 students.

Given our sampling strategy, our sample should be treated as a convenience sample and not as a representative sample of students at UiB. 57% of the respondents come from the Faculty of Humanities and the findings are likely somewhat skewed towards the attitudes prevalent in these disciplines. Likewise, 65% of our respondents are female which can also potentially skew the results given the relatively small overall sample size. That said, we received a considerable number of responses to our survey, enabling us to conduct statistical analysis to answer our four research questions. 426 respondents participated in our study. 373 responded in Norwegian and 53 in the English version. 57% of the respondents are affiliated with the Faculty of Humanities, 22% from Faculty of Science and Technology, 17% from the Faculty of Social Sciences, and the remaining 4% from either Faculty of Medicine, Faculty of Fine Art, Music and Design, or another unit. 65% of our sample is female and 47% are currently working toward a bachelor's degree. Because we did not want to risk any respondents being indirectly identifiable, we chose not to ask about age, since information on age, gender identity, degree program, and faculty combined could make some respondents indirectly identifiable. For the same reason, while we also included "other gender identity" and "prefer not to say" as options in our gender variable; we do not report these in the analyses featured in this article.

The survey was devised in Norwegian and English versions accessible via browser and/or smartphone. The survey questions can be found in the Online Appendix.

1.5 Analysis

To address RQ1-3, we performed OLS regression analyses, and, for ease of interpretation, we reported these results as figures (so-called coefplots) that report the coefficients and 95% confidence intervals in the regression models, but all analyses are also available in table format in the Online Appendix.

For RQ1, we conducted a regression analysis with frequency of use of AI tools as the dependent variable, as well as gender and self-reported AI familiarity, as independent variables. In addition, we included the following variables as controls: Faculty, current ongoing degree, and survey language.

For RQ2, we conducted two separate regressions analyses using the following two variables as dependent variables: the degree to which respondents wanted more (a) general and (b) specific training from UiB in terms of the use of AI tools for academic purposes. For each model, we used gender, self-reported AI familiarity, and self-reported frequency of use of AI tools for academic/study purposes as independent variables. In addition, we included Faculty, current ongoing degree, and survey language as controls.

To address RQ3, we used items measuring level of agreement to a range of statements as dependent variables, and for each model we used gender, self-reported AI familiarity, and self-reported frequency of use of AI tools for academic/study purposes as the independent variables. In addition, we included the following variables as controls: Faculty (e.g., Social Sciences, Humanities, Science and Technology), current ongoing degree (e.g., Bachelor level), and survey language (Norwegian or English). We have highlighted three different AI attitudes, but all attitudes show the same overall pattern in terms of a positive effect of frequency of use of AI tools.

For RQ4, we conducted OLS regression analyses, clustered on the respondent level, to estimate the Average Marginal Treatment Effects (AMCE) models, which are standard within analyses of conjoint experiments [13,19]. To understand our analytical strategy, it is important to provide further details on the procedure of our experiment. Each respondent was exposed to three separate 'tasks'—vignettes, describing a hypothetical situation involving a student who had submitted a mandatory assignment at Universtiy of Bergen. Using JavaScript in the *Qualtrics* survey software, we programmed a vignette that randomly varied information about a hypothetical student's gender (male/female) age (20/24), study field (rhetoric/sociology/medicine), and use of AI ("The student has chosen not to use AI in their assignment"/"The student has chosen to use AI to improve the structure of the text"/"The student has chosen to use AI to automatically generate an answer to the assignment"). For instance, one possible version of this vignette could read: "Imagine that a 20 year old male medical student has submitted a mandatory assignment at UiB. The course allows the use of AI as long as it is clearly stated how AI has been used. The student has chosen to use AI to automatically generate a response to the assignment. What is your stance on the student's choice?" Respondents answered on a five-point scale from 1 "Do not support at all" to 5 "Support completely». Because each respondent answered three experimental tasks in a row, we have 1047 observations (i.e., 350 respondents answered at least one task). We thus cluster the analysis on respondent level and use robust standard errors as our standard errors need to be corrected for within-respondent clustering [19].

2 Results

2.1 Trends in students' engagements

First, it is interesting to note that a subset of the student population demonstrates limited awareness, with 13% reporting little to no knowledge of AI services. This finding highlights a gap in basic AI literacy that may hinder equitable access to emerging digital tools.

Second, it is relevant that the data reveals a high frequency of use: 45% of respondents indicated that they use AI tools such as ChatGPT on a weekly basis or more often in connection with their academic work. This suggests that nearly half of the students have already integrated AI into their study routines, reflecting a growing reliance on such technologies in everyday academic practices.

Finally, we see that a substantial majority, 69%, disagreed with the statement that they receive sufficient training in the use of AI tools as part of their education. This points to a perceived lack of institutional support in fostering students' ability to use AI critically and effectively and underscores

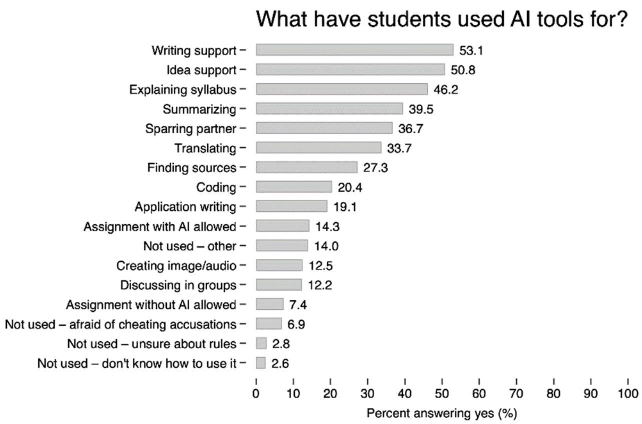

Fig. 1 Bar graph of students' use of AI tools (percent)

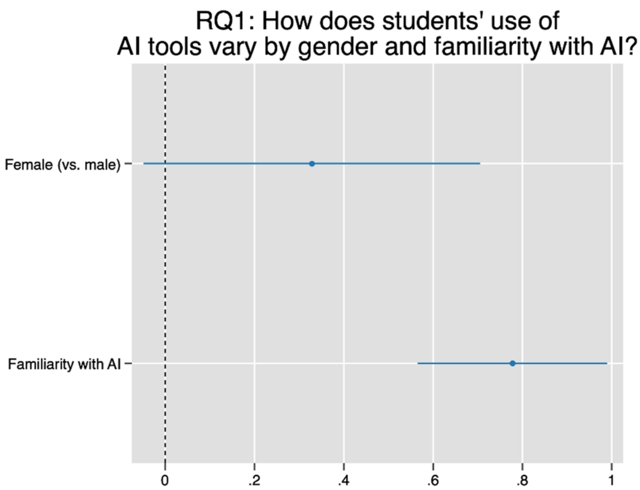

Fig. 2 OLS regression model with students' use of AI as the dependent variable and gender and self-reported familiarity with AI as the independent variables (Not shown in this figure: controlling for faculty, degree, and survey language. See the online appendix for a table showing the full model). The dots represent the point estimates, and the vertical lines represent 95% confidence intervals

the need for more structured and inclusive approaches to AI literacy in higher education.

2.2 Use of AI tools

We wanted to find out what the students are using GenAI for in their studies and academic work. Figure 1 illustrates how the students replied to this in the survey.

The most common applications include writing support (53.1%), idea generation (50.8%), and help in understanding curriculum content (46.2%). A sizable portion also reported using AI for summarizing texts (39.5%), as a sparring partner (36.7%), and for translation tasks (33.7%). Other uses mentioned include finding sources (27.3%), coding assistance (20.4%), and writing applications (19.1%). A smaller group (14%) indicated that they had completed assignments using AI tools.

Some students reported limited use or barriers to adoption. The barriers include reasons such as not needing the tools (12%), concerns about cheating (6%), uncertainty about rules (6%), and lack of knowledge on how to use AI tools (2%). Some students report using AI to create images or sounds (12%) or when participating in group discussions (7%).

Overall, the data suggests a broad and varied use of AI tools among students, while also highlighting areas where further guidance and support may be needed. The data indicate that there is no significant difference in AI usage between male and female students. This is presented visually in Fig. 2 and refers to research question 1 (RQ1): How does students' use of AI tools vary by gender and AI familiarity? However, greater familiarity with AI correlates with higher levels of usage. As one would think would be the case; usage correlates with familiarity. The more familiar the students report to be with GenAI-tools, the more they use it.

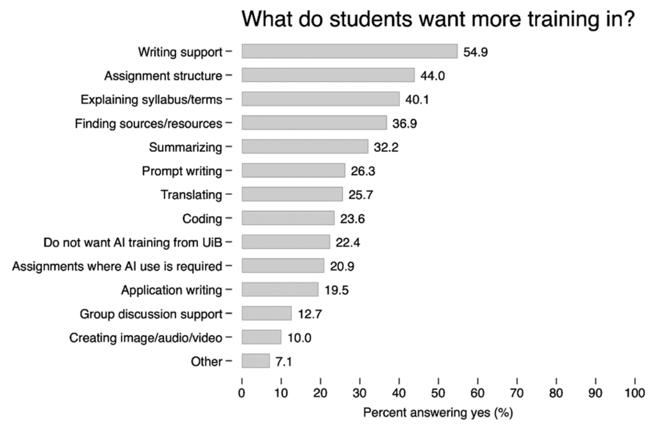

Fig. 3 Bar graph of students' AI training needs (percent)

2.3 Desire for more training

The students were asked which areas where they would like more training in the use of AI tools as part of their education at UiB. Figure 3 presents student responses regarding the areas where they would like more training.

The most requested area is writing support, with 54.9% of students expressing a desire for more guidance. This is followed by structuring assignments (44.0%) and explanations of curriculum content (40.1%). Other frequently answered areas include finding sources (36.9%), summarizing texts (32.2%), and writing effective prompts (26.3%). Students also showed interest in translation tasks (25.7%), coding (23.6%), and application writing (19.5%). Interestingly, 22.4% of respondents indicated that they do not wish to receive AI training, while 20.9% expressed interest in learning how to use AI in assignments where this is permitted. Less commonly requested areas include group work support (12.7%) and creating images, sound, or video (10.0%).

These results suggest a demand for practical, curriculum-related AI training, particularly in writing and academic support tasks, while also highlighting a need for clarity around permitted use and integration into collaborative learning. The analysis considers three variables: gender, self-reported familiarity with AI, and actual usage of AI tools. As seen in Fig. 4, data show that gender does not significantly influence students' desire for either general or specific AI training.

Similarly, familiarity with AI does not appear to be a strong predictor of training interest, although it does signal a slight lessened interest. In contrast, students who report higher levels of AI usage consistently express a greater desire for both general and specific training. This suggests that practical engagement with AI tools is the key factor driving students' motivation to seek further education in this area thus answering our research question 2 (RQ2): How does students' interest in learning more about AI differ based on gender, AI familiarity, and AI usage patterns? Usage patterns are the only factor affecting the variation in interest.

2.4 Students' attitudes towards AI

The findings, as presented in Fig. 5, reveal that gender and self-reported familiarity with AI do not significantly influence students' overall attitudes toward the use of AI in academic work. The only variable associated with a statistically significant difference is the extent of AI usage: students who actively use AI report more positive attitudes, thus addressing Research Question 3 (RQ3): How do students' attitudes toward AI differ based on gender, AI familiarity, and AI usage patterns? Similarly, when examining concerns about being caught cheating due to AI use, gender again shows no significant effect. Familiarity with AI is associated with slightly reduced concern, but it is students' actual use of AI that correlates with increased anxiety about potential academic misconduct detection.

Finally, as shown in Fig. 5, regarding students' desire for more AI training at the University of Bergen, neither gender nor familiarity with AI significantly affects this interest. However, students who report higher levels of AI usage express a notably stronger desire for formal training. These results suggest hands-on engagement with AI, not demographic factors or perceived knowledge, is the primary driver of student attitudes, concerns, and educational needs related to AI in higher education.

2.5 The conjoint experiment

Responses to the conjoint experiment as shown in Fig. 6 are distributed across a five-point scale, ranging from complete disapproval ("Do not support at all") to strong endorsement ("Support to a very large degree").

The data show that no use of AI receives the highest level of endorsement, indicating that students strongly support academic practices that exclude AI involvement, suggesting a principled opposition to forms of AI use that may compromise academic integrity or be perceived as dishonest. Support for structural improvement through AI, such as enhancing clarity or organization, is moderate, reflecting a

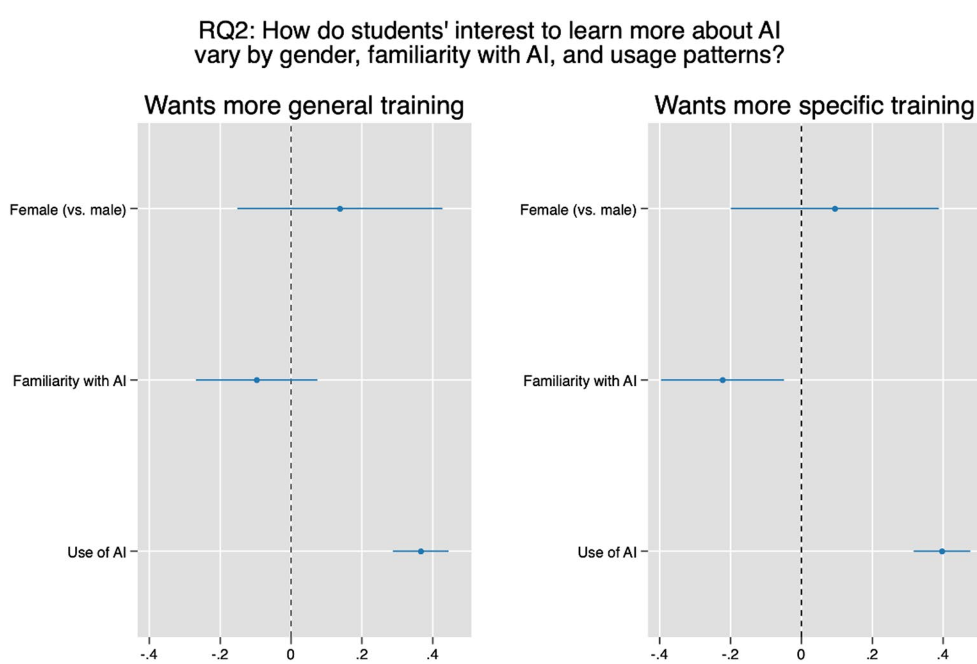

Fig. 4 OLS regression model with students' stated interest in receiving further training in AI (distinguishing between general and specific types of instruction) as the dependent variables and gender, self-reported familiarity with AI, and self-reported use of AI as the independent variables (Not shown in this figure: controlling for faculty, degree, and survey language. See the online Appendix for a table showing the full model). The dots represent the point estimates, and the vertical lines represent 95% confidence intervals

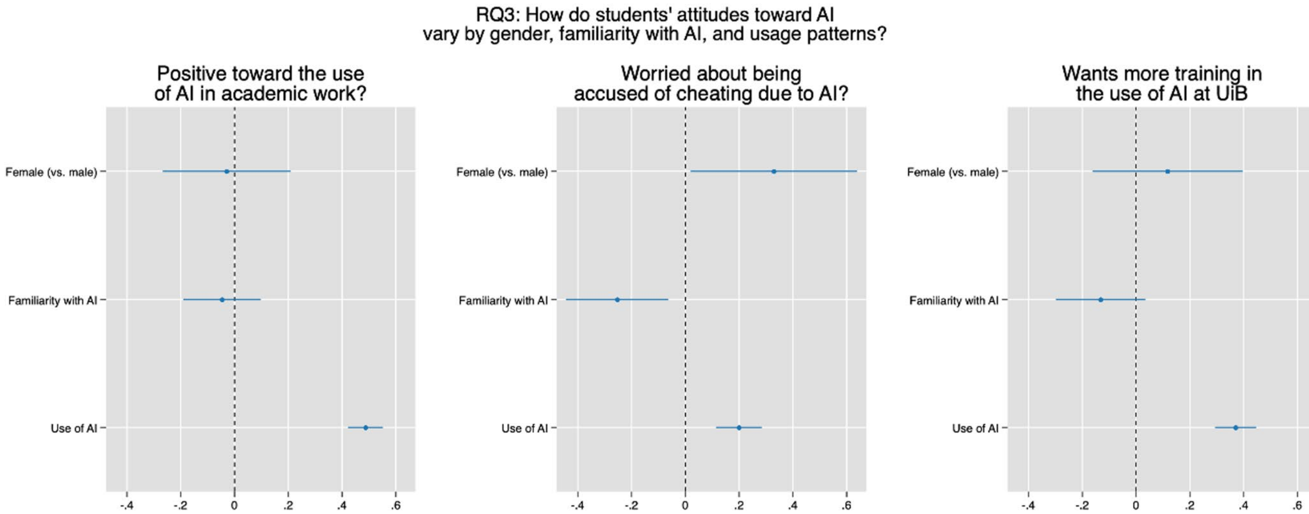

Fig. 5 OLS regression model with students' attitudes towards the use of AI as the dependent variables and gender, self-reported familiarity with AI, and self-reported use of AI as the independent variables (Not shown in this figure: controlling for faculty, degree, and survey language. See the online appendix for a table showing the full model). The dots represent the point estimates, and the vertical lines represent 95% confidence intervals

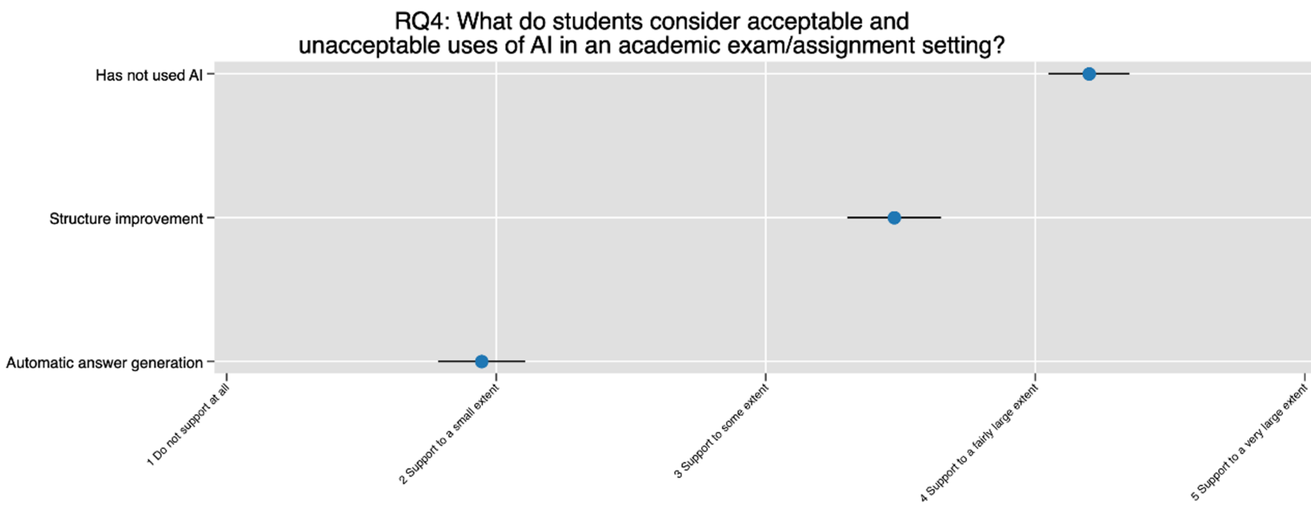

Fig. 6 Average marginal component effects (AMCE) showing the result from the conjoint experiment, with level of support for the use of AI as the dependent variable and different uses of AI as the treatment variables (not shown in this figure: treatment effects of hypothetical student's age, gender, and study program. See the online appendix for a table showing the full model). The dots represent the point estimates, and the vertical lines represent 95% confidence intervals

conditional openness to AI when it serves a supportive role. In contrast, automatic generation of answers is viewed as the least acceptable, with many students expressing clear disapproval.

We find no effect of gender and age but find that respondents are less supportive of AI use among rhetoric students than sociology and medicine students, indicating that there are differences between disciplines in terms of support for AI use in mandatory assignments (these results are available in Table 6 in the online appendix). In sum, these findings suggest that students are not resistant to innovation per se but are critically engaged with the ethical boundaries of AI use. Their preferences reflect a concern for maintaining fairness and integrity in academic work and point to the need for clear institutional guidelines that distinguish between legitimate and illegitimate uses of AI, thus answering research question 4 (RQ4): What do students consider acceptable and unacceptable uses of AI in an academic exam/assignment setting?–with an answer towards strongly supporting academic practices that exclude AI involvement.

3 Discussion

3.1 Student use of AI tools and their training needs

The survey results reveal a relationship between how students currently use AI tools and the areas in which they wish to receive more training. The most frequently used AI applications, such as writing support (53.1%), idea generation (50.8%), and explaining curriculum content (46.2%), are also among the top areas where students request further instruction. Specifically, 54.9% want more training in writing support, 44.0% in structuring assignments, and 40.1% in understanding curriculum material. This alignment suggests that students are actively engaging with AI tools in their academic work but feel they lack the necessary skills to use them effectively and responsibly. For example, while 39.5% use AI for summarizing, 32.2% want more training in this area. Similarly, translation and coding are used by 33.7% and 20.4% respectively, and 25.7% and 23.6% of students seek more guidance in these tasks. Additionally, 22.4% of students report not wanting any AI training, which may reflect either confidence in their current skills or skepticism about AI's role in education.

The students who use AI consistently also express a greater desire for both general and specific training. Consistent engagement with AI tools is the key factor driving students' motivation to seek further education in this area, which closely aligns with the findings of Bewersdorff et al.,'s study [3] on university students in the United States, the United Kingdom, and Germany, focusing on AI self-efficacy and its correlation with AI interest, usage, and literacy. We did not, however, find signs of gender gaps or differences related to faculty affiliation in how much the students use GenAI, their desire for more learning, or their attitudes towards GenAI, contrary to Møgelvang and Grassini's findings in their study on attitudes towards AI that point to clear attitudinal gaps related to demographic factors [25] Reference 25. Still, as stated in Sect. 2, with 57% of respondents being humanities students, it is difficult to robustly assess differences arising due to faculty affiliation. AI literacy is a necessary skill in most careers as noted by Hornberger et al., in their review of what university students know about AI [15]. However, it is worth noting that up to 22,4%, almost a quarter of the students, express that they do not want AI training. Among these students we might find the 13% who have little or no knowledge of AI, since use of AI is correlated with a desire for more training, but 22,4 is still quite a high percentage. This AI skepticism or even aversion suggests that curriculum-integrated training must be given with precision and high relevance and be founded on critical adaptation. The adaptation must entail a consciousness about where AI might enhance learning and or extend our capabilities, as well as where technology might hinder academic growth. Studies have shown that students with the right guidance will by themselves reach the conclusion of wanting to protect their academic writings skills from over reliance [37], because they learn through experience that over reliance might cause their own capabilities to be underdeveloped. Nikerk et al.,'s study might be an example of how a conscious and cautious adaptation might look like.

3.2 Faculty assumptions vs. student realities

Instead of pedagogically founded measures, faculty discourse around student use of GenAI does seem to center around distrust, fears of academic dishonesty, and calls for stricter assessment regimes such as in-person exams and surveillance-based control mechanisms. In Norway, this skepticism has been voiced in national higher education media (Khrono), where faculty express growing concern about whether students are completing their academic work independently. Similar sentiments have been echoed internationally, notably in Australia, where debates have emerged about the need to return to traditional summative assessments [18]. Compared to other nations, Australia has made considerable progress in setting up regulatory frameworks and institutional strategies for AI integration in higher education. (*Gen AI Strategies for Australian Higher Education: Emerging Practice*, [11]).

Tlili et al., [36] also note that while public sentiment around tools like ChatGPT is largely optimistic, concerns persist regarding cheating, misinformation, emotional detachment, and inconsistent output quality when it comes to university students. These concerns are fundamentally about trust. Trust in technology, in students, and in the educational system. This climate of distrust was a key motivation for our study. We sought to investigate how students actually use GenAI, their attitudes toward academic integrity, and their need for institutional guidance. Research question 4 aimed to test whether the assumption that students use AI almost to avoid learning holds true.

Our findings challenge the narrative of students letting AI do their work for them. Students in our survey showed a high level of ethical awareness and a clear desire for guidance on responsible AI use. In the conjoint experiment, they showed restraint, advocating avoidance of AI use unless it was explicitly allowed. This suggests a mismatch between faculty fears and student behavior. We found no evidence of problematic gender differences in AI use relating to how advanced the students were. Instead, the only significant factor influencing student attitudes was practical experience and know-how. In our view, this reinforces the need for institutions to provide structured training and support.

3.3 The core dilemma: integrity vs. preparedness

The dilemma facing higher education is twofold: On one side, it refers to safeguarding academic integrity (authorship, accountability, source verification). On the other hand, fulfilling the social mission of preparing graduates with AI literacy for the future of work. In our view, faculty concerns and distrust may lead to an overemphasis on the first obligation, potentially at the expense of the second. If we look at the results from the conjoint experiment described in Sect. 3.5 and noted above in Sect. 4.2, they strongly suggest that the students are already aware of integrity issues; they know what is right. Still, they are largely mistrusted by faculty. And some would argue that this is rightly so. Knowing what is right, is not necessarily enough.

One could argue that knowing what is right, although a necessary condition for intentionally doing what is right, may still not be sufficient to ensure that the right action is carried out. Most people know what is right, still they often act differently. There are many reasons for this. Reasons which have been quite extensively investigated philosophically. According to some of these accounts, habit or the fact that certain ways of acting are common or usual, is one such reason. And unusual immoral acts carried out with intent are, as Sinnott-Armstrong argues, more immoral than common acts [33]. In his example, a person sees others attempting to push a car, with people still inside, off a cliff, and chooses to help them. Helping to push the car in such a situation is taken to be far more immoral than performing ordinary actions that harm the planet, like driving a diesel fueled car, even if these actions also indirectly contribute to loss of life. Habit, and the sense that "everyone else is doing it," make the common acts appear less immoral. This may seem like an extreme comparison, but it bears some clear similarities to students' use of AI against institutional rules, as far as the perceived prevalence of a practice affects its moral status.

Studies on cheating show that its prevalence varies with the level of competition within a field of study [14], indicating that cheating is shaped by features of the study environment and that the frequency of immoral acts can shift what individuals experience as morally acceptable. Much like in the moral dilemma of individual responsibility for climate change, personal responsibility becomes diluted when acts of cheating or grey area behavior become common. This thus induces a form of collective action problem. Students might overuse AI, contrary to how they would respond in a hypothetical situation, such as in the conjoint experiment, since in practice this may appear to be the most reasonable course of action, or simply the easiest way out.

A weakness in the conjoint experiment is that it only asks the students to assess what the right action is when the rules on AI use are clear. But there being clear rules is not always the case. And the students themselves request better guidelines. In the absence of adequate guidance, students may develop habits that are counterproductive to their own learning. This could help explain the finding that actual use of AI correlates with increased anxiety about potential detection of academic misconduct, as shown in Fig. 5. Students who use AI frequently may come to understand the possibilities and forms of support the tool offers, and this awareness may also make them more wary of how easy it is to become over reliant on it. Recognizing both its potential for their own work and the threat it poses to academic integrity may help explain why these students express a heightened desire for guidance on how to use AI responsibly.

The concerns from faculty saying that students use AI to do their assignments, might add to the feeling of how common this is, increasing the habitual thinking in the lines of "I know it is wrong, but if everybody is doing it, I must do it too, to keep up with the competition", a response that would be in line with higher levels of cheating in studies with more competition. Here we want to underline that the core dilemma is *a dilemma also for the students;* they want to act with integrity, but they also want to position themselves well for further advancement in the job market. It is the university's responsibility to handle both. The challenge or even potential threat posed by AI towards higher education is real, not because of student dishonesty, but because GenAI challenges the writerly, scholarly model with focus on authorship [4]. Students should not be left alone to handle this challenge.

Earlier challenges to academia caused by digital technology, such as paper mills [6] and predatory journals have also threatened academic standards, but these are largely byproducts of the digital transformation of scholarly publishing, including the otherwise positive Open Access movement. In contrast, GenAI represents a more fundamental shift: it does not merely affect the dissemination of research, but directly impacts the processes of learning, authorship, and knowledge production across all sectors of academic life as noted by many [10, 12, 21]. The emergence of GenAI especially challenges the notion of the boundaries of individual work. Institutions must therefore engage in deliberate and evidence-informed processes to figure out how AI can be integrated in ways that support both learning outcomes and academic integrity. Integrating generative AI into higher education thus presents a set of difficult and multifaceted challenges. These are not limited to questions of academic integrity, but extend to pedagogical design, institutional trust, and the broader social mission of universities.

A potential solution, that could also improve what educators have complained about for decades, is to do something about assessment. Increasing the complexity of final exams has been advocated for by Deng et al., [8]. This is one way to go. But a shift towards more formative assessments, delivered along the way in class situations, could be more beneficial as these encourage the students to work on their learning in a continuous manner rather than simply measuring outcomes via summative assessments at the end of the term. Formative assessment can contribute to the development of essential skills such as critical thinking, problem-solving, and teamwork [34], and therefore goes beyond measuring knowledge and control. Our recommendation to prioritize in class formative assessment, echoes recent national guidance (Malthe-Sørenssen Committee, [26]) and can be articulated through concrete, classroom-based practices such as AI use statements, in class peer review, and low stakes milestones.

3.4 Limitations

Some limitations should be acknowledged. The study is based on a convenience sample of students from a single university within one national context, which limits the generalizability of the findings.

Moreover, beyond the conjoint experiment itself, caution is warranted when interpreting the results in terms of causal relationships. Although the design allows for the analysis of stated preferences under controlled conditions, it does not capture the full complexity of students' situated use of generative AI.

These considerations underscore the need for further research across diverse contexts and using complementary methodological approaches to inform ongoing ethical and pedagogical debates on the use of generative AI in higher education.

4 Conclusion

Our findings highlight a paradox: while faculty fear that students misuse AI to bypass learning, students themselves express both ethical restraint and a desire for guidance. This mismatch reflects the broader dilemma described in that higher education must simultaneously safeguard integrity and prepare graduates for a career where AI competency is expected. The true challenge, then, is not student dishonesty, but whether institutions are able to respond to the opportunity that lies within this crisis and bridge the gap with pedagogy that includes how to use AI in both a useful and responsible way.

While it is important to acknowledge the potential of generative AI to support learning and academic work, it is equally necessary to critically assess its implications for core academic values. Our findings suggest that students are engaging with AI tools in ways that intersect with key academic tasks. This calls for a considered institutional response, not one that simply views AI as a threat, nor one that embraces it uncritically, but one that recognizes the need for pedagogical adaptation and ethical reflection.

Ultimately, the responsible integration of AI in education is not a question of whether, but of how. The challenge lies in designing systems that uphold academic values while giving room for technological change. This will require sustained institutional effort and interdisciplinary collaboration, but it is also an opportunity to let student learning be a guideline for faculty-driven changes. Academia needs to figure out the simple question: "What do our students need to learn and how can we teach them this?"

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s43681-026-01085-4.

Author contributions G.A.V.L. led the writing and conceptual framing of the manuscript. I.J.N. contributed to theoretical contextualization and discussion. E.K. designed and analyzed the conjoint experiment and prepared all figures. E.K. and S.S. conducted the OLS regression analysis. G.A.V.L., I.J.N., and S.S. contributed to the background section. All authors contributed to the design of the survey questions and reviewed and approved the manuscript.

Funding Open access funding provided by University of Bergen (incl Haukeland University Hospital)

Data availability Sequence data that support the findings of this study will be deposited in an open repository if needed for publishing.

Declarations

Conflict of interest The authors declare no conflict of interest.

References

1. Bauer, E., Greiff, S., Graesser, A.C., Scheiter, K., Sailer, M.: Looking beyond the hype: understanding the effects of AI on

learning. Educ. Psychol. Rev. **37**(2), 45 (2025).https://doi.org/10.1007/s10648-025-10020-8
2. Betz, U.A.K., Arora, L., Assal, R.A., Azevedo, H., Baldwin, J., Becker, M.S., Bostock, S., Cheng, V., Egle, T., Ferrari, N., Schneider-Futschik, E.K., Gerhardy, S., Hammes, A., Harzheim, A., Herget, T., Jauset, C., Kretschmer, S., Lammie, C., Kloss, N., Zhao, G.: Game changers in science and technology–now and beyond. Technol. Forecast. Soc. Chang. **193**, 122588 (2023).https://doi.org/10.1016/j.techfore.2023.122588
3. Bewersdorff, A., Hornberger, M., Nerdel, C., Schiff, D.S.: AI advocates and cautious critics: how AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy. Comput. Educ. Artif. Intell. **8**, 100340 (2025). https://doi.org/10.1016/j.caeai.2024.100340
4. Blum, S.D.: My word: plagiarism and college culture. Cornell University Press (2009)
5. Cai, Q., Lin, Y., Yu, Z.: Factors influencing learner attitudes towards ChatGPT-assisted language learning in higher education. Int. J. Human–Computer Interact. **40**(22), 7112–7126 (2024).https://doi.org/10.1080/10447318.2023.2261725
6. Christopher, J.: The raw truth about paper mills. FEBS Lett. **595**(13), 1751–1757 (2021). https://doi.org/10.1002/1873-3468.14143
7. Cotton, D.R.E., Cotton, P.A., Shipway, J.R.: Chatting and cheating: ensuring academic integrity in the era of ChatGPT. Innov. Educ. Teach. Int. **61**(2), 228–239 (2024). https://doi.org/10.1080/14703297.2023.2190148
8. Deng, R., Jiang, M., Yu, X., Lu, Y., Liu, S.: Does ChatGPT enhance student learning? A systematic review and meta-analysis of experimental studies. Comput. Educ. **227**, 105224 (2025).https://doi.org/10.1016/j.compedu.2024.105224
9. Dikilitaş, K., Klippen, M.I.F., Keles, S.: A systematic rapid review of empirical research on students' use of ChatGPT in higher education. Nordic J. Syst. Reviews Educ. **2** (2024). https://doi.org/10.23865/njsre.v2.6227
10. Elbana, H.H., Emara, M.M., Saad, A.M., Shehata, I.M., Viswanath, O., Rehman, M.: AI in Research. In I. M. Shehata & O. Viswanath (Eds.), How to Successfully Publish a Manuscript: A Step-by-Step Guide (pp. 265–275). Springer Nature Switzerland. (2025).https://doi.org/10.1007/978-3-031-92538-2_17
11. Gen, A.I.: strategies for Australian higher education: Emerging practice. TEQSA. (2024). https://www.teqsa.gov.au/sites/default/files/2024-11/Gen-AI-strategies-emerging-practice-toolkit.pdf
12. Giouvanopoulou, K., Ziouvelou, X., Papademas, M., Karpouzis, K., Karkaletsis, V.: Identifying AI Challenges in Research Practices Through Research Ethics Reviews. In I. Alvarez, M. Arias-Oliva, A.-H. Dediu & N. Silva (Eds.), Ethical and Social Impacts of Information and Communication Technology (pp. 15–26). Springer Nature Switzerland. (2026).https://doi.org/10.1007/978-3-032-01429-0_2
13. Hainmueller, J., Hopkins, D.J., Yamamoto, T.: Causal inference in conjoint analysis: understanding multidimensional choices via stated preference experiments. Polit. Anal. **22**(1), 1–30 (2014).https://doi.org/10.1093/pan/mpt024
14. Harper, R., Prentice, F.: We' share but 'They' cheat: student qualitative perspectives on cheating in higher education. Int. J. Educ. Integr. **20**(1), 1–19 (2024). https://doi.org/10.1007/s40979-024-00171-6
15. Hornberger, M., Bewersdorff, A., Nerdel, C.: What do university students know about artificial intelligence? Development and validation of an AI literacy test. Comput. Educ. Artif. Intell. **5**, 100165 (2023).https://doi.org/10.1016/j.caeai.2023.100165
16. Kelly, A., Sullivan, M.: ChatGPT in higher education: considerations for academic integrity and student learning. J. Appl. Learn. Teach. (2023). https://www.academia.edu/download/100141561/ChatGPT_in_higher_education_Sullivan_Kelly_and_McLaughlan.pdf
17. Kingma, D.P., Welling, M.: Stochastic gradient VB and the variational auto-encoder. Second International Conference on Learning Representations, ICLR. **19**, 121. (2014). https://pdfs.semanticscholar.org/60ea/adac49b19d1f41925df3bbbb7983a113acec.pdf
18. Kizilcec, R.F., Huber, E., Papanastasiou, E.C., Cram, A., Makridis, C.A., Smolansky, A., Zeivots, S., Raduescu, C.: Perceived impact of generative AI on assessments: comparing educator and student perspectives in Australia, Cyprus, and the United States. Comput. Educ. Artif. Intell. **7**, 100269 (2024). https://doi.org/10.1016/j.caeai.2024.100269
19. Knudsen, E., Johannesson, M.P.: Beyond the limits of survey experiments: how conjoint designs advance causal inference in political communication research. Polit. Commun. **36**(2), 259–271 (2019). https://doi.org/10.1080/10584609.2018.1493009
20. Khrono-nyheter om universiteter, høgskoler og forskning (News on Universities, Higer Education and research). (2025) https://www.khrono.no/
21. Knöchel, T.-D., Schweizer, K.J., Acar, O.A., Akil, A.M., Al-Hoorie, A.H., Buehler, F., Elsherif, M.M., Giannini, A., Heyselaar, E., Hosseini, M., Ilangovan, V., Kovacs, M., Lin, Z., Liu, M., Peeters, A., van Ravenzwaaij, D., Vranka, M.A., Yamada, Y., Yang, Y.-F., Aczel, B.: Core principles of responsible generative AI usage in research. AI Ethics. (2025). https://doi.org/10.1007/s43681-025-00768-8
22. Lepp, M., Kaimre, J.: Does generative AI help in learning programming: students' perceptions, reported use and relation to performance. Comput. Hum. Behav. Rep. **18**, 100642 (2025). https://doi.org/10.1016/j.chbr.2025.100642
23. Lim, W.M., Gunasekara, A., Pallant, J.L., Pallant, J.I., Pechenkina, E.: Generative AI and the future of education: ragnarök or reformation? A paradoxical perspective from management educators. Int. J. Manage. Educ. **21**(2), 100790 (2023). https://doi.org/10.1016/j.ijme.2023.100790
24. McCarthy, J., Minsky, M.L., Rochester, N., Shannon, C.E.: A proposal for the dartmouth summer research project on artificial intelligence, August 31, 1955. AI Magazine. **27**(4), 12–12 (2006). https://doi.org/10.1609/aimag.v27i4.1904
25. Møgelvang, A., Grassini, S.: Validating the AI attitude scale (AIAS-4) and exploring attitudinal differences in a large sample of Norwegian university students. Discover Educ. **4**(1), 212 (2025). https://doi.org/10.1007/s44217-025-00657-6
26. Malthe-Sørenssen Committee: Foreløpige vurderinger: Notat fra utvalget om kunstig intelligens i høyere utdanning, med anbefalinger om eksamen, sensur og karakterbegrunnelse. Kunnskapsdepartementet. (2025). https://files.nettsteder.regjeringen.no/wpuploads01/sites/589/2025/12/Forelopige-vurderinger-notat-fra-utvalget-om-KI-i-hoyere-utdanning.pdf
27. Ness, I.J., Smith-Nunes, G.: Polyphonic creativity: navigating the opportunities and challenges of AI in education. In: Beghetto, R.A. (ed.) The Oxford handbook of human creativity x generative AI in education. Oxford University Press (in press)
28. Nokut, Nokut, S.: 2024, Rapport for resultater for UiB (2025). https://www.nokut.no/globalassets/studiebarometeret/2025/studiebarometeret-2024-hovedtendenser_1-2025.pdf
29. Park, J.S.: Re-examining the role of time in human-algorithm interaction [Thesis]. (2020). https://hdl.handle.net/2142/108025
30. Radford, A., Narasimhan, K., Salimans, T., Sutskever, I.: Improving language understanding by generative pre-training. (2018). https://www.mikecaptain.com/resources/pdf/GPT-1.pdf
31. Rowland, D.R.: Two frameworks to guide discussions around levels of acceptable use of generative AI in student academic research and writing. J. Acad. Lang. Learn. **17**(1), T31–T69 (2023)

32. Rumelhart, D.E., Hinton, G.E., Williams, R.J.: Learning representations by back-propagating errors. Nature. **323**(6088), 533–536 (1986)
33. Sinnott-Armstrong, W.: It's Not My. In W. Sinnott-Armstrong & R. B. Howarth (Eds.), Perspectives on Climate Change: Science, Economics, Politics, Ethics (Vol. 5, p. 0). Emerald Group Publishing Limited. (2005).https://doi.org/10.1016/S1569-3740(05)05013-3
34. Solis, B.P. Trujillo, Velarde-Camaqui, D., Gonzales Nuñez, C.A., Castillo Silva, E.V., Gonzalez Said de la Oliva, M. del P.: The current landscape of formative assessment and feedback in graduate studies: a systematic literature review. Front. Educ. **10**, Article1509983 (2025). https://doi.org/10.3389/feduc.2025.1509983
35. Tekna: Tekna survey on students' use of AI: (2024). https://www.tekna.no/globalassets/filer/media/studentundersokelsen-2024-ki-i-studiene.pdf
36. Tlili, A., Shehata, B., Adarkwah, M.A., Bozkurt, A., Hickey, D.T., Huang, R., Agyemang, B.: What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. Smart Learn. Environ. **10**(1), 15 (2023). https://doi.org/10.1186/s40561-023-00237-x
37. van Niekerk, J., Delport, P.M.J., Sutherland, I.: Addressing the use of generative AI in academic writing. Comput. Educ. Artif. Intell. **8**, 100342 (2025). https://doi.org/10.1016/j.caeai.2024.100342
38. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A.N., Kaiser, Ł., Polosukhin, I.: Attention is all you need. Advances in Neural Information Processing Systems, 30. (2017). https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html
39. Wang, J., Fan, W.: The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: insights from a meta-analysis. Humanit. Social Sci. Commun. **12**(1), 1–21 (2025)
40. Watson, S., Shi, S.: Generative AI Integration in Education: Challenges and Approaches. In P. Ilic, I. Casebourne & R. Wegerif (Eds.), Artificial Intelligence in Education: The Intersection of Technology and Pedagogy (pp. 59–73). Springer Nature Switzerland. (2024). https://doi.org/10.1007/978-3-031-71232-6_4
41. Zohny, H., McMillan, J., King, M.: Ethics of generative AI. J. Med. Ethics. **49**(2), 79–80 (2023). https://doi.org/10.1136/jme-2023-108909