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Comparing the positive and negative impacts of AI: A large-scale study of student perspectives

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Higher education students are incorporating generative artificial intelligence into many aspects of their studies, yet the ways they judge its positive and negative impacts remain poorly understood. Using qualitative content analysis supported by code-frequency analysis, this paper examines open-ended comments from 2,802 participants drawn from a survey of 8,021 students across four Australian universities. Reported impacts clustered around four themes: study practices, quality, efficiency, and institutional practices. Positive impacts were more frequently coded overall, particularly when students described using AI to support their own study practices and efficiency. Negative responses centred on the inaccuracy of AI outputs. Although relatively few participants commented on institutional teaching and assessment practices, these responses were predominantly negative. The findings suggest that students value AI not only for the quality of its outputs, but also for its role in helping them begin, continue, refine, and complete academic work. Rather than uncritically accepting or categorically rejecting AI, students appeared to make situated judgements about its usefulness and limitations, shaped by concerns about accuracy and trust, as well as by the agency and control they retained over its use. Institutional responses should therefore engage with the complexity of students' practices and the conditions under which they perceive AI to be useful or problematic.

Keywords: AI, artificial intelligence, studying, study practices, higher education, thematic analysis

Introduction

The complexity of artificial intelligence (AI) in higher education owes much to the fact that the technology simultaneously produces contrasting effects. Recent studies of students' experiences of AI show that it can have both positive and negative impacts on learning (Dickinson & Marshall, 2026; Walton et al., 2025). Students are constantly faced with marketing of AI tools as study aids (Corbin & Walton, 2025), yet when involving the technology as part of their studies, students grapple with questions around ownership of their work, as contributions from themselves and the technology are difficult to disentangle (Bearman et al., 2026; Walton et al., 2025). It is, as such, unsurprising that interactions with AI in the context of study can lead to emotions such as guilt and stress (Chan, 2025; Hadinejad et al., 2025; Oberg et al., 2026), complicated by the fact that students are sometimes unclear on institutional policies relating to AI use for study (Bearman et al.

2026). To make matters more difficult, students may be cognisant of the fact that working with AI invariably involves making learning trade-offs, but may not accurately recognise those trade-offs for themselves (Crawford et al., in press; Tierney et al., 2025; Walton et al., 2025).

While prior research makes clear the willingness of students to navigate simultaneous positive and negative impacts of working with AI (Bearman et al., 2026; Chan & Hu, 2023; Hadinejad et al., 2025; Lin & Chen, 2024; Walton et al., 2025), the question remains as to how students decide that it is worth the effort of navigating this complexity, and the kinds of value judgements that inform this. In response, this paper examines students' reports about the impacts of AI on their experiences of studying at university, as a subset of findings from a survey of more than 8,000 Australian university students across four institutions. One of the challenges in understanding the impact of AI in students' experiences is that there are many possible ways AI can be used (Chung et al., 2026; Dickinson & Marshall, 2026). Nonetheless, students' uses of the technology also reflect existing study practices: for example, summarising texts (Corbin & Walton, 2025; Corbin et al., 2026), reading (Corbin et al. 2026; Xia et al., 2025), writing (Deep & Chen, 2025), and seeking feedback on their work (Henderson et al., 2025; Öztürk & Çebi, 2026). In this study, we thus conceptualise impact broadly, simply as changes to students' experiences of studying resulting from the involvement of AI in some way. Focusing on the impacts of AI on students' experiences of study enables us to capture information about the practices within which their uses of the technology are organised, as well as the role of AI in changing wider conditions (for example, changing approaches to assessment) that frame those practices. This study draws on students' self-reported experiences to examine the perceived impacts of AI on their study practices. It is guided by the following research question: *How are university students reporting the impact of AI on their study practices?*

Three observations arise from our analysis. The first is that AI appears to be impacting the shape of students' studies in ways that are not reducible to instrumental, one-directional gains or losses (for example, making study "faster"). Second, the relative inaccuracy of AI tools is not perceived as a deal-breaking problem for students, who appear to feel that the benefits of working with AI outweigh this limitation. Third, the role that students have in the use of the technology may be associated with the ways that AI is legitimated in the context of study—it is striking that participants in this study seemed to associate positive impacts with their own use of it, but that the technology was felt to be problematic in the hands of others. We conclude by suggesting that this study challenges assumptions about homogenous student relationships with AI, and that institutional approaches to learning, teaching, and assessment will need to appreciate students' situated judgements about the role of the technology in their study practices.

Method

This paper reports on open-ended responses from a large-scale cross-sectional survey examining students' use and perceptions of generative AI in their university studies. The survey was conducted across four Australian universities (the University of Queensland, the University of Technology Sydney, Monash University, and Deakin University), and was open between August and October 2024. The survey was anonymous and was approved by the human research ethics committees from all four universities. Students were recruited in different ways at each institution depending on variations in institutional clearances (for example, differences in which student-facing sites were available for recruitment). Further detail about recruitment is provided in Chung et al. (2026). Participants were not able to complete the survey until they had provided consent to participate in the research.

The analysis focuses on students' responses to the final two optional open-ended survey questions:

- What are the ways GenAI has positively impacted your learning or university experience? Please share any specific instances or examples.
- What are the ways GenAI has negatively impacted your learning or university experience? Please share any specific instances or examples.

Of the 8,021 fully completed surveys, 4,082 respondents (50.9%) provided usable answers to at least one of the open-ended questions. These responses totalled 189,776 words, with an average response length of 46 words and a maximum length of 325 words. 4,051 responses were provided to the first question, and 3,886 responses were provided to the second. 3,729 participants responded to both questions. The analysis

developed in this study is a smaller part of a larger study, and focuses only on a subset of 2,802 of the usable responses.

Analysis

The analytic approach we describe here is reflective of the larger study from which this particular paper is developed. We conducted a qualitative content analysis of the open-ended responses (Granehiem & Lundman, 2004; Lindgren et al., 2020) wherein code-based categorisation of the data was developed in conjunction with a frequency analysis of the codes. In adopting this approach our focus was on eliciting wider discursive patterns that characterised the data set as a whole, rather than on individual student accounts: rather than serving the purpose of measurement, the quantitative elements of the data offered a point of reference for the research team to contextualise their qualitative inferences (Maxwell, 2010). As such, our reportage of frequencies is to indicate the relative prominence of each category identified within the data, and to enhance the validity of claims about recurrence of the codes (Maxwell, 2010). Coding of the data followed an inductive approach with a semantic emphasis, where the focus was on the explicit meanings conveyed in students' comments, while also drawing on our own understandings as researchers in the domain of student experience (Varpio et al., 2017). This approach was appropriate given the brevity and breadth of open-ended survey responses, where interpretation of latent meaning can be limited (LaDonna et al., 2018).

A subset of the data, comprising responses from 851 participants, was initially analysed iteratively by the seven members of the research team to develop an initial set of codes. Each team member began by analysing a sample of 30 responses. The team then met to revise and expand the coding framework, progressively applying it to further responses until it provided a stable and sufficiently comprehensive account of the dominant patterns in the data. Central to this process was the development of codes that were sufficiently abstract to categorise responses without obscuring their meaning (Lindgren et al., 2020).

During this process, the team determined that the unit of analysis would be each respondent's combined answers to the two questions. Respondents sometimes framed their answer to the second question in relation to their first answer, or relied on context established there, meaning that the two answers needed to be interpreted together. Each combined response was coded according to the type of impact described and its valence (positive, negative, or absent). A response could be assigned multiple impact codes, including multiple codes with the same valence. However, a particular impact code could be assigned only once for each valence within a response. The same impact code could therefore be assigned twice only when the response described that impact both positively and negatively. Consequently, the total number of coded instances could exceed the number of participant responses.

After the authors had reached agreement on an initial set of codes, one of the authors, SH, coded the majority of the data. This author coded the data in stages, beginning with two intervals of 500 responses before proceeding through the majority of the data set. Through each stage, SH calibrated her perspective against several other authors (JW, MH, and SL, who also coded several hundred additional responses each) by keeping a live record of responses that seemed ambiguous or where the appropriate coding was otherwise unclear. The team communicated both asynchronously and through real-time meetings to resolve these ambiguities, including through refining the code set where it was clear that codes were redundant or that additional codes were needed to capture nuances not previously indicated.

Through the coding process, our approach moved gradually from de-contextualisation of the data (through code-based representation of the data) to re-contextualisation, as the codes were gradually grouped to reflect larger patterns (Lindgren et al., 2020). The team intentionally avoided developing higher-order themes under which to cluster the codes, in order to avoid pre-emptively assigning a broader narrative to the data. Instead, the developing codes were grouped in terms of implicit "family resemblances" where the authors intuited that they fell together in coherent ways. Toward the end of the process, authors JW, MH, and SH reviewed the codes to identify wider themes by which to organise the data. These themes were determined on the combined grounds that they both represented the family resemblances inherent in the code book, while also "speaking back" to wider discussions at play in the literature on AI in higher education. This process overlapped with the coding of the final 1,300 responses.

Across the 4,082 usable responses, the dataset was coded 9,979 times. Of these coded instances, 1,344 indicated either valence without a clear impact, or impact without a clear valence, and were excluded from the final analysis since they did not provide semantic content that could be analysed within our coding framework. The remaining 8,635 coded instances captured cases where participants described AI as affecting their studies in a positive or negative way. Of these, 57.6% were positively valenced (*n* = 4,971) and 42.4% were negatively valenced (*n* = 3,664). The final coding framework for the entire survey comprised 30 codes, each with positive and negative valence, organised under four parent themes, which were: impacts on studying, impacts on affect, impacts on knowledge, and impacts on integrity. The analysis we report in this paper focuses only on the first of these parent themes, "impacts on studying," comprising 13 codes across four themes (summarised in Table 1, below). Of the total data set, the 2,802 usable responses analysed in this paper were coded 4,271 times.

Limitations

Our purpose in this research was to identify wider patterns across qualitative data collected at scale, rather than to undertake detailed analysis of individual accounts. The data are self-reported and therefore reflect participants' perceptions and interpretations of their experiences. While this provides insight into how students understand and describe the impact of AI, it cannot establish changes in their actual learning behaviours or outcomes. The open-ended questions were optional and appeared at the end of a longer survey. This may have introduced self-selection and non-response bias: students with stronger views or greater interest in AI may have been more likely to respond, while survey fatigue may have discouraged others. We did not compare students who answered these questions with those who did not. Consequently, the reported frequencies indicate the relative prominence of themes among the responses analysed and should not be interpreted as estimates of the prevalence of these experiences or perspectives across the participating institutions or the wider university student population.

Findings

The findings of our analysis identify ways in which students' experiences of studying were understood to have changed through the involvement of AI. In what follows we distinguish between *participants' responses* and *coding instances* to distinguish unique responses provided by students from instances of codes assigned to those responses. This is to reflect the fact that one response may be assigned multiple codes. Overall, the analysis presented here is premised on data provided by 2,802 unique participants. The responses were coded a total of 4,271 times with the codes that are of interest to our analysis in this study. Overall, 87% of responses were coded with a positive valence (*n* = 2438 responses) while 38.2% (*n* = 1071) responses were coded with a negative valence. Four themes were identified: study practices (*n* = 1,557 responses, 1,727 coded instances of total coded instances across the dataset), quality (*n* = 1,269 responses, *n* = 1,413 coded instances), efficiency (*n* = 922 responses, n = 1,010 coded instances), and institutional practices (*n* = 120 responses, *n* = 121 coded instances).

Table 1 presents the responses and coded instances across the four themes, codes and valence. As individual responses could be assigned to multiple codes within a theme, theme response totals represent unique responses rather than summed code-level counts. Our results indicate that students perceive AI as having more positive impacts than not, and that these offset negative aspects of their experience (for example, the perceived inaccuracy of AI tools). Notably, positive valuation of AI seems to be founded on students' interactions with the technology, and is not simply premised on the quality of AI outputs alone. Our findings also suggest, however, that students tended to report positive impacts when they were responsible for its deployment, but found impacts to be more negative when the technology was deployed by institutional actors.

Table 1
Codes within the impact on study theme by frequency and valence

Theme	Code	Coded instances	Individual student responses		
		n (% total; % within Theme)	Responses, n (% total)	Positive, n (% responses)	Negative, n (% responses)
Study practices	Finding solutions	1149 (26.9%; 66.5%)	1143 (40.8%)	1131 (99.0%)	18 (1.6%)
	Summarising	220 (5.2%; 12.7%)	220 (7.9%)	219 (99.5%)	1 (0.5%)
	Feedback	159 (3.7%; 9.2%)	159 (5.7%)	155 (97.5%)	4 (2.5%)
	Searching	102 (2.4%; 5.9%)	101 (3.6%)	98 (97.0%)	4 (4.0%)
	Analysing	97 (2.3%; 5.6%)	97 (3.5%)	95 (97.9%)	2 (2.1%)
	Theme total	1727 (40.4%; 100%)	1557 (55.6%)	1543 (99.1%)	29 (1.9%)
Quality	Accuracy	794 (18.6%; 56.2%)	794 (28.3%)	12 (1.5%)	782 (98.5%)
	Output	542 (12.7%; 38.4%)	537 (19.2%)	509 (94.8%)	33 (6.1%)
	Academic achievement	77 (1.8%; 5.4%)	77 (2.7%)	41 (53.2%)	36 (46.8%)
	Theme total	1413 (33.1%; 100%)	1269 (45.3%)	556 (43.8%)	842 (66.4%)
Efficiency	Time	788 (18.5%; 78.0%)	772 (27.6%)	678 (87.8%)	110 (14.2%)
	Productivity	136 (3.2%; 13.5%)	134 (4.8%)	105 (78.4%)	31 (23.1%)
	General efficiency	86 (2.0%; 8.5%)	86 (3.1%)	77 (89.5%)	9 (10.5%)
	Theme total	1010 (23.6%; 100%)	922 (32.9%)	805 (87.3%)	148 (16.1%)
Institutional practices	Teaching practices	63 (1.5%; 52.1%)	63 (2.2%)	12 (19.0%)	51 (81.0%)
	Assessment practices	58 (1.4%; 47.9%)	58 (2.1%)	5 (8.6%)	53 (91.4%)
	Theme total	121 (2.8%; 100%)	120 (4.3%)	17 (14.2%)	103 (85.8%)
Dataset total		4271 (100%)	2802 (100%)	2438 (87.0%)	1071 (38.2%)

Note. A "coded instance" is when a code has been applied to a response; the same code could be applied twice to a response with different valences. Responses refer to unique student comments, with one response per participant. As responses could be coded positive, negative or both valences, the number of coded instances may exceed the number of responses. *Theme totals* and *Dataset totals* of the Coded instances column is the summed total of the coded instances (individual students can be counted more than once). *Theme totals* and *Dataset totals* of the *Individual student responses* columns is the summed total of all individual students' responses applied to the theme (individual students are only counted once—*Theme totals* reflect individuals counted once within a theme, and the *Dataset totals* reflect individuals counted once across the dataset as a whole).

Study practices

Study practices was the most frequently coded theme with 1,557 (55.6%) unique participants' responses and accounting for 40.4% of coded instances across the data as a whole (*n* = 1,727). This theme captured responses that described how students' study practices were affected by AI, including how they used AI to support specific study-related tasks. Responses coded under study practices were overwhelmingly positive, with 99% of participants' responses (*n* = 1,543) coded with a positive valence.

The most frequently reported impact within this theme was "finding solutions" (*n* = 1,131 participant responses), representing 66.5% of coded instances associated with Study practices). This code included references to problem-solving activities such as brainstorming, overcoming obstacles, generating new ideas, or responding to a task. Responses coded under "Finding solutions" were also almost entirely positive in valence (*n* = 1,131 responses, 99% of the code total), with only 18 responses assigned a negative valence. Students often described AI as useful when they were not sure how to begin or continue with study tasks. For example, they explained that AI reduced the "roadblock of starting assessments," and helped them "overcome study slumps when [they were] struggling to understand some parts of theory." This suggests that students

frequently associated the impact of AI with practical support to move their study tasks forward, such as in situations where they needed to generate ideas or overcome obstacles in their work.

The other codes in the theme of study practices were also almost entirely positive. "Summarising" (*n* = 220 responses; 12.7% of coded instances in the theme) referred to the use of AI to summarise content, including students' own work and external sources. Students considered AI to be useful for condensing reading materials, and making difficult content easier to manage as a result. It also helped them "summarise notes for studies" and "reduce word count" in their essays. "Feedback" (*n* = 159 responses, 9.2% of coded instances within the theme) captured instances in which AI provided information about students' work to improve it or support learning. Students used AI as a source of feedback for "proof-checking [their] work based on certain criteria." "Searching" (*n* = 101 responses, 5.9% of coded instances within the theme) referred to AI's impact in helping students find material, and "analysing" (*n* = 97 responses, 5.6% of coded instances within the theme) captured analytical activities, such as reviewing sources, synthesising information, or analysing data or literature. The pattern across study practices shows that students' positive accounts of impact of AI were associated with practical study activities, therefore being positioned by students as a support across multiple points in the study process.

Quality

Quality was the second most frequently coded theme (*n* = 1,269 participants' responses, 45.3% of total responses), capturing responses that referred to the impact of AI on the quality of students' work or study-related outcomes. In contrast to *Study practices*, these responses were more often negative (*n* = 842 responses, 66.4% of total responses in the theme) than positive (*n* = 556 responses, 43.8%). The largest code within quality was "accuracy" (*n* = 794 responses, 56.2% of coded instances within the theme). This code included references to the correctness of AI-generated information or outcomes such as concerns about trust, misinformation, and reliability. "Accuracy" was coded as an almost entirely negative impact (only 12 respondents identified positive impacts) which makes it the most negative code reported in this study. Concerns about accuracy were therefore an important part of students' accounts of AI's impact on studying. Students described that AI produced answers that were "way off," "extremely unreliable," or simply "false information." They explained that "[s]ometimes it just doesn't know the answers so it makes them up," therefore, "critical thinking is required when using AI." Some responses also described how inaccurate AI outputs required them to spend "an annoying amount of time investigating this and correcting it before submission."

The *Quality* theme, however, was not uniformly negative. "Output" is the second largest code within this theme (*n* = 537 responses, 38.4% of coded instances in the theme) and refers to the quality of outputs produced through interaction with AI, including writing, composition, coding, or other produced work. Contrary to "accuracy," "output" was coded mostly with a positive valence (94.8% of responses within the code). Students valued AI for improving the clarity, structure, or representation of their work. For example, they believed AI helped them "look at other options to write the same idea with different words" and that their "writing products have improved significantly." This data shows that students may have distinguished between the usefulness or quality of AI-supported outputs and the reliability of the information they contain.

"Academic achievement" (*n* = 77 responses, 5.4% of coded instances within the theme) was more evenly distributed across positive and negative valence. Some students referred to positive impacts, for example, it helped them "make greater progress in [their] learning journey," while others referred to negative consequences, including losing marks because AI gave them incorrect information. All in all, AI's impact on study quality was not experienced as strongly negative or positive, as students appeared to identify benefits in producing study-related outputs while also raising concerns about correctness, trust, and the relationship between AI use and academic achievement.

Efficiency

The theme of *Efficiency* captured responses that referred to the impact of AI on time, productivity, and efficiency more generally. Of the 922 responses (32.9% of total responses) coded under *efficiency*, most were positive (*n* = 805, 87.3% of responses within the theme). The largest code within this theme was "time" (*n* =

772 responses, 78.0% of coded instances within the theme), which included references to time efficiency, speed, task duration, time saved or spent, and the availability of AI. Most instances coded under "time" were positive, which indicates that students frequently associated AI with completing study tasks more quickly and saving time. In many instances students' responses connected time saving to specific study activities such as summarising, brainstorming, understanding content, and working through difficult tasks. They stated that AI "saves [them] so much time summarising" and helps them "fast-track brainstorming." One student explained that AI helped them "understand complex contents faster and quicker rather than waiting for an in-person feedback." In some cases, students framed these time savings as helping them to redirect effort toward other aspects of learning; for example, one student explained that, as a learner of English as an additional language, AI helped them to "redirect energy into focusing on the content and message rather than grammar and word choice," and to "build on [their] disciplinary knowledge much faster" than they could without it. However, in some responses students acknowledged the positive impacts on AI on their studies while at the same time describing AI as a "waste of time," especially when its outputs were incorrect. For example, some believed AI helped them check their work rather than having someone else check it, while at times it took them longer to generate their desired results than doing the work independently without AI.

"Productivity" (*n* = 134 responses, 13.5% of coded instances within the theme) and "general efficiency" (*n* = 86 responses, 8.5% of coded instances within the theme) were less frequently coded but still followed the same broader pattern of positive responses outweighing negative ones. "Productivity" captured references to the quantity of work accomplished and "general efficiency" captured broader references to efficiency that were not specific enough to be coded as "time" or "productivity." Under the theme of "efficiency," students associated AI with making their study faster and more productive. For example, students mentioned that AI helped them "consolidate [their] study to focus on [their] important tasks" and "stay productive and on top of [their] work." However, the presence of negative coding within both "time" and "productivity" shows that efficiency was not necessarily experienced as an uncomplicated benefit. Some participants mentioned completing their tasks independently would have been more efficient, and several students explained that the use of AI increased workload in group assessments because they were unsure whether other students had used AI-generated content, requiring them to check if the work was "genuine and factual." One student, for example, mentioned that although AI has helped them to "structure [their] sentences" and "write coherent essays," "[w]hilst doing group work, some of [their] peers use GenAI to write their components. This has caused them to go off topic which impacts the quality of the essay [negatively]." The findings, therefore, show that AI can support students in completing study tasks more quickly, but it can also introduce forms of work or concern that may reduce or complicate these efficiency gains.

Institutional practices

Institutional practices captured responses about AI's impact on institutional approaches to learning and teaching, including teaching and assessment practices. Although this theme accounted for a small proportion of coded instances across the dataset (*n* = 120 responses, 4.3% of total responses), it was mainly negative in valence (85.8% of responses). "Teaching practices" (*n* = 63 responses, 52.1% of coded instances within the theme) and "assessment practices" (*n* = 58 responses, 47.9% of coded instances within the theme) captured references to changes or effects on what teachers do and ways assessment was affected, respectively. Both codes were overwhelmingly negative, including 81% of responses coded with "teaching practices" and 91.4% of responses coded with "assessment practices." In terms of teaching practices, one student, for example, expressed concern that "teaching staff is using GenAI to mark [their] answers and give [them] feedback" and they believed it resulted in being marked down for wording an answer differently from the keywords the tool expected. Another student believed that tutors and lecturers "waste a lot of time in class talking about Generative AI instead of demonstrating practical skills." Regarding assessment practices, students referred to concerns around assessment design and the consequences of institutional responses to AI. One student explained that assessment descriptions and assessment tasks had become "more convoluted in an attempt to prevent students from using GenAI." Moreover, students mentioned that they were required to add "extra components to assessments, such as an oral defence, to prove that [their] work is [their] own."

The pattern in this theme is different from "study practices" and "efficiency." Students' responses were often positive when referring to their own uses of AI for study purposes; however, responses were mostly negative when they were referring to institutional practices, especially assessment. The students therefore considered

AI to have a positive impact on their own study practices while identifying concerns about how teaching and assessment practices were responding to AI.

The findings across the four themes show that positive coding was concentrated around practical study activities and efficiency, especially in finding solutions and saving time. In contrast, negative coding focused on quality, especially accuracy, and around institutional practices.

Discussion

The findings suggest that AI is valued for its role in studying processes, as distinct from the quality of individual outputs. The results also suggest that more positive impacts of AI tend to associate with student-directed uses of the technology, while negative impacts are more strongly associated with what others do with it. We offer three observations as to the implications of these findings.

Observation 1: AI is reorganising study practices

Our findings suggest that students perceive AI as changing the shape of studying in ways that cannot be simply reduced to instrumental gains and losses, such as speed or accuracy. Although efficiency was an important part of students' accounts, the data suggest that the impact of AI cannot be reduced to only saving time. The largest theme was *study practices*, which included finding solutions, summarising, feedback, searching, and analysing. These codes describe changes to the ordinary activities through which students study, rather than merely the speed with which they complete them.

AI appears to be entering the workflow at multiple points before work begins, as students generate ideas or outlines; during work, as they search, summarise, analyse, and seek feedback; and, after initial production, as they refine outputs or check quality. For example, one student described AI as an "initial launchpad for sourcing information" that was "effective in establishing broad ideas that are at the crux of the assignment" and supported later research, in which they could "elaborate on these ideas." Another student described a more distributed workflow, noting that they could "summarise notes," "write paragraphs," ask AI to "proofread and improve" their writing, and use it to "research on Google quicker."

The significance of AI, then, is not only in making existing study practices more efficient, rather, it is that students are beginning to reorganise study around the availability of AI-mediated support. This embeddedness helps to explain the difficulty educators face in establishing "the line" for acceptable AI use in higher education (Corbin et al., 2025).

Observation 2: Students value AI as a process tool despite concerns about inaccuracy

Accuracy was by far the most prominent negative impact identified within the study, accounting for 69.0% of all negative coded instances included in this analysis. However, this concern did not appear to undermine students' overall perception that AI could support their study practices. Instead, the data suggest that students treated AI less as a source of authoritative knowledge and more as a process tool. For example, our data shows that AI was valued for generating possibilities, such as ideas, outlines, summaries, explanations, prompts for further thinking, or initial directions for problem solving. In these cases, the usefulness of AI does not necessarily depend on students accepting the factual accuracy of its outputs. Rather, it seems plausible that the utility of these uses exists outside of true or false propositional content, such as in the value of a starting point or an alternative viewpoint. In such cases, students may well position themselves as retaining responsibility for judging, revising, and completing the work.

Across the data, there were multiple instances of students reporting different positive impacts on their study practices and efficiency while acknowledging AI's inaccuracy. One student, for example, reported positive impacts of AI on finding solutions, but noted that they had "very little trust in the accuracy of the answers" provided by GenAI. This helps explain how strong concerns about inaccuracy can coexist with strongly positive accounts of AI's role in finding solutions, improving output quality, saving time, and supporting productivity.

While concerns are commonly expressed about the accuracy of AI tools for learning and teaching purposes in higher education (Melisa et al., 2025), this is likely to be dependent on the context in which the tools are deployed—some more recent studies find that under appropriate conditions, AI tools can, for example, produce acceptably accurate feedback information (Cengiz & Aptoula, 2026). Our finding that students do take a critical view of the accuracy and reliability of AI technology is consistent with other recent studies (for example, Bearman et al., 2026; Dickinson & Marshall 2026); however, it is unclear to what extent the students in this study are able to exercise that criticality in practice.

Observation 3: AI is "helpful in my hands, harmful in theirs"

A striking pattern in the studying data is not simply that students describe AI as useful, but that its perceived value appears to depend on how they were involved in its deployment. Student-directed uses of AI were overwhelmingly positive: finding solutions, summarising, feedback, searching, and analysing were all coded as positive in 99.1% of responses. These uses position AI as a tool students can recruit into their own study practices, particularly to get started, overcome obstacles, generate ideas, or improve work in progress.

By contrast, the two codes concerned with institutional practices were much more likely to be negative (85.8% of the total responses within the theme). It is important to note that these codes were assigned to only a small number of the total responses, and these data should be read in light of the limitations mentioned earlier in this paper: namely, it is possible that these responses reflect the perspectives of a minority of students who were more motivated than most to make negative reports about the impact of AI as experienced through teaching and assessment practices.

Some students reported positive impacts on their study practices while at the same time expressing negative impacts of AI on their universities. For example, one student mentioned that AI helped them in "brainstorming ideas for an assignment, helping [them] get over a writing block for an assignment, [and] helped [them] cut down words on an assignment," while also locating AI's negative impact in how their university was changing assessments by "making them harder or more complex so it's more difficult to use GenAI." Another student believed that "the attempts of university staff to prevent the use [of AI] through the creation of convoluted assessment tasks" had a negative impact on their learning, while acknowledging AI's positive impacts on their study practices and efficiency. These responses suggest that students are not simply pro- or anti-AI. Rather, they appear to welcome AI when it extends their control over study, but resist it when it is experienced as part of the institutional conditions under which their learning is organised, monitored, or judged.

Against this account, it is useful to recognise the tendency for students to experience ambiguity around the acceptability of AI use in higher education (Bearman et al., 2026), and that some students knowingly deploy the technology in ways that are likely to contravene local academic integrity frameworks (Stone, 2025). Some caution in the interpretation of our findings is needed: namely, that the data do not establish that institutional AI deployment is always viewed negatively by students in general, nor that student-directed and institution-directed uses are directly comparable. Nonetheless, it is likely that more productive collaboration between students, educators, and their institutions is needed, and that this will mean navigating complex trust dynamics wherein trust between these groups of actors is not accepted as a given (Joubert & Strever, 2025) but need to be "earned through continuous practices of living, leading, and learning" (Eaton, 2024, p. 6; as cited in Joubert & Strever, 2025, p. 71).

Conclusion

This paper examined how higher education students reported the positive and negative impacts of AI on their study practices. These impacts are complex and sometimes contradictory, with students weighing the practical value of AI against concerns about accuracy, trust, effort, and control. However, the findings also suggest that students' judgements are not simply about whether AI is good or bad for learning. Rather, students appear to value AI because it is becoming part of the organisation of studying itself: helping them begin, continue, refine, and complete academic work. Concerns about inaccuracy remained prominent, yet did not preclude positive accounts of AI because students could still value it as a provisional or generative tool within the study process. These findings do not establish that students can reliably identify inaccurate outputs, or that the reported benefits translate into improved learning outcomes. They do, however, suggest that educational responses

need to attend both to what AI produces and to how its availability may reorganise the processes through which students study.

The perceived value of AI also appeared to vary according to context, agency, and control. Students predominantly described positive impacts when discussing their own uses of AI, while the smaller number of responses concerning institutional teaching and assessment practices were largely negative. Given the limited number of comments about institutional practices and the possibility of response bias, this finding should not be interpreted as evidence of widespread student opposition to institutional responses. Nevertheless, the consistency of the pattern warrants attention. Students' judgements concerned not only whether AI was useful, but also who controlled its use, how it affected their work, and whether institutional responses were experienced as legitimate and trustworthy. This complicates portrayals of students as either enthusiastic adopters or uncritical users of AI. Instead, the findings indicate that students make situated judgements about when AI helps, when it introduces costs or risks, and what role they are able to exercise in its use.

Several cautious implications follow. First, because students describe AI as distributed across the study process, institutional guidance may need to move beyond lists of permitted and prohibited tools or tasks. Students also need support to judge how AI use at different points in their work may contribute to, alter, or displace learning. Second, AI literacy should include the capacity to evaluate and verify outputs, recognise situations in which accuracy is particularly important, and make deliberate decisions about when AI provides useful support. Finally, changes to teaching, assessment, or monitoring in response to AI should be explained transparently and, where possible, developed through dialogue with students. Student participation does not remove institutional responsibility for protecting learning and academic integrity, but it may contribute to responses that are better understood and considered more legitimate.

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