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Exploring student-AI interaction in assessment through the lens of learner agency: case studies in UK higher education

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ABSTRACT

This study explores students-AI interaction, specifically in assessment, through the lens of learner agency, in the context of UK higher education. Using self-regulated learning as the theoretical foundation, this paper used a qualitative approach, namely focus groups, to collect data. Ten focus groups, with forty-two students, were conducted in two Russell Group universities. The findings suggest that even though some have begun moving towards challenging AI outputs and engaging in reflection on the responses provided, the current usage of AI among students appears to be mainly for information retrieval, and/or for accelerating certain routine tasks in their learning. This level of usage therefore only strengthens lower-level thinking skills. The significance of the paper lies in two areas. Firstly, we propose a framework showing the dimensions of student-AI interaction and the connection with self-regulated learning. This framework will influence policy, practice and guidance on AI integration in learning and teaching in higher education. And secondly, this paper serves as guidance on how policy makers and educators can encourage and support effective AI usage among students throughout their learning process.

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Introduction

Human-AI collaborative learning has recently become a focal point in higher education research (Atchley et al. 2024; Nguyen et al. 2024). Amid the growing adoption of generative AI (GenAI) in higher education, students' use of AI tools has gradually evolved from using them to *assist* learning to engaging in human-AI *collaborative* learning. Both terms, AI-assisted learning and human-AI collaborative learning, have appeared in research frequently. Even though they both involve the use of GenAI tools in learning, the meanings are very different.

AI-assisted learning refers to the use of AI for information retrieval, automating academic tasks (e.g. summarising long text, data transcription) and/or providing customised help or feedback based on students' input. For this type of usage, learning occurs in a one-way process. AI tools are used to provide simple assistance to students, and the goal is to help them obtain information or answers quickly. For this reason, the term is associated more closely with lower-level learning, as AI tools are used mainly for knowledge acquisition (Pham et al. 2023). Human-AI collaborative

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learning may be considered a type of collaborative learning. It refers to the use of AI to explore problems and to generate options that students are able to evaluate and synthesise. For this type of usage, learning occurs in a two-way process, because both students and AI become intellectual partners or collaborators and jointly create new knowledge and/or ideas. The goal is to enable and support students to analyse, synthesise and evaluate content and options and make final decisions. Therefore, this type of collaboration is concerned with higher-level learning and is able to foster and enhance students' metacognition. Some of the activities reported regarding effective human-AI collaborative learning include AI providing personalised feedback and recommendations towards the learning goals (Ouyang et al. 2022), collaborative problem solving with AI (Wei et al. 2025) and prompt-driven human-AI collaborative coding for problem solving (Zhao et al. 2025). However, it is important to recognise that human-human collaboration and human-AI collaboration are fundamentally distinct forms of interaction.

The rapid feedback and data-driven insights provided by AI tools are likely to shift learning towards higher-level metacognitive skills, such as self-awareness, critical thinking, decision making and self-regulation (Essien et al. 2024). These skills are important for cultivating learner agency in students; that is, taking ownership of their own studies and engaging in self-directed, continuous learning (Torres Castro and Pineda-Báez 2023). Given the proliferation of GenAI in recent years, it is important to explore human-AI collaboration and to consider the extent to which it facilitates or hinders learner agency development. Exploring human-AI interaction is timely and critical, since the use of AI tools by students is likely to become even more widespread (Abbas, Jam, and Khan 2024). Additionally, universities are still in the process of investigating effective ways in which AI can support and enhance student learning.

The present study uses self-regulated learning (SRL) as the theoretical foundation. SRL describes how students plan, monitor and reflect on their own learning. It conceptualises learners as active, intentional, agentic participants who are able to use their own resources to set and achieve personally meaningful learning goals. Drawing on this theory, this paper aims to explore the affordances of student-AI collaborative learning by exploring the following questions:

RQ1: To what extent do student-AI interactions cultivate learner agency?

RQ2: How can universities support the shift from AI-assisted learning to student-AI collaborative learning?

Data were collected using focus groups with undergraduate and postgraduate students studying at two Russell Group universities in London. The findings offer a more nuanced understanding in this area and make contributions to the literature. The paper also makes recommendations to key university stakeholders, particularly academic staff and students, on how such disruptive technology can be integrated more effectively to enhance the student learning experience and better prepare them for future continuous learning in the workforce.

Self-regulated learning

Self-regulated learning (SRL) (Zimmerman 2000) describes cyclical processes in that students actively take control of their metacognition, motivation and action to achieve their learning goals. Metacognition is a higher-level thinking skill and is concerned with self-awareness and controlling one's own thinking and related cognitive activities proactively. Metacognition and motivation are closely inter-related (Jiang and Kleitman 2015). The latter is considered a key driver for effective metacognition. To develop a high level of metacognition awareness, students need to have a strong motive to do so. Key actions include setting goals, selecting strategies, monitoring processes and reflecting on outcomes (Brenner 2022).

The theory includes three cyclical phases covering before, during and after learning, namely forethought, performance and self-reflection. The forethought phase involves considerable planning. The focus is on setting goals, choosing strategic plans and being prepared to engage in learning activities. Self-motivation during this phase includes mainly reflecting on the goals and activities

set. Drawing on concepts such as self-efficacy and outcome expectations, the aim is to ensure that the goals and activities set are realistic (Panadero 2017). The emphasis of the performance phase is on action. It refers to the execution of learning tasks. During this phase, self-control (e.g. task strategies and time management) and self-observation (e.g. metacognitive monitoring and self-recording) play an important role in motivating students to stay focused on task, to track their learning progress and to optimise their effort. Self-reflection is the final phase. After completing the learning tasks, students evaluate their performance against the goals set, review and reflect on what worked and what did not. The evaluation and reflection will then be used for future improvement (Zimmerman 2000).

SRL is appropriate for this paper because it provides a strong foundation for learner agency. Students who take better control of their own learning and work effectively through interactions with their peers and environments can better foster learner agency (Mairitsch et al. 2023). The theory has been applied in a range of studies, including research on staff and student co-creation of learning materials (Villatoro Moral and de-Benito Crosseti 2022), and investigations into how self-regulation can be taught, supported and measured (Cleary, Callan, and Zimmerman 2012). Similarly, some researchers investigated how the theory can be used as an effective pedagogical approach to develop student self-regulation (Kong and Lin 2023).

Learner agency and human-AI collaboration

In education generally, agency is seen as a key skill for twenty-first century learners, both as an end goal in itself as well as a process of building confidence to negotiate learning environments and content (Torres Castro and Pineda-Báez 2023). As is the case with many human-focused theoretical constructs, however, it is difficult to define precisely what is meant by agency. Definitions often refer to a learner's ability to take control of their learning and act accordingly within a given sociocultural context. For example, Ahearn (2001, 112) defines agency as 'the socioculturally mediated capacity to act.' Others place emphasis on the learner's motivations and emotions in relation to their capacity to act (e.g. Gao 2010). Taking the sociocultural and the motivational aspects into account, Mercer (2011) views agency from two perspectives: the extent to which learners feel they have the capacity to act – their sense of agency; and the learner's outward behaviors, actions, or deliberate non-participation within a given social context. From this point of view, agency is not only about what can be seen in terms of how a learner behaves, but also concerns delving into the learner's thoughts, beliefs, and feelings in relation to their learning.

There are also nuances in how learner agency is understood depending on disciplinary cultures and beliefs. For example, in psychological disciplines, there is often a focus on intentions, motivations, and beliefs about the learner's own capacity to act, aligned with key concepts such as self-efficacy.

(Bandura 2006). In educational studies, there is closer alignment with Mercer's (2011) conceptualisation outlined above, emphasising engagement with others and the social construction of knowledge (Mameli, Grazia, and Molinari 2023; Martin 2004), whereas there is some evidence of less focus on the social elements of agency in science, technology, engineering, and mathematics (STEM) disciplines (e.g. Garibay 2015; Gupta et al. 2024). The extent to which agency is 'socioculturally mediated', in Ahearn's (2001, 112) terms, is important when considering how learner agency is developed – or hindered – in the context of collaborative learning, where the disciplinary context and social construction of knowledge are key factors contributing to the collaborative learning process.

The affordances of learner agency, as well as barriers to learners developing their agency, have been researched in many studies across various disciplinary contexts. In a systematic review, Stenalt and Lassesen (2024) explored primary research findings on learner agency in higher education from 42 studies conducted between 1980 and 2021. Across the studies, it is clear that interaction-rich pedagogies, such as feedback dialogue, collaborative projects, peer learning, as well as teacher responsiveness to students' decision-making, play a crucial role in cultivating learner

agency. However, the literature highlights several potential limitations of human-human interaction, such as over-reliance on the teacher if there is a lack of balance between teacher-student interaction and opportunities for interaction with peers and self-reflection (e.g. Carless and Boud 2018). Teng (2021) also found that some students may self-censor their ideas to conform to the social norms within their peer group. This leads to the question of potential affordances of non-human collaborators in students' learning. One possible form of non-human collaboration, which has become ubiquitous in recent years, is human-AI collaboration. A key difference between human-human and human-AI collaboration lies in enabling the learner to offload unnecessary cognitive load to a GenAI tool, leaving the student with more capacity for higher-order tasks. For example, Atchley et al. (2024) argue that such offloading of lower-order tasks can facilitate the development of the student's metacognitive skills.

However, it is questionable whether simply offloading lower-level tasks to AI will result in enhanced metacognition. In a systematic review of studies investigating opportunities and risks of AI in higher education, mainly ChatGPT, Kardiensyah and Qodriani (2024) found several positive effects of GenAI on students' learning. However, the authors also caution that there can be negative effects on students' skills as well as their interactions with peers and their teachers. That is to say, any enhancement to metacognition and students' ability to reflect on and understand their own learning processes does not happen if AI is simply used as a shortcut rather than as a collaborator (Owoseni, Kolade, and Egbetokun 2024).

In a recent study, Nacereddine (2025) explored how proactive use of GenAI can help to develop students' metacognitive skills through structured and scaffolded prompts. Nacereddine (2025) used AI-powered prompts to encourage students to reflect on their learning and to explain their thought processes and understanding of materials provided by the teacher. This research illustrates how a link can be made between collaborating with GenAI and developing students' sense of control over their learning, i.e. their agency, as they are using GenAI proactively to stimulate reflection rather than relinquish control to the AI tool.

In a study in the context of business education, the link between learner agency and human-AI collaboration is evidenced even more explicitly. Razmerita (2024) conducted 16 interviews to explore how students use GenAI for their studies. Data from this method were used to inform the development of a survey to gain broader insights into students' interactions with GenAI. Based on the interviews and 215 survey responses, Razmerita found that some students engaged in practices that could hinder learning, whereas others engaged more collaboratively and interactively, aligned with the social constructivist, agentic notions discussed above. Razmerita (2024) concludes that collaboration between students and AI hinges on well-developed student agency. So far, as explored above, the literature shows some evidence that human-human interaction might play an important role in developing agency. This raises questions about the extent to which human-AI collaboration can cultivate learner agency.

Methods

To address the research questions, this paper adopted a qualitative approach and used focus groups to collect data, as the authors aimed at gaining rich insights into the group's opinions and attitudes. This method was deemed appropriate also because it cultivates and encourages lively and engaging discussions, idea sharing and debates among the participants through social gathering and interaction (Parker and Tritter 2006). Ethical approval was granted at both institutions, and informed consent was obtained from all participants. Data were collected between May and September 2024. Both universities are pre-1992 and consider themselves to be research-intensive institutions.

The sample population included all students (full time and part time; in person and remote) studying at each institution at the time. A purposive sampling strategy (Campbell et al. 2020) was adopted with the inclusion criteria stipulating that participants were either using AI tools or had

done so recently. They were subsequently recruited using email (see Appendixes table 1 for participant information). Focus groups were conducted either online or in person, depending on participants' preferences, with the aim of fostering an inclusive environment that encouraged open expression of their thoughts and opinions.

In order to further enhance the trustworthiness of the research, the following strategies were implemented. This was to address the potential power imbalance between the researchers and the focus group participants (Cameron, Kothari, and Fiolet 2025), as the participants in this study were students: 1) participants were not recruited from cohorts that the researchers were teaching or had taught; 2) all participants were explicitly informed that their participation, including any comments shared during the discussions, would have no impact on their academic performance or assessment outcomes; 3) it was made clear that the research was being conducted independently by the researchers, and was not on behalf of the universities and 4) participants were also informed that the findings would be reported in an anonymised form, and neither the university nor the students would be able to be identified. We also emphasised to participants that there are no right and wrong answers, recognising that discussions about the use of AI in assessment contexts can be sensitive. Our aim was to create an open and non-judgmental space in which participants feel comfortable sharing their views and experiences.

A selection of principal questions is listed below. In total, there were 10 focus groups (University A: FG 1–3 and University B: FG 4–10) and 40 participants (University A: 14 and University B: 26), from disciplines across STEM, medicine and business. Each focus group was around 90 min and included four to six participants. Responses and participant identities were anonymised (Table 1).

Upon completion of the focus groups, the recordings were transcribed verbatim and anonymised prior to analysis. To ensure theme consistency, we adopted an inductive, reflexive thematic analysis approach (Braun and Clarke 2019). This approach was chosen because it is designed to understand and interpret rich, nuanced and subjective data (Byrne 2022). The analysis was carried out through the following steps: 1) data familiarisation, 2) data coding, 3) theme searching, 4) thematic review, 5) defining each theme and 6) naming themes. As a starting point, the emphasis was on developing a deep understanding of the data collected. During this process, the authors familiarised themselves with the depth and breadth of the data through an iterative process of transcript reading. The authors then worked independently to identify the initial codes and produce the themes independently. As the next step, the authors conducted systematic debriefings, where each explained how they derived themes from the data, coding processes, examples of the key patterns identified, and the supporting participant comments (McMahon and Winch 2018). The main themes and example codes are presented in Appendix Table 2.

Findings

AI-assisted learning

For many participants, the role of AI was primarily conceptualised as a tool to assist with academic tasks. This often involves using AI as an information retrieval mechanism, described by one student as 'a substitute for a search engine' (Max, FG8). Students also reported using AI to locate additional information in academic contexts specifically, to 'clarify certain sentences in a paper or in a textbook' (Kabir, FG9). Additionally, AI is used as an additional support tool for assessments, such as

Table 1. A selection of principal questions.

1. Can you describe a recent time when you used a GenAI tool for a learning task or assessment?
2. When using GenAI for assessments, what aspects do you find most helpful for your learning?
3. Have you experienced any challenges while using GenAI tools in your assessments? If so, what were they?
4. What happened if the GenAI tool gave you a wrong or not so helpful answer? Did you do anything to fix it? If the answer is yes, what did you do?
5. To what extent do you trust GenAI tools and how would you evaluate their reliability, competence, and integrity?

examination preparation. In this context, AI was perceived as a reliable resource for this type of task, and was frequently associated with efficiency:

'I usually use it like before exam because we always get some practice MCQ questions, but they don't give us like explanation for each choice. So I would ask ChatGPT to help me to like explain each statement and maybe you point out the source where it comes from.' (Jia, FG5)

'... so whenever I'm struggling with understanding something, whether that's a concept and especially like again a lot in my BSc here from going through papers and stuff, it was really good especially when you don't have to fully review a paper, you just wanted to kind of get its key insights. It was good to just you could put a lot of that through ... and get a very quick and very digestible summary.' (Kamal, FG10)

AI's perceived advantage lay in its potential to accelerate tasks that would otherwise be time consuming and might have a perceived lower cognitive value. This sentiment was echoed by other participants, who noted using AI to decide 'if I want to carry on reading the paper instead of reading everything first of all' as well as for identifying suitable papers to read (Pravit, FG6). Therefore, the value of AI seems to lie in 'cutting down the hours' (Aarush, FG7). Another common use amongst students is using AI to assist with accuracy and clarity of expression:

'I did use it to check grammar, but that's about it because I was like, I was a bit worried about the plagiarism like thing found out about like AI being involved ...' (Xiang, FG9)

It appears that students perceived that such usage was acceptable as they felt that it was not linked to plagiarism concerns that other uses might raise. In this context, AI was attributed a level of linguistic expertise that some students, particularly international students, felt they did not possess to the same extent. This attribution of a level of expertise that students lacked was also evident in the examples discussed above, as well as in the literature. AI-generated responses were often accepted as accurate, with little critical consideration of their appropriateness for a given task.

Transition to human-AI collaborative learning in assessment contexts

When prompted to elaborate on their thoughts and experiences of using GenAI tools to support their assessment practices, students tended to comment on their use for formative assessments and more broadly on how these tools supported their studies. While the majority described using GenAI primarily for lower-level cognitive tasks, some students appeared to move beyond efficiency and information retrieval and towards a more two-way collaborative process involving active and critical engagement for higher-order learning. For example, Ling (FG5) explained:

'When using like AI for assessments, I tend to not use it necessarily to give answers, but ideas where I could find an answer. So not necessarily like I guess it's kind of the critical kind of thinking ... where it's like, this is an idea that I can expand on and look into it because it might not be right.'

Such usage indicates a strong awareness of AI's limitations, alongside a reflective and analytical approach that ensures students maintain responsibility for the final decision. Similarly, Leena (FG9) and George (FG1) reported using GenAI to initiate their thinking processes, particularly when they were unsure where to begin. For Leena, it provides 'a good starting point in the spring-board' for generating options she can then build on while George noted that 'I am currently using GenAI tools to basically help me with my summative essays ... I am using them to generate research questions. It helps me size up from different perspectives'.

Additionally, some students elaborated on how they use GenAI to simulate 'authentic' scenarios as part of preparing for assessments. For instance, Fred (FG5) used Gemini to generate potential questions that 'someone [scientists] could ask about my presentation to kind of 'prepare me beforehand' for his research presentation defense. He described the experience as 'just like talking to an expert. You had good questions, and it was some I hadn't thought of'. In this instance, the student used AI as a kind of 'mock examiner' to strengthen his ability to defend his ideas and prepare for challenging questions. Another student, Kabir (FG9), also reported using AI to create

mock patient scenarios to practice his clinical reasoning or to test or teach others in his study group. These use cases demonstrate a more sophisticated and strategic form of AI use in which human-centric input prompts AI to make cognitive contributions, enabling it to act as an ‘intellectual partners’ or ‘collaborators’.

Furthermore, GenAI was used to refine student work and receive more tailored, personalised feedback by supplying relevant contextual information.

‘So I don’t know if anyone else does this, but like for the lab reports for example, what I’ve done is I’ve used my old lab report plus the feedback given that to the ChatGPT and basically asked it how do I write a better one? So now it has my original template, the feedback how to make it better, and then I’ll give it the marking rubric and basically ask it how can I refine this?’ (Malik, FG4)

This strategy of providing multiple contextual files shows strong awareness of the information AI often needs to generate more personalised feedback. It also demonstrates how AI can potentially help students interpret feedback and translate it into actionable steps for refinement. Similarly, Fred (FG5) described uploading the mark scheme for AI to mark his assignment draft and then improving his work based on the feedback before ‘[getting] it regraded again’, noting that ‘it very much improved it in ways I wouldn’t have thought of before, which was quite cool’. However, it seems that many students remained skeptical about using AI for feedback and preferred to consult peers and instructors if they had doubts about their work or the feedback provided by tutors.

Students also demonstrated increasing awareness of the limits of GenAI and the need to apply their own knowledge and expertise when tasks are more complex.

‘Regarding coding in general like recently I built a website, it was able to give me the boilerplate code and just the backend of it. But the rest of it, because of the complexity and the integration, it wasn’t able to figure it out. So that’s something I had to do myself.’ (Malik, FG4)

‘It is mainly I use ChatGPT for the Python programming side because I know it’s not as good as doing the actual math or physics.’ (Aarush, FG7)

This process of developing awareness and building the habit of co-creating with AI involves recognising where one’s own knowledge is more appropriate and where AI can provide support. In other words, it appears that students started developing a sense of when their own knowledge base is essential and when AI can help fill specific gaps. This indicates a more agentic approach to human-AI collaborative learning.

Awareness of limitations extended beyond the realisation that AI-generated content was sometimes unfit for purpose, prompting reflection on the tool’s value and its role in learning:

‘Because another thing that ChatGPT does, especially in coding in physics, it’s either gets it or it does something that’s wrong, but in coding sometimes majority of the times it takes like a shortcuts like in logic and it’s not as easy to follow in terms of the code logic. It’s more basically the most efficient, the best the shortest code to write down for it to work. And well, I never really coded before university so. For someone who’s got basically like a year and a half of, like, broken coding experience. The shortest answer isn’t usually the best for me. I want something that actually makes sense.’ (Paul, FG4)

The quote above demonstrates a deeper understanding of the steps involved in learning coding and how AI can potentially bypass important learning opportunities for beginners. This reflects a nuanced awareness of where AI can facilitate skill development and where it may impede it. Additionally, student comments supported the literature and indicated that better prompt engineering skills helped improve the quality of AI interactions and yielded more useful results:

‘I learnt how to prompt better. You have to be specific [about the questions asking]. I know it is a skill we need to develop in how to find [the best answers].’ (Lisa, FG3)

Additionally, this dimension demonstrates a clear sign of SRL, which aligns well with the existing literature (Xu et al. 2025). SRL refers to the process that learners actively take charge of their own learning. It appears that these students moved beyond passive consumption of information. They

intentionally manage how they use AI to support, challenge and improve their learning, and the activities they engage in with AI, such as reflection, evaluation and iterative improvement, are core elements of SRL. Through these activities, they take greater control of their learning.

Motivational drivers of AI use in formative and summative tasks

Motivation is a core component of SRL, particularly at the forethought stage. The comments below indicate students' motivations for using AI in both formative and summative assessments as well as their emerging awareness of its potential benefits and limitations for learning.

Discussions also revealed polarised views regarding the appropriateness of AI use in formative versus summative assessments. For some, formative assessment was conceptualised as a critical vehicle for learning, where AI use could pose a perceived threat to creativity, independent thinking and skill development. Helena (FG7) articulated this concern:

'So formative assessments. The whole point of them is to kind of make you learn, right? And if you're just putting it into ChatGPT, it's probably not going to be the best for you as an individual. And it also kind of, I think, with the nice thing with formative assessments is you kind of get more room to be creative sometimes if, like, and, you know, actually reflect on your experiences.'

This perspective was echoed by Paul (FG4), who valued formative assessment as a 'safe space to learn and fail', framing it as an opportunity to engage deeply with content. Within this conceptualisation, AI use was perceived as diminishing opportunities for learning, skill development and student agency. Similarly, Kabir (FG9) expressed concern that AI might 'take away [his] thinking skills.' However, Kabir also acknowledged that greater proficiency with AI positioned it as a supplement to learning rather than an impediment, reflecting an understanding of AI literacy.

One valued aspect of AI interactions was the possibility of iterative dialogue in a judgment-free environment. Leena (FG9) described this benefit:

'I can ask it the stupid questions that I feel too scared to ask in person. And whenever it gives me an answer I don't like, I don't understand. I actually like ask it to like, can you rewrite that in a more simpler way? And I keep going. But like more simple, more simple until I can finally understand it. And then I can work my way back through the more complex stuff. So it's good for like the topics you find really difficult.'

Leena's account highlights how AI can provide a low-stakes platform for students to engage with challenging material without fear of embarrassment, a key motivational driver for learning. Hana (FG10) shared a similar view, noting that AI is 'very good at breaking things down and explaining what it does.' These examples illustrate how AI can support comprehension in formative contexts, where the primary aim is understanding rather than performance.

While the views presented above paint a picture of formative assessments being valued, some students perceived them as a burden. This is where AI could offload tasks considered unhelpful, particularly when there were no consequences for detection. Kabir's (FG9) account below further illustrates how students distinguish between assessments that feel meaningful and those they view as lacking purpose:

'I think if [...] an assignment where it doesn't test anything and it just tests a bunch of random facts, then [...] people use AI against it, to be honest. But if [lecturers are] gonna actually set an assignment where it's an actual application and synthesis of knowledge, then obviously it's wrong to use that.'

Some students appeared to perceive AI as a tool that could help them maximise their grade outcomes in summative contexts:

'... if it's summative, obviously I want good grades ... so I will try my best to then maximise my grades and that would mean obviously using ChatGPT.' (Paul, FG4)

Given the competitive nature of research institutions, it is unsurprising that AI was framed as a tool for achieving optimal outcomes. However, concerns about plagiarism and academic integrity were prevalent. Malik (FG4) explained:

'For a graded task, obviously you don't want to be flagged for AI, right? So for graded task instead of getting it to write me an essay, for example, I'll get it to write me an essay plan and then I'll write me own essay.'

Malik's approach demonstrates a cautious yet strategic use of AI, reflecting an understanding of how to integrate AI to enhance learning without outsourcing the entire task, a sign of developing AI literacy.

Discussion and conclusion

Students' comments suggest that student-AI interactions can be understood through three broad dimensions: *AI-assisted learning*, *transitional uses of AI* and *student-AI collaborative learning*. These dimensions are not intended to represent fixed stages or a linear developmental pathway. Instead, they capture different ways in which students described their engagement with AI in relation to their learning and assessment practices.

As the findings suggest, for AI-assisted learning, students act as 'information recipients' and use AI mainly to support lower-order cognitive work and routine task completion (e.g. remembering, understanding and summarising). AI tools appear to be used across assessment-related activities, including preparation for essays and exams. AI was used by and large for simple information retrieval, obtaining direct outputs and for surface level revisions, including grammar and language enhancement. This form of engagement aligns with previous research which indicates that this type of basic task does not necessarily improve student cognition (Kardiansyah and Qodriani 2024).

The second dimension, transitional uses of AI, captures examples where students described engaging with AI in more interactive and evaluative ways. Here, the level of usage has increased, and students begin to show emerging signs of SRL. They use the technology not only to gather information, but more importantly to start investigating complex problems, evaluating and critiquing the outputs. In this context, AI begins to be used to support greater learner control over the learning process, with students showing increased motivation towards self-regulated learning behaviors. The interactive dialogue and the feedback provided by and to AI, in particular, could help stimulate student cognitive activities. In this context, students begin to act as 'information responders/participants', and become more engaged with the outputs of AI. This aligns well with existing literature, which shows that learner agency is fostered through interaction-rich pedagogies (Stenalt and Lassen 2024), and dialogic interaction with AI falls within such pedagogies.

The third dimension, student-AI collaborative learning, refers to instances in which students reported collaborating with AI in more co-constructive ways. In this form of engagement, AI was positioned less as a source of information and more as a partner in idea generation, content development and refinement. In this collaborative relationship, students take on the role of primary decision-makers. This indicates a high level of SRL, while AI is used to support and enhance their learning progress, and may subsequently support the development of learner agency, because increased SRL enables students to take greater control over decision-making, goal setting and the monitoring of their learning. Such collaboration is more closely associated with higher-order thinking skills (e.g. analysing, evaluating and creating) (Essien et al. 2024). Existing research has also highlighted certain early adopters among students transitioning into more advanced forms of AI engagement, for example, through the use of structured and scaffolded prompts (Nacereddine 2025). This type of two-way communication can promote self-reflection, which may in turn enhance learning effectiveness.

During the iterative processes, specifically within dimensions 2 and 3, students gradually develop self-regulated learning skills which support them in cultivating learner agency. For example, the transitional uses of AI correspond to the performance stage of SRL. In this context, students use AI to help regulate time and effort through task planning and self-efficacy. Student-AI collaborative learning appears to relate to both the performance and the self-regulation stages. Some students use AI to support task execution by regulating their thinking processes, monitoring progress and engaging

in active self-observation. Others have developed the ability and habit to critically reflect on AI use, evaluating its limitations and making informed judgements about human-AI collaboration.

However, it should be noted that the data collected in this study seem to align mainly within the first two dimensions (e.g. predominantly low-level usage, partially in the next stage). The level of usage in the final dimension is still comparatively low. This observation is derived from an interpretive analysis of participants' accounts and given the qualitative nature of the study, reflects an analytical rather than objective classification. This finding responds to what has already been reported (Wei et al. 2025; Zhao et al. 2025), which suggests that students are beginning to move beyond viewing GenAI as a source of information towards recognising its potential as a learning partner.

The discussions above identify student-AI interaction patterns that are represented in the tentative framework shown in Figure 1 below. To the best of the authors' knowledge, the dimensions of student-AI interactions have not been classified previously, even though the terms such as AI-assisted learning and human-AI collaborative learning have been mentioned in existing research. Additionally, there has not yet been a framework showing the connection between student-AI uses and SLR. This framework helps bridge the gap.

It is also important to point out that the sample does not cover all disciplines, and therefore limits the transferability of the findings. Disciplinary and culture differences may shape how learner agency is developed (Qu, Tan, and Wang 2024) and how GenAI is engaged with in learning. As such, motivations for and responses to AI use are likely to vary across disciplines. Therefore, the findings of this study should be interpreted as primarily relevant to the disciplines represented in the sample (e.g. STEM, medicine and business). Further research should explore learner agency and AI use across a wider range of disciplines to gain a more profound understanding.

With regard to learner agency in particular, our findings not only support existing studies (Mercer 2011), but more importantly, they make a contribution by showing that, in the context of students-AI collaboration, our findings suggest that many of our students hold differing perspectives on the use of AI in formative and summative assessments. Their decisions about whether, when and how to involve AI tools in their assessment processes are strongly shaped by their motivation and by how they perceive the purpose of the task, which links closely to self-regulated learning. For example, some students described using AI to maximise their grades while others emphasised

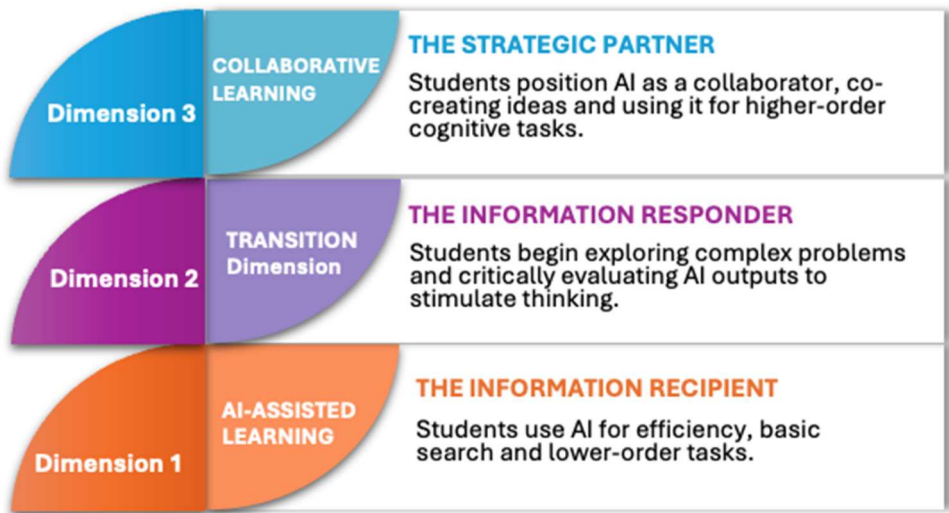


Figure 1. The dimensions of student-AI interactions and the connection with self-regulated learning.

Source: the authors' own work.

that formative assessment is for learning and therefore felt that AI would not facilitate that process. These views influence their motivation, and in turn, motivation drives how AI tools are used. Some students also noted that the nature of the task and its authentic application matters more than whether an assessment is formative or summative. This indicates that motivational shifts are key in supporting students to navigate their use of AI, as these shifts relate to their sense of agency and how they regulate their metacognitive strategies. In other words, scaffolding students to make conscious decisions about when to use AI without compromising or shortcutting their learning is essential. For example, educators can prompt students to reflect by asking: How does using AI in this way for this task make you feel? Do you feel empowered or do you feel that your learning has been outsourced? When navigating this uncertain space alongside students, recognising the emotional and motivational dimensions becomes critical as these relate directly to the self-regulated learning where goal-setting, choice of strategies and self-evaluation are central to developing AI literacy.

Based on the literature and the data, the overarching goal for universities in the age of AI should be supporting students to progress from how to use AI tools to how to think with the tools, and to how to govern the co-creation process. To achieve this goal, the following two approaches may be considered. Firstly, students should be provided with continuous and dedicated AI literacy training, with a particular emphasis on advanced prompt engineering skills. In recent years, some universities have started offering GenAI literacy training, either as a core curriculum activity or an extra curriculum activity (O'Dea et al. 2026; Kong, Cheung, and Zhang 2022). This kind of training has built a solid foundation for helping students understand how to use AI tools. Moving forward, to support more critical, reflective and collaborative forms of student-AI engagement, AI literacy training should be made more widely available to students across universities. More importantly, training in this area should focus more on advanced prompt engineering skills, so that students get to know how to start challenging and critiquing AI outputs, and also how to think about complex problems or questions that can be used to support their learning and stimulate their thinking (Wang et al. 2024). This approach can help support more productive dialogues between students and AI, while fostering the mindset and ability to challenge AI outputs.

Secondly, dedicated in-class and independent learning activities should be provided to support students in moving from basic uses of AI towards more collaborative learning dimension (Xiao and Yi 2021). The activities should be scaffolded and accommodated by detailed examples and guidance that are relevant to the particular subject disciplines, and appropriate to the level of study. It is also important to consider students' broader learning processes, rather than focusing only on assessment, so that students understand that the applications of AI can be much broader and more versatile, and their use is not limited to, or should not be restricted to assessments. Furthermore, students should be guided to cultivate their self-regulated learning skills (Blair 2009), particularly how to progress from preparation to performance to self-evaluation while they are using AI tools.

To ensure both approaches work effectively, it is essential and critical to develop an ongoing and nuanced understanding of student usage of AI in their studies. To ensure a more comprehensive understanding, both quantitative and qualitative data should be collected. When collecting data, the framework proposed above can be used as a theoretical foundation, with equal attention given to all three dimensions, and also how such usage is associated with self-regulated learning. To date, student perceptions and usage have been collected predominantly through surveys, either at the institutions or at the national level by various organisations, such as Jisc, HEPI and Pearson plc. While these surveys provide valuable overviews, they appear to focus mainly on broad patterns of AI use. Less attention has been paid to more collaborative forms of student-AI engagement. As student use of AI continues to increase and the patterns of their use are also shifting gradually, a deeper understanding of these practices will help universities provide more tailored training and support for students.

Using self-regulated learning as the theoretical foundation, this paper suggests that the usage of AI could support aspects of learner agency. However, the effectiveness depends on how and what

the AI tools are used for. Based on the findings, we propose a framework for understanding the dimensions of student-AI interactions and how these relate to self-regulated learning. Whilst the study does not focus on the teaching perspective, existing research has highlighted the benefits of developing students' AI literacy through formal classroom learning in higher education (Hamamra, Khlaif, and Mayaleh 2025; Ng et al. 2026). The framework can be used as a useful foundation for designing teaching and training materials. Further research should examine the effectiveness of the framework in different learning contexts, as well as the variables that shape students' movement between different forms of AI engagement.

Our research has the following limitations. Firstly, the sample size is small, and the participants were predominately from STEM and business disciplines in two Russell Group universities. The scope of future research should be expanded to include more students from diverse disciplines, and in a wide range of institutional contexts. Nevertheless, this study provides a useful foundation for future research. While the study is based in the UK context, particularly within two London-based universities, the framework can be applied in other higher education contexts, within and outside the UK. Additionally, the data collected focused primarily on assessments only. Whilst the findings provided insightful observations, further research can expand beyond assessment to explore how students use AI across their broader learning experiences.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Focus group participants.

Focus group	Participant (Pseudonym)	Discipline	Level of study
1	Anna	Marketing	PG
1	James	Finance	PG
1	Ollie	Marketing	Final year, UG
1	Raj	Public policy	PG
1	Daisy	International management	PG
2	Si	Business Management	Final year, UG
2	David	Public Policy	PG
2	Lucy	Psychology	Final year, UG
2	Mandy	Biomedical Science	Second year, UG
3	Davy	Psychology	PG
3	Sam	English language	PG
3	Mia	Psychology	PG
3	Emily	International management	Final year, UG
3	Daniel	Financial analytics	Second year, UG
4	Moon	Computing	First Year, UG
4	Mei	Physics	Second year, UG
4	Paul	Physics	Second year, UG
4	Malik	Physics	Second year, UG
5	Ling	Life Sciences	Second year, UG
5	Jia	Life Sciences	First Year, UG
5	Fred	Life Sciences	Third Year, UG
5	Theo	Physics	Third Year, UG
6	Sophia	Life Sciences	Third Year, UG
6	Pravit	Life Sciences	Second year, UG
6	Aisha	Life Sciences	Third Year, UG
6	Dylan	Engineering	Third Year, UG

(Continued)

Table A1. Continued.

Focus group	Participant (Pseudonym)	Discipline	Level of study
7	Alaia	Physics	Second year, UG
7	Helena	Physics	Second year, UG
7	Aarush	Physics	First Year, UG
8	Daniel	Life Sciences	First Year, UG
8	Anika	Life Sciences	Third Year, UG
8	Max	Computing	First Year, UG
8	Amelia	Life Sciences	First Year, UG
9	Kabir	Medicine	Final Year, UG
9	Leena	Medicine	Fourth Year, UG
9	Xiang	Medicine	Second year, UG
9	Maya	Medicine	First Year, UG
10	Hana	Medicine	First Year, PGR
10	Kamal	Medicine	Final Year, UG
10	Felix	Medicine	Final Year, UG

Table A2. Main themes and example codes.

Main themes	Example codes
AI-assisted learning	■ A tool for efficiency ■ Information retrieval ■ Acceptance of output ■ Using AI for immediate assistance ■ Help-seeking for difficult concepts ■ AI as safe space for exploration ■ Supplementing formal educational resources ■ Balancing speed with understanding ■ Task-specific strategy selection
Transition to Human-AI collaborative learning in assessment contexts	■ Using own judgment ■ Learner awareness of own limitations ■ Criticality towards the AI output ■ Reflecting on the value of AI ■ Value of own knowledge ■ Understanding human and AI strengths ■ Using AI to support critical thinking ■ Assessment use shaped by caution ■ Using AI while preserving ownership of learning process ■ Balancing usefulness with scepticism ■ Using AI to bridge the gap between feedback and performance
Motivational drivers of AI use in formative and summative tasks	■ Realising limitations of AI for different aspects of learning ■ Resisting AI uses that short-circuit learning ■ Seeing some assessment spaces as needing to remain human ■ Goal-directed use of AI ■ Scepticism about outsourcing formative tasks ■ Reflecting on learning needs ■ Value of own learning ■ AI impedes learning ■ Tension between convenience and educational growth ■ Using AI to protect oneself from perceived judgement