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Learners Do Not Trust GenAI, but They Find It Useful Anyway: Pedagogical Implications of the Enduring Allure of GenAI for Learning

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Abstract: This paper explores how learners integrate generative artificial intelligence (genAI) as part of their wider education. It used a constructivist grounded theory analysis of 35 former first-year writing students' experiences with AI tools. The paper reports on the results from a secondary analysis of the semi-structured interview portion of the project. This analysis suggested that there was a discrepancy in how students used genAI to support their learning: while learners demonstrated skepticism about genAI's reliability, they continued to find genAI tools alluring for learning support. The results place a spotlight about the quality of learners' abilities to distinguish the quality of genAI's outputs from its accessibility as a tool to support learning. In one sense, learners were able to determine when and how genAI might be best used to support their learning. In another sense, their discussions placed less emphasis on evaluating the outputs themselves. This paper will grapple with this discrepancy to consider ways that teachers could support learners as they integrate genAI in their learning processes.

Keywords: artificial intelligence, genAI pedagogies, evaluative judgements, higher education, learning technologies

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Learners Do Not Trust GenAI, but They Find It Useful Anyway: Pedagogical Implications of the Enduring Allure of GenAI for Learning

The widespread impact of generative artificial intelligence (genAI) has left teachers and students alike grappling with the implications of genAI for pedagogies. Early reports of student genAI use and its role in education highlighted uncertainties around when and how genAI could be used to support learning (e.g., Chan & Hu, 2023; Johnston et al., 2024). This uncertainty is especially prominent in essay writing (see Bedington et al., 2024; Fyfe, 2022), where students and teachers alike have expressed difficulties in determining how these tools can support writing. At issue are two overlapping dimensions: how learners use the tools and how the accuracy of their outputs can be ensured throughout the processes learners use to write. As Fyfe's (2022) students discovered, the way learners understand and use genAI can vary but also have significant effects on how they may integrate genAI in future writing situations.

This qualitative project began as an attempt to understand learner AI use from student narratives of experience and an evaluation of how participants worked with AI-generated texts from chatbots such as Claude, ChatGPT (3.5 or 4.0 at the time), or Co-Pilot (the system to which our school subscribed at the time). Using constructivist grounded theory, the project initially asked:

1. How do former first-year writing students think with and about genAI as part of their writing processes?
2. What writing skills do learners need to effectively integrate genAI into their essay writing?

While the initial questions prioritized writing processes, the results revealed that learners' genAI use transcended their writing skills and processes to speak to how genAI tools were integrated as part of their learning more broadly. After the initial data analysis, it became apparent that a learner-focused data analysis could complement the initial analysis. With this in mind, Aiya, an undergraduate student, was invited to participate in a secondary analysis of the project data. As she examined the data, a new, closely related question developed:

3. How were learners integrating genAI into their learning processes?

This third question is the focus for this paper. Aiya's secondary analysis of data came after the initial data collection and emerged as a response to reviewing the data available. A focus on genAI as a learning tool seemed prominent in the interview responses, and Aiya formulated a question that could investigate this emergent thread. This third question builds on how learners think with and about genAI tools by examining how this thinking translates into practice. It draws attention to how learners use genAI and how their integration of AI tools relates to their understanding of how these tools relate to their learning in writing classrooms.

While some research on genAI and learning has been about learners (e.g., Fyfe, 2022; Johnston et al., 2024; Urban et al., 2024), the analyses have not been conducted by learners themselves. Learners offer a unique positionality within the quickly changing pedagogical landscape around genAI use. They are incorporating genAI tools such as ChatGPT, Claude, and Perplexity into their learning, and, as Johnston et al.'s (2024) analysis revealed, they are navigating an uncertain postsecondary environment that has not settled guidelines for fair, equitable, or acceptable genAI use. It also comes at a time when teachers are trying to develop classroom and programmatic curricula that respond to, accommodate, and navigate learner use of

genAI systems. An analysis on genAI data that includes a student lens could offer informative insights from the other side of the pedagogical relationship.

This paper reports on the results of this secondary analysis on the data from the project's semi-structured interviews. The analysis revealed a discrepancy between learners' wariness about the reliability of genAI outputs and its attractiveness as a tool to support learning. On one hand, participants were skeptical about genAI's ability to provide accurate answers or help them with certain aspects of their writing. On the other hand, the allure of genAI as a tool they could quickly access to support parts of their learning meant that many learners continued to use genAI despite reservations. In the analysis, we will consider the implications of this discrepancy, as well as possible ways that educators may build on pre-existing funds of technological knowledge to help learners navigate genAI use to support essay writing.

Literature Review

Empirical research on genAI's effect on pedagogy is still developing. Scholarship from Cope et al. (2021), Holmes et al. (2019) , and Mollick and Mollick (2023) offered broad, early accounts about AI's potential uses for pedagogy. Cope and Kalantzis (2015) demonstrated how technologies with generative capabilities can support learners through multimodal visualizations and metacognition. There have also been accounts of genAI's potential to positively impact learning. For example, Wu and Yu's (2023) meta-analysis emphasized genAI's significant effect on students' learning outcomes, especially in higher education. They underscored the benefits of using generative genAI on learners' performance, self-efficacy, and motivation. Moreover, Urban et al. (2024) tested whether genAI use could benefit learners' creative problem-solving performance and found that genAI tools helped learners create original solutions that aligned better with task goals. There are also positive instances of learners using genAI as a coach (Lu et al., 2024; Song & Song, 2024), as well as situations where genAI could help learners integrate prior knowledge into new learning (Lee et al., 2022).

Moreover, student-focused insights on genAI often highlight the complexities that exist in a learning environment that is influenced by genAI. Scholarship from Chan and Hu (2023) and Markauskaite et al. (2022) detailed a wide range of possible tasks to which learners may apply genAI, from brainstorming ides to supporting research and analysis. This range seems attractive to learners. For example, many participants in Bedington et al.'s (2024) experiential accounts of AI concluded that, despite certain reservations around how and when to use AI tools, they were intrigued by the prospect of AI supporting various points in their knowledge-making processes.

Theoretical Framework: Evaluative Judgement and AI Literacy

A useful theoretical framework that has emerged in response to genAI is evaluative judgement. While evaluative judgement was introduced before genAI's influence (see Tai et al., 2018), the lens has gained new emphasis with the need for learners to accurately assess genAI outputs to use the technology well. This emphasis is prominent in the literature, with Liu et al. (2024) outlining assessing outputs as a key to learners' success in developing high-quality texts. Similarly, Fyfe's (2022) analysis was largely predicated on learners' abilities to evaluate and reflect upon AI outputs, and Markauskaite et al. (2022) noted evaluating outputs as integral to pedagogies that account for genAI's influence.

This emphasis on evaluation also responds to AI literacy frameworks. Most frameworks developed around learner AI literacy are still theoretical, but most have identified evaluating or assessing outputs as a central pillar. For example, Lin et al.'s (2025) IDEA framework identified evaluation as one of four crucial dimensions for language learners to hone to use genAI well. Su and Yang's (2023) IDEE framework identified "evaluating effectiveness" as an important dimension of their framework. It is also notable that evaluation is the only praxis-oriented dimension. The other three—identifying the desired outcome, determining the level of automation, considering ethics—relate to planning how to use genAI. In this framework, evaluation seems to be the nexus for effective genAI use.

As such, evaluative judgement is a theoretical lens that has potential to positively influence pedagogies, especially in writing classrooms where genAI use and knowledge making are increasingly intertwined. Tai et al. (2018) framed evaluative judgement as the assessment of genre quality. They emphasized the need for learners to gain repeated practice at making these judgements within their disciplines since "making an evaluative judgement requires the activation of knowledge about quality in relation to a problem space" (p. 472). Bearman and Ajjawi (2023) proposed evaluative judgement as a complementary feature to learners developing critical digital literacies for an AI-mediated world. However, as Eaton et al. (2025) found, learners have difficulty assessing the quality of content and source material in written texts. Still, learning to make quality these judgements could help learners navigate what Bearman and Ajjawi call the "black box" that comes with genAI output, where the origin and means by which outputs are developed can sometimes be unknown. Bearman et al. (2024) built upon this idea, noting that it is better to focus on the quality of output, a notion which has since been echoed and expanded upon by Dawson et al. (2024). Bearman et al. (2024) stated that learners should "develop their ability to judge the quality of the processes they use with generative AI" (p. 11). The implication is that learners can use genAI to assess quality, and, at the same time, they can develop their own capacity to use genAI in their learning. This idea will be important once we reach our discussion.

Methodology

Constructivist Grounded Theory

Constructivist Grounded Theory (CGT) was the methodology that guided the study's design. CGT was chosen because of its ability to respond to emergent themes and patterns in data analysis (Charmaz, 2014). CGT often relies on interviews to capture participants' experiences (Charmaz, 2014; Rieger, 2019) because these narratives of experience offer an opportunity to capture how participants reflect on their experiences. This project had three data collection methods: semi-structured interviews, focus groups, and think-alouds during the focus groups. Because of the prominence of semi-structured interviews in the study design and in the analysis, this paper will focus on results from interview data.

The goal with using CGT was not necessarily to reach a new theoretical insight. The lack of research foundation on genAI, writing, and pedagogy at the time of data collection made developing theory complicated. The goal was more to develop a series of ideas that could then be tested, expanded, and explored from different angles. From here (and in time), we hoped that these ideas could contribute foundations from which theory could eventually emerge. So, while CGT allows for development of new theory, it also accommodates sensitizing concepts

(Charmaz, 2014; Watling & Lingard, 2012) that researchers may consider alongside other theoretical perspectives that may be relevant to the research. These concepts may alert researches to new possibilities in their data and facilitate the questions they ask around those possibilities (Watling & Lingard, 2012). This was the case with this project. CGT offered a flexible and adaptable framework that met the rapidly-shifting needs of the technological context. It also positioned us to consider the data in relation to promising theoretical ideas. We did not begin the project with evaluative judgement in mind, but evaluative patterns were evident in the data. For a secondary analysis that followed CGT data collection, then, evaluative judgement became a useful lens to filter ideas and consider new possibilities in our data set.

CGT promotes knowledge co-construction between researcher and participant, creating meaning from participants' experiences and interactions (Breckenridge et al., 2012; Charmaz, 2014). To do this, CGT methods do not separate data collection and analysis. Instead, these processes inform each other (Holton, 2010). CGT depends on iteration, where themes developed through one round of data analysis inform the next round of data collection. This allows researchers to adapt their research to emergent ideas, explore those ideas further, and then analyse the results. CGT's inductive approach means research does not begin with preconceived theories or hypotheses (Charmaz, 2014). Instead, the research is open to various possibilities that may emerge from the data.

Secondary Analysis

This flexibility was useful for our context given the evolving nature of genAI and its impact on learning. Responding to emergent patterns in the data also made it possible to conduct a qualitative secondary analysis. We followed a secondary analysis pattern that focused on analytic expansion (Thorne, 2013), which is where the original dataset is used to ask a new question that was not envisioned initially. Thorne (2013) explained that "a researcher makes further use of a primary data set in order to ask new or emerging questions that derive from having conducted the original analysis" (p. 397). Our analysis of a new research question aligns with Heaton (2004)'s notion of a supplementary analysis, which is a deeper investigation of emergent patterns in data that were not fully addressed in the primary study analysis.

Alignment with the original helps determine whether secondary analysis is appropriate for the research context. Tate and Happ (2018) and Thorne (2013) emphasized the need to ensure that the new question being asked aligned with the original research questions. Given that the new question being asked in this project ("How were learners integrating AI into their learning processes?") aligned closely with the original questions about how learners thought with and about AI in their writing processes, the data set addressed the ideas asked by this new question. In this case, the question formed after Chris's initial examination of the data, so the question directly responded to the initial data set.

Primary Data Collection

Once ethical approval was obtained from our university, participant recruitment began. Participants were recruited from former students who had successfully completed our university's introductory writing class. This class aims to support learners as they transition from secondary to postsecondary studies. Over 100 sections of this class were offered in 2023-2024 (course capacity 25 students), with a team of instructors teaching the sections framed around a

common syllabus. The syllabus contains the same learning outcomes, the same essay assignments, and the same rubrics, but instructors have flexibility on readings, the assignment explanations, and in how they teach concepts. The class is designed to provide learners with writing, research, and—to an extent—study skills that they can apply to their disciplinary contexts. Many disciplines deem the class mandatory for graduation, which means that participants came from diverse disciplines, such as environmental studies, forensics, chemistry, computer science, and information technology. This is a class where genAI's influence is acute since the generative capabilities of the technology have made it a useful tool for learners. It is also an environment (like many) where genAI uptake moved faster than instructors' abilities to develop pedagogies that could respond to this uptake. The gap that emerged made it timely to understand both how learners were using genAI for writing essays but also how those insights might inform pedagogy.

Recruitment and data collection occurred between August 2023 and January 2024. In the first round of recruitment, there were 23 participants. After this initial round, data was coded and analyzed. More detail on the coding and analysis is provided later in this section. After this initial round, another round of recruitment occurred, and 12 more participants joined. The goal of this second recruitment was to explore thematic areas from the first round of analysis more closely. The data from this new cohort was then analyzed relative to the first cohort. The project had 35 total participants total, and every participant completed the semi-structured interview.

Method and Analysis

The initial semi-structured interview was intended to begin constructing how participants thought about generative AI. These narratives of experience establish a useful foundation from which constructivist grounded theory could build (Charmaz, 2014). The flexibility of the semi-structured interview questions allows researchers to adjust their questioning according to participant responses (Charmaz & Thornberg, 2021). This structure allowed the interviews to ask more focused questions as data collection progressed. For example, after the first round of data was collected (with 23 participants), it was coded. Based on this coding, the interview strategy was adjusted to ask about emerging themes more specifically. Appendix A contains the list of interview questions. These questions were designed as prompts into larger conversation, and most questions led to more discussion with participants.

Data Analysis

Coding for the secondary analysis involved several steps. It began with open coding, which is the first step in CGT analysis (Walker & Myrick, 2006) and involves examining the data line-by-line to develop as many codes as possible. This stage led to dozens of codes across the 35 interview transcripts. The next steps drew upon Adu's (2019) guide to qualitative coding, which was influenced heavily by Charmaz's (2014) outline of CGT approach. Adu (2019) detailed how the initial open coding could build into more focused coding, where researchers identify prominent codes from open coding and arrange them into categories. From here, Adu explained that the categories could develop into themes that could lead to theory. Theory building was not the desired end goal of the secondary analysis, so we ended our individual coding with categories that could inform themes at the next coding stage.

After we coded independently, we came together to discuss implications for this coding for the new research question. This allowed us to probe, expand, and consider each other's ideas, which Breckenridge et al. (2012) framed as an important part of CGT because it allowed the analysis to be modified once it was exposed to new data. The combined analysis and discussion helped us distill our codes and categories into themes that best represented the data as it related the question of how learners integrated AI into their learning processes. Table 1 offers a sample of the categories developed and how they led to common themes.

Table 1

Sample coding categories and themes

Codes	Categories	Theme	Participants
Limits of genAI comprehension	GenAI tends to have difficulty distinguishing between similar ideas and sources. Can lead to mistakes in outputs	Participants have clear ideas of genAI's limitations and how to navigate them in their writing process.	01, 02, 04, 06, 07,08, 09, 11, 13 14, 15, 16, 17, 19, 21, 22, 23, 24, 27, 28, 30, 33, 34, 35
GenAI hallucinations or misattributions			
Lack of chatbot interpretative ability			
GenAI difficulties with nuance	GenAI often generalizes, which leads to surface level engagements with sources and ideas. Touching the surface leads to a lack of trustworthiness in the output		
Better Suited for short form writing	Chatbots get stuck in the same train of thought, which makes shorter forms of writing with genAI more favourable to strong results		
GenAI writing can be repetitive			

Chris then worked through the themes (and the categories that led to these themes) to count the number of instances each one arose in the interviews. This counting occurred in two ways: how often a category arose in individual transcripts and how often it came up across transcripts. These counts helped to ensure that the themes represented a common discussion point among participants. This helped to form the themes discussed later in this discussion. It also helped to select the quotes we use in the following section, which articulate common discussion points both for an individual participant and across interviews.

Results

The secondary analysis on AI usage among first-year undergraduate students suggested a discrepancy between their use of genAI tools like ChatGPT, Claude, and Perplexity and their trust in the outputs made by these tools. As we investigated our third research question—how were learners integrating genAI into their learning processes?— this discrepancy stood out. Participants expressed a wariness at genAI's reliability, but they nevertheless continued to see value in genAI as a support for their learning. Many participants (24) expressed a lack of trust in genAI due to the uncertain reliability of the outputs. The primary concerns they noted included the low-quality of secondary source materials and engagements genAI can generate, inconsistencies in matching outputs to context, and a tendency for outputs to remain too generalized for knowledge making tasks (like writing essays). However, most participants (33 of 35) discussed the allure of genAI as an accessible and versatile tool that could support several dimensions of learning, from generating ideas, to organizing thoughts, to enhancing writing skills such as paragraph structure and introducing and analysing source material.

Judgements and Wariness about GenAI Use

Many learner interviews suggested that their assessments of the tools for learning concentrated largely on the suitability of genAI to produce trustworthy outputs. In total, 24 of 35 participants discussed genAI's accuracy as a reason they're wary to use the tools. For example, participant 35 expressed that "one of the weird things that I noticed was often, when it couldn't find a source, it would make up sources, and I thought that to be really concerning." Similar comments came from participant 9, who emphasized how AI "gets random information from like anywhere in the world" and how writers must "realize when they look at what ChatGPT spits out they have to, make a judgement [on whether it] is correct." This uncertainty was common among the 24 participants who expressed wariness around trusting genAI too much. For many, it was about the reliability of the secondary sources suggested or the engagements with those sources. Participant 9's comment equally speaks to the need to make a judgement of whether to trust the output or not, which suggests that the question of accuracy loomed large. As the codes in table 1 highlight, participants (e.g., 14, 27, 23) were often concerned with how genAI would interact with a secondary source on a surface level or in a way that did not align with the source idea. As a result, it became difficult to trace the origins of an idea and make a clear judgement of content.

Participants generally expressed the most confidence in genAI outputs that were smaller and more limited in scope. As participant 09, a frequent genAI user to support writing noted, checking grammar and condensing paragraphs played into AI's strengths and fit well with the revision: "AI is a pretty good summarizer, [so] I think you could copy and paste paragraphs into QuillBot and put them in the summarizer to see what what [AI] thinks is most important." Participant 33 used genAI more generally to clarify concepts from readings that could inform papers, but they described that this was best done in small increments or else the meaning would become to generalized. Similarly, participant 27 saw genAI as a useful means of breaking ideas from an article or draft into smaller paragraphs: "that actually makes it easier for you to not only understand the text but also gives an outline of that text" that was easy to understand. They also expressed concerns, however, that genAI would provide generalized or "false" information. This concern was expanded upon by other participants (01, 02, and 23 stand out most) who found that

genAI outputs would miss important nuances if it was not used in smaller instances where the chatbot had all the necessary context.

It can be useful to think of how learners are evaluating outputs and where the emphasis for these evaluations is placed. Rather than making judgements on the quality of the ideas generated with genAI, participants tended to describe judgements about the output's accuracy more generally and whether they could be confident working with an output for knowledge making. The descriptions of how participants used genAI to break ideas into smaller content reflected a judgement about chatbots as a curator of existing content but less of an accurate generator of content. Their interview responses focused on evaluating genAI's suitability for a learning task (and why) rather than the meaning they would create using the tool as a generative device. It seems that their evaluative judgements were less on creating content and more on developing process with genAI. This is not to say that evaluations of content did not occur, but rather these content-based evaluations were subordinate to how and when to use genAI (and maximize results).

The Enduring Allure of AI

The enduring allure for many participants was the possibilities for genAI to complement their learning. Despite some skepticism about genAI as a tool for knowledge creation, most participants found enduring uses for genAI because of its availability and versatility to make learning more accessible. This was a point that arose in some fashion with 33 of 35 participants. Participants described the novelty of having an aid with which they could interact at any time. Participant 34 highlighted the simplicity and conversational nature of AI, describing it as akin to having a dialogue. They expressed that "it's like having a conversation. 'Don't say that, fix this or like. That's not what I meant'…it's easy to communicate." There is a dialogic dimension to AI tools that allow learners like Participant 34 the ability to build ideas through conversation; they can evaluate the output by determining whether they understand the content, and they can recalibrate their inquiry according to this judgement.

The draw of genAI's interactive qualities was further exemplified by Participant 32, who contrasted the promptness of genAI's feedback with traditional communication methods. As a tool to support learning, genAI is readily available and accessible for learners to consult (despite its flaws). They asserted how "if I were to email you, you must take time to get back to me. But if I were to put that in AI I would get instant feedback. That is more reliable to me than going to a study group or like a resource center." We include this example because it highlights another side to this promptness: risking potential inaccuracies or missing details for the expedience of information. Here, the exigence of receiving information seems to take precedence over its quality. Despite potential challenges with the quality of the output, the ubiquity of genAI, its ability to adapt output through dialogue and prompting, and the possibilities for instantaneous feedback were all draws for learners that made genAI a prominent dimension of their learning.

When seen through the lens of evaluative judgement, students seem to make judgements about the effects the technology can have on their learning. They have a learning need that can be filled by genAI more promptly than other channels (such as emails and study groups). GenAI offers a conversational space that, while coming with a risk of inaccurate or fragmented information, meets or satisfies an immediate pedagogical need. This does not preclude asking an instructor or seeking feedback/clarification elsewhere. It does, however, mean that the evaluative

judgements that learners make are more about situation and context than about the content and trustworthiness of what they are finding.

Discussion

Early literature on genAI—often case studies or surveys of students—have showed how learners and teachers alike determine how, when, and how much genAI can/should support learning (e.g., Bedington et al., 2024; Chan & Hu, 2023; Fyfe, 2022; Johnston et al., 2024). Participants in this project demonstrated a strong understanding of how genAI could support their learning. They also demonstrated awareness that genAI outputs can have issues, such as hallucinations, generalizations, or getting stuck in surface-level trains of thought. Despite these challenges, the fact that genAI is a readily available space for them to work through these ideas seemed to be an important factor in their decision to use genAI to support learning. There is a discrepancy between these two threads. GenAI tools have proven useful to support learners despite the potential unreliability of their outputs. Learners seem to recognize that there is a limit to the trust genAI deserve. On one hand, learners are using AI tools despite their limitations, primarily because of the accessibility and speed at which they can receive information. On the other hand, most participants recognized AI limits and seemed to shy away from using genAI to generate content en mass.

Evaluative judgement offers a useful lens to untangle some implications of these decisions. As a lens, evaluative judgement can draw attention to how learners are using genAI and the potential effects of this use on learning. Because evaluative judgement prioritizes assessing the validity or truthfulness of outputs withing a given context (Bearman et al., 2024), it draws attention to the quality of genAI use. Bearman et al.'s focus was on the importance of evaluating AI output, but our participants' responses suggest that it's equally important to develop the ability to evaluate when and how AI tools can be used to support learning.

This is an area where learners seemed to have a good grasp on genAI. Most participants (32 of 35) provided clear indications of how, when, and why they would draw upon genAI to support their learning. They could evaluate how genAI could fit into their learning context. They could also describe where limitations made a chatbot an inefficient or unreliable tool for use. There is a challenge, however, in that recognizing limitations did not seem to act as a deterrent for genAI use. Participants may have known about limitations, but they were sure to encounter these limitations in using genAI. Breaking tasks into smaller outputs may help, as might a general knowledge of hallucinations. Learners may recognize the limitations of AI tools, but it remains unclear how they account for these limitations in their work; our data did not reveal evidence that participants did. There may be instances among the participants where a learner may express a recognition that AI tools are limited but continue using them anyway in ways that intersect with these limitations. For example, learners seem to use AI to generate feedback, though many (like Participants 9 and 13), recognize that AI doesn't necessarily read context well. It's conceivable that feedback generated without training AI with proper context could be of limited use to a learner.

They may still benefit from strategies and support in evaluating the quality of outputs in more contextually-specific situations. They may also benefit from guidance in how to connect disciplinary knowledges or practices to their genAI use. Bearman et al. (2024) highlighted that students may not be able to make strong evaluative judgements: determine what is valid in context. This is where teachers can support learners and add depth to both their disciplinary

knowledge and to their use of genAI to support learning withing a discipline. Our participant interviews suggest that many learners have clear ideas of how they can use genAI more generally. They are aware of its limitations, and they are confident in navigating those limitations generally (e.g., using shorter blocks of texts or outputs, clarifying concepts, getting into dialogue with more prompting). What they need is a bridge to evaluate how those methods may be adapted for more disciplinary tasks or knowledge making practices so that they can develop more specific processes and knowledge foundations that will help them navigate the limitations of genAI in specific situations. Below we propose three ways that teachers may help to build this bridge.

How Teachers Can Help Learners Navigate GenAI within Disciplines

The following suggestions are intended to offer a starting point for adapting pedagogies to account for genAI's influence in classrooms. They may especially help teachers in classrooms where pedagogies depend on writing or text as primary means of learning, knowledge making, and assessment.

Suggestion 1: Build from Learners' Technological Knowledge Foundations

The participants in this study articulated clear understandings of how they integrated genAI in various aspects of their learning. They also understood why the used genAI for some tasks and not others. They had a host of technological experiences with genAI that could inform their use of the technologies, and they had a degree of digital literacy that allowed them to make these judgements of how and when to use generative technologies. Teachers might give space to discuss these experiences with learners and establish a foundation of what learners know about genAI and how it might apply to the classroom context. These conversations may be complemented by giving space for the class to contemplate how these experiences might inform parameters for appropriate, effective, and trustworthy use of genAI in the class. As Bearman et al. (2024) proposed, learners must "develop their ability to judge the quality of the processes they use with generative AI" (p. 11). Developing parameters together would offer space for learners to judge the quality of their processes within the class context. This strategy would allow a co-construction of parameters based on the evaluation of genAI's capabilities and potential for learning that responds to both the learning outcomes of the class and to the collective experiences of the learners within it.

Suggestion 2: Emphasize the Need to Evaluate GenAI Outputs, Not Just Processes

Another element that stood out with the participants was how they evaluated genAI. The way they discussed evaluating outputs from genAI, the trustworthiness if these outputs, and their suitability for meaning making focused largely on the process of using genAI rather than the content itself. They could highlight common difficulties with genAI (e.g., hallucinations, generalizations). Evaluating the outputs beyond a surface evaluation of the text was not a prominent focus. While this does not mean that participants did not have deeper evaluations of outputs, Bearman et al. (2024) and Eaton et al. (2025) stressed that learners are often not positioned to make strong evaluative judgements. So, while learners may have clear ideas of processes they may use with genAI, it may be useful for teachers to develop pedagogies around

evaluating the outputs themselves. This will draw attention to the deeper, more context specific ways that outputs need to be mediated to properly use genAI within many learning contexts. It would enhance learners abilities to scrutinize and modify texts, placing emphasis on learners abilities to integrate themselves thoughtfully and effectively into situations where they use genAI.

Suggestion 3: Create Space for Learners to Evaluate their Own Assumptions about GenAI and Its Role in Learning about Disciplinary Knowledge Making Practices

The assumptions learners make about genAI can have a strong influence on how they take up the tools in their learning. Taken one step further, these assumptions may vary from class to class, from discipline to discipline. As such, the assumptions learners make and the way that they manifest in their learning will also shift. Bearman and Ajjawi (2023) suggested that asking learners to examine their assumptions about AI can build an "understanding of what students' relationships with AI produce, within their particular disciplinary contexts" (p. 1168). These relationships with AI shape how learners experiment with AI in different contexts, evaluate its output, and use these evaluations to implement AI in other learning situations. This suggestion derives from an absence in the discussions with learners. With such a large focus in the interview transcripts being on how genAI can be used to support learning, learners did not really discuss the distinctions between genAI use in different contexts or how that would shift. There is a risk that genAI can be seen as a tool that can be deployed similarly across contexts and, while the processes may be the same generally, the way learners adapt these processes to new contexts will allow them to accommodate the demands of those contexts.

This is where teachers could influence both learning and genAI use. By creating space for learners to question their assumptions, reflect on them, and ground them in the new learning context, teachers can position learners to think about what it means to make and engage with knowledge in a discipline. If teachers can then model how genAI might meet or fall short of disciplinary requirements for knowledge making, they can provide pathways for learners to become more socialized into disciplinary norms and to develop more the ability to adapt their genAI skills to new contexts.

Limitations and Next Steps

Tracing the quality of evaluative judgement of genAI processes and the connection to how genAI is integrated into student learning will be a useful next area for research. What is the effect of good and bad evaluative judgements on learners' abilities to effectively integrate AI as a tool to support their learning? Our analysis investigated how genAI was integrated into participants learning more broadly, but the project did not extend to exploring the effects of good and bad judgements on student learning. It may be too simplistic to assume that good judgements of genAI use in one context will lead to good implementation in other contexts or that bad judgements necessarily produce poor integration elsewhere. GenAI's generative nature may mask certain flawed judgements, and even poor evaluations and poor integrations of genAI for learning may still yield positive future uses. It is conceivable, for example, that a learner could use genAI to generate a new draft of a paper and end up with an improved output over what they could do by themselves, especially if they provide appropriate context to the chatbot.

It is also possible that participants did not disclose the entirety of their genAI use in the interviews. Even though genAI was permissible within the confines of the project, participants may generally have been hesitant to detail more generative uses of LLMs because of the inconsistent and sometimes strict genAI policies that existed at our institution at the time the research was completed. While the skepticism learners expressed existed across all dimensions of the project, it would be useful to consider how learners' perception may change—and how documents like the revision plans may shift—as AI tools become more embedded in learning environments.

Conclusion

Having a student-led analysis offered another dimension to how results were interpreted. Whereas the initial analyses were concentrated primarily on how skills developed in prior writing classes could inform learners' AI use, this secondary analysis positioned the project to contemplate what dispositions and tendencies were already in place among students as they considered AI's role in their learning. It drew attention to a foundation that already existed that could support future AI literacies development.

The three suggestions we propose—building on knowledge foundations, emphasizing the need to evaluate genAI outputs and modeling how, and building space for learners to scrutinize their assumptions about genAI—can all build off each other. They each promote a degree of reflexive practice for learners, and they encourage teachers and learners to collaborate on establishing parameters for successful genAI use in the classroom. The suggestions respond the idea that participants in this study seemed to recognize genAI's limitations and used that knowledge to establish processes for how they would use technologies like ChatGPT, Claude, and Perplexity. The knowledge of limitations, however, did not deter future use, suggesting that learners persist in using genAI despite downsides. This opens space for collaborative moments in classrooms where teachers and learners may acknowledge genAI use, build upon their respective knowledges of the discipline and of generative technologies, establish parameters for genAI use that can help learners adapt their knowledge of genAI for new contexts.

It is important for teachers to account for how learners' prior digital literacy understandings impact the ways they integrate AI tools to support their learning. Some of this knowledge derives from learners' lived experiences with digital tools, social media, and the internet. These experiences have all informed—to a degree—students' skepticism and optimism around AI tools for learning. Considering the ways these prior experiences shape the judgements learners make can help build pedagogies that expand their pre-existing foundation with AI tools. Building on this foundation can make it easier to draw learners' attention to the judgements they make and how these judgements can shape their ability to use AI to support their learning.

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Appendix A: Semi-Structured Interview Questions

1. What are your general impressions of generative AI as a tool to support writing?
2. What is your experience combining generative AI software with your writing processes?
3. If you have used AI with writing before, how do you believe it impacts your writing process? If you have not used AI with writing or do not use it regularly, why not?
4. What kinds of interactions about generative AI have you had with others (this can be peers, family, friends, etc.), and how have these interactions influenced your thinking about AI?
5. How has your exposure and use of other digital tools influenced your use of AI tools? How has it informed your adjustment and approach to using AI tools?

6. How do you think AI, long term, can affect a writer's approach to developing texts? What kinds of challenges do you think exist when we're stitching "texts" and modalities together?
7. What other resources for writing do you seek (e.g., writing centre support, tutoring, peer feedback, instructor feedback and questions)? Have any of these changed with the reality of AI tools? What might AI tools offer compared to these other resources on campus?
8. What skills do you think writers need to properly implement AI in their writing processes?
9. Have you used Ai tools to help with class readings or to develop research? If so, how has it influenced the way you read academic materials, make sense of their contents, and then apply them?
10. How might a writer make up for the shortcomings of generative AI as a tool to support writing?
11. Detractors might say that people might take the AI output for granted, as inherently correct. How would you respond to this concern/criticism as it relates to your own experience with generative AI?
12. How might your previous experiences with writing influence how you think about generative AI in your writing process, if at all?
13. How might these previous experiences with writing affect how you use and/or adjust to a work and academic reality where generative AI is a tool that can be used to support writing?

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