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Factors Influencing Faculty Decision-Making on Student Use of Generative AI in Higher Education

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ABSTRACT

As generative AI (GenAI) becomes increasingly integrated into higher education, faculty encounter growing uncertainty and complexity in responding to student use of these tools. This study examines how faculty make sense of and navigate decisions about student use of GenAI in graduate-level courses, with particular attention to student learning processes. Drawing on sociotechnical systems theory and sensemaking theory, this study employed reflexive thematic analysis of open-ended interviews with 15 full-time faculty in graduate-level Library and Information Science (LIS) programs in the United States. The findings revealed the nuanced nature of faculty decision-making when navigating students' AI use, highlighting how they engage in ongoing sensemaking as they interpret ambiguous situations, weigh competing pedagogical and professional priorities, and adapt to evolving academic expectations. The faculty members considered four interconnected factors in their decision-making: student meaning-making and cognitive engagement, transparency and disclosure of AI use, AI's role in the student learning process, and institutional policies and disciplinary norms. Across these factors, the faculty described persistent tensions between preparing students for AI-integrated future work environments and preserving the cognitive development essential to meaningful learning.

Keywords: AI in education, artificial intelligence, faculty decision-making, higher education, sensemaking, sociotechnical systems theory, teaching

INTRODUCTION

As GenAI has gained widespread adoption, it has begun reshaping the landscape of teaching and learning. AI is not new to education; it has long been integrated into educational practices (Nadler, 2024; Humble & Mozelius, 2022; Cope et al., 2021; Baker, 2000). However, GenAI's capacity to generate human-like content raises distinct concerns about responsible use and the development of students' essential skills, as these technologies can directly affect core learning processes, including knowledge construction, skill development, and assessment (Nadler, 2024; Xia et al., 2024). Faculty, who are at the forefront of teaching and assessing student learning, face particular challenges in making decisions about and navigating student use of GenAI in their courses. Specifically, in the U.S. higher education landscape, where faculty are largely responsible for determining classroom policies and assessment practices, their decisions play an important role in shaping how students' use of GenAI is understood, regulated, and effectively integrated into teaching and learning (An et al., 2025).

Despite GenAI's growing integration into higher education, research on faculty decision-making regarding student AI use in coursework remains limited. Many faculty members report an "awareness-to-practice" gap: they recognize GenAI's relevance but remain unsure how to operationalize it in their teaching (Almisad & Aleidan, 2025). Others report actively seeking guidance on appropriate uses (Baytas & Ruediger, 2025). However, empirical research examining the decision-making factors that faculty employ in practice remains scarce (Sutedjo et al., 2025). This study addresses this gap by asking: what factors do faculty consider when making decisions about student use of GenAI in graduate-level courses? Specifically, this study focuses on faculty teaching in master's-level Library and Information Science (LIS) programs in the U.S.

GenAI and Higher Education

Following the launch of ChatGPT in November 2022, GenAI tools saw rapid uptake, with reports estimating that ChatGPT reached more than 100 million users within two months (Hu, 2023). These tools have grown increasingly sophisticated, generating new content across multiple formats, including audio, code, images, text, simulations, and videos (IBM, n.d.; Chiu, 2023). Tools such as

the GPT family of models, Gemini, Claude, and Copilot have since become widely embedded in students' everyday academic and personal use.

The emergence of GenAI has prompted significant debate in higher education about how to develop students' essential skills as these tools become increasingly widespread. Academic institutions have adopted diverse policies and guidelines regarding GenAI, ranging from complete prohibition to permission under specific conditions. Some institutions have embraced GenAI as an opportunity rather than a threat by integrating it into courses and allowing students to experience both the potential and limitations of these tools firsthand (Hashmi & Bal, 2024; Rana, 2024). Rana (2024) assessed policies at selected higher education institutions and found that most institutions had not banned the use of GenAI. However, Rana further emphasized that this decision also raises questions about academic integrity and student learning. Despite these concerns, these policy approaches often aim to build students' AI literacy and critical evaluation skills, recognizing that familiarity with these technologies will be important for future professional success.

Furthermore, many institutional policies remain inconsistent, and educators often lack clear criteria for guiding student AI use. A 2025 American Association of University Professors (AAUP) survey found that while 90% of respondents reported that their institutions had introduced AI-related initiatives, these initiatives had not translated into clear implementation and use policies (AAUP, 2025). Similarly, Jiang et al. (2025) found that students recognized classroom-level policies but perceived institutional guidelines as unclear, whereas faculty highlighted implementation challenges stemming from practical constraints and insufficient training. Research also suggests that many institutional policies use ambiguous language and provide limited guidance on when and how GenAI tools can be used appropriately (Azevedo et al., 2025; Hashmi & Bal, 2024; Farazouli et al., 2023).

Concerns persist about academic dishonesty and the risk that students may bypass learning by submitting AI-generated work without meaningful engagement. Paustian and Slinger (2024) reported that approximately 46.9% of students use AI in their coursework. Of those, 39% reported using GenAI tools to answer questions on exams or quizzes, while 7% admitted using GenAI to complete entire assignments. At the same time, AI-generated content may be biased or inaccurate (Athanassopoulos et al., 2026; Dilinika, 2026; Siraj et al., 2026; Hamzah et al., 2025; Kong et al., 2025; Tlili et al., 2025; Li et al., 2024; Simelane & Kittur, 2024; Chan & Hu, 2023; Harrer, 2023; Peres et al., 2023; Zhai, 2022).

Graduate-level education presents distinct pedagogical concerns because students are expected to demonstrate advanced scholarly reasoning, independent synthesis, and research writing. Emerging research suggests that GenAI is increasingly embedded in graduate students' academic workflows, particularly in

writing-intensive and research-focused tasks. Wu et al. (2026) found that postgraduate students actively integrated GenAI into academic writing for publication, raising important questions about how these tools influence scholarly development and disciplinary writing practices. Similarly, recent studies examining graduate student writing reported that GenAI tools can improve writing productivity and efficiency when accompanied by structured instruction and critical engagement (Pensky et al., 2025). At the same time, researchers caution that increased reliance on AI-supported writing may shift the educational challenge from content production to verification, critical evaluation, and epistemic judgment, especially in advanced graduate-level research contexts (Saito et al., 2026). These findings suggest that faculty in graduate-level programs must navigate complex decisions regarding when GenAI use meaningfully supports learning and when it risks replacing the cognitive processes central to graduate education.

Beyond policy and integrity concerns, researchers have raised alarms about GenAI's impact on students' cognitive development. The convenience of GenAI tools has been linked to "cognitive offloading," in which heavy reliance on GenAI is associated with declines in analytical reasoning and reduced motivation to study (Jose et al., 2025). Zhai et al. (2024) highlight that overreliance can occur when students accept AI-generated content without critical evaluation, potentially diminishing their capacity for independent decision-making. Together, these findings underscore a central pedagogical concern: while GenAI can support learning when used critically, unreflective reliance on it may undermine the cognitive skills that higher education seeks to develop.

Faculty Decision-Making on Student AI Use

Faculty decision-making regarding student use of GenAI has emerged as a significant challenge in the current educational landscape. As AI tools become deeply embedded in academic and professional contexts, faculty are increasingly required to make nuanced judgments about when, how, and to what extent students should use these technologies in their courses. The notion of appropriate AI use varies widely, and research suggests that simple binary distinctions between appropriate and inappropriate use are insufficient (Hashmi & Bal, 2024).

Research on faculty perceptions reveals a complex picture. While many faculty members report moderate to high familiarity with GenAI concepts, their use of these tools for direct instructional tasks remains limited (Liang et al., 2025). Shata and Hartley (2025) found that faculty attitudes toward GenAI adoption are shaped by perceived ease of use and usefulness, with willingness to integrate these tools often depending on confidence and understanding. The Digital Education Council's 2025 Global AI Faculty Survey likewise found that while 61% of faculty reported using GenAI in teaching, 88% did so only minimally (Weaver, 2025). Furthermore, Liang et al. (2025) emphasized that trust and distrust in GenAI

appear to be related yet distinct constructs; high trust does not necessarily imply low distrust, suggesting that faculty members have a more nuanced relationship with these tools.

A growing body of evidence suggests that faculty are often left to navigate AI integration independently, without adequate institutional guidelines. An et al. (2025) investigated higher education institutions' guidelines and policies related to GenAI and reported that faculty were advised to develop their own course policies for GenAI use. In the absence of clear usage policies or shared ethical criteria, integrating GenAI in teaching can create ambiguity and insecurity, prompting some faculty to avoid these tools to protect their professional autonomy (Alcántar et al., 2024; Farazouli et al., 2023). As a result, individual faculty may rely on pedagogical judgment to determine appropriate boundaries for student use of GenAI, judgments shaped by disciplinary norms, teaching philosophies, and personal experiences with technology.

Studies also show that GenAI can offer students opportunities for interactive, personalized learning, content generation, and enhanced educational experiences (Sampah et al., 2026; Crompton & Burke, 2024; Essien et al., 2024; Nguyen et al., 2024; Pesovski et al., 2024). GenAI has also enhanced accessibility for nonnative learners through real-time translation and support for resource comprehension (Tlili et al., 2025; Crawford et al., 2024; Ding et al., 2023; Tan et al., 2022). However, faculty must simultaneously navigate concerns about academic integrity, skill development, and the risk that students may bypass essential learning processes when using these tools. Understanding faculty decision-making in this context is essential for developing evidence-based guidance that supports responsible AI integration while protecting student learning.

While prior research has examined institutional policies, student usage patterns, and the perceived benefits and risks of GenAI, fewer studies have explored how faculty interpret and evaluate student use of GenAI in specific pedagogical contexts (Almisad & Aleidan, 2025; Bamasoud et al., 2025; Zhou, 2025). Thus, research on faculty perspectives remains scarce compared to the growing literature on student perceptions (Mah & Groß, 2024). Moreover, this gap is particularly pronounced in the Library and Information Science (LIS) context, where GenAI raises distinctive concerns given the field's emphasis on information literacy, ethical information use, and the professional preparation of information practitioners (Bridges et al., 2025; Kizhakkethil & Perryman, 2024). LIS faculty must consider not only general pedagogical questions about GenAI and learning but also how GenAI may reshape the information practices their programs are designed to teach. This gap highlights the need for qualitative research that can capture the complexity of faculty reasoning in context and identify the factors shaping decisions about student GenAI use in professional graduate education.

In sum, as GenAI rapidly emerges with both opportunities and pressing challenges, faculty find themselves at the forefront of navigating evolving pedagogical decisions amid ambiguous and inconsistent institutional policies, making critical judgments about student use of GenAI in their courses. Building upon the literature reviewed above, this study employs the following theoretical framework to guide the inquiry.

Theoretical Framework

To understand how faculty make decisions about student use of GenAI in graduate education, this study integrates two theoretical perspectives: sociotechnical systems theory and sensemaking theory. Sociotechnical systems theory situates GenAI within interconnected social and technical systems that shape teaching, learning, and assessment practices. Sensemaking theory, in turn, explains how faculty construct meaning in response to emerging technologies, uncertainty, and evolving academic norms as they navigate decisions about appropriate student use of GenAI tools.

GenAI from a Sociotechnical Systems Theory Perspective

Sociotechnical systems theory emerged in the 1950s through the work of Trist and Bamforth at the Tavistock Institute. The theory conceptualizes technology as embedded within social systems, where outcomes emerge from interactions between technical and social elements (Trist & Bamforth, 1951). It distinguishes between two main components: technical systems, which include tools and software, and social systems, which involve people, roles, and relationships (Tarisayi, 2024; Mumford, 2006). In simple terms, sociotechnical systems theory seeks to achieve mutual benefits by aligning social and technical elements within a system (Emery, 1980). The theory therefore provides an interdisciplinary approach for examining the complex interplay between a system's social and technical elements (Tarisayi, 2024), which cannot be understood in isolation. Effective systems require a balance between these components (Mumford, 2006).

In the context of this study, GenAI represents the technical system, while students and their learning processes represent the social system. Effective GenAI integration, therefore, depends on joint optimization, where technological tools support rather than replace students' cognitive engagement. When properly aligned, GenAI can complement and support active learning. However, when AI tools replace the cognitive processes that students need to develop, the effectiveness of the learning system may be compromised. From this perspective, faculty play a critical role in determining what constitutes appropriate student use of GenAI. Their decisions involve evaluating how GenAI integration aligns with pedagogical goals and supports student learning rather than undermining the development of essential cognitive skills.

GenAI from a Sensemaking Theory Perspective

Sensemaking theory, developed by Weick (1995), describes the process through which individuals construct meaning in response to ambiguous, uncertain, or novel situations (Strike & Rerup, 2016; Weick, 1995). Weick (1995) identifies seven key properties of sensemaking, including its grounding in identity construction, its retrospective nature, and its social dimension. These characteristics emphasize that meaning-making is not purely an individual cognitive activity but is shaped by social interaction and organizational context.

In educational research, sensemaking has been widely applied to understand how educators interpret and respond to organizational change, policy shifts, and technological disruption (Maitlis & Christianson, 2014). Sensemaking theory is therefore particularly relevant for examining how faculty interpret and respond to the emergence of GenAI in teaching and learning environments (Silvola et al., 2025).

The growing prevalence of GenAI in higher education challenges long-standing assumptions about learning, assessment, and academic integrity. Faculty often need to interpret evolving institutional expectations, disciplinary norms, and pedagogical goals when determining how students should use these tools. Sensemaking theory provides a useful lens for understanding how faculty navigate these uncertainties and construct interpretations that guide their decisions about appropriate student use of GenAI.

Together, sociotechnical systems theory and sensemaking theory provide a complementary framework for examining faculty decision-making about student use of GenAI. Sociotechnical systems theory situates GenAI within the interconnected social and technical contexts of teaching, learning, and assessment, while sensemaking theory explains how faculty interpret ambiguity, competing pedagogical priorities, and evolving institutional expectations. In combination, these perspectives help explain how faculty construct judgments about appropriate student GenAI use in graduate-level courses.

Accordingly, this study addresses the following research question:

What factors do faculty members consider when making decisions about student use of GenAI in graduate-level courses?

RESEARCH METHOD

Research Design

This study employed a qualitative research design using open-ended interviews to explore faculty perspectives on appropriate student use of GenAI in graduate education. A qualitative approach was selected because the study seeks to understand the nuanced and contextual factors that inform faculty decision-making. The flexibility of qualitative inquiry allows for in-depth exploration of faculty reasoning, values, and the complex considerations they navigate when determining appropriate student use of GenAI.

Guided by sociotechnical systems theory and sensemaking theory, this study views AI not as an isolated technology but as embedded within educational, cultural, and professional contexts. These theoretical lenses informed the development of the interview questions. Sociotechnical systems theory emphasizes that technology and social practices are mutually constitutive. Thus, understanding faculty decision-making about student GenAI use requires examining how institutional norms, disciplinary values, pedagogical goals, and technological capabilities intersect.

Participant Recruitment and Sample Selection

A purposive sample of 15 faculty members teaching in master's-level LIS programs in the United States was recruited. Recruitment criteria included (1) being a full-time faculty member in an American Library Association (ALA)-accredited LIS program, (2) representation across program delivery methods, including online, hybrid, and face-to-face formats, and (3) institutional diversity across public and private institutions. Potential participants were identified through publicly available faculty directories on LIS program websites. Email invitations were sent in August 2025 using institutional email addresses to request voluntary participation. The invitation email included an information sheet outlining the study details. All participants provided informed consent after receiving information about the study's purpose, procedures, risks, and benefits. Initial recruitment emails were sent to 28 faculty members across multiple programs. The study received approval from the Institutional Review Board at the University of Pittsburgh (STUDY25060038).

The final sample of 15 participants was considered sufficient based on the principle of information power (Malterud et al., 2016) and the achievement of thematic saturation. Saturation was monitored throughout the data collection process, and no new themes emerged during the final three interviews. This indicated that sufficient depth and diversity of perspectives had been captured. Table 1 presents the demographic characteristics of the participating faculty members (N = 15), including age, gender, teaching experience, primary teaching modality, and university type.

As Table 1 shows, participants identifying as female constituted the majority of the sample (86.7%), which was broadly consistent with the gender composition of the LIS profession. According to the U.S. Bureau of Labor Statistics (2024), women comprised 74.4% of education, training, and library occupations overall, including 84.9% of librarians and media collection specialists. This suggests that the sample's gender distribution reflects the field rather than a recruitment bias. This suggests that the sample's gender distribution reflects the field rather than a recruitment bias. Similarly, the sample's institutional composition, with 73.3% of participants from public universities and 26.7% from private universities, was consistent with the broader distribution of ALA-accredited LIS programs, where most programs are offered by public universities (American Library Association [ALA], 2025). In addition, participants' substantial teaching experience and career stage may have shaped how they interpreted GenAI use, particularly in relation to pedagogical values, academic integrity concerns, and prior experiences with educational technology change.

Table 1: Demographic Characteristics of Participating Faculty Members (N = 15)

Characteristic	Categories	*n*	%
Age	35–44 years	5	33.3
	45–54 years	7	46.7
	55–64 years	2	13.3
	65+ years	1	6.7
Gender	Female	13	86.7
	Male	2	13.3
Teaching Experience	1–5 years	3	20.0
	6–10 years	2	13.3
	11–16 years	4	26.7
	17–23 years	4	26.7
	24+ years	2	13.3
Primary Teaching Modality	Online Only	3	20.0
	Hybrid/Multiple Modalities	10	66.7
	Primarily In-Person	2	13.3
University Type	Public	11	73.3
	Private	4	26.7

Data Collection

Interviews were conducted via Zoom videoconferencing between August and October 2025. Prior to the interview, each participant provided informed consent, including permission for audio recording and transcription. The interviews lasted between 40 and 50 minutes, allowing sufficient time for in-depth discussion while respecting the participants' time.

The interview questions were designed to explore how faculty members defined appropriate GenAI use and the key considerations they took into account when evaluating students' use of these tools (see Table 2). Probing questions were used flexibly to explore emerging ideas and encourage participants to elaborate on their experiences and perspectives.

Table 2: Open-End Interview Questions

Questions
1. Could you walk me through a time when you received student work that you considered an "appropriate" or positive use of GenAI?
2. Could you walk me through a time when you received student work that you considered an "inappropriate" use of GenAI?
3. Are there any instances where you found it challenging to determine whether a student had used GenAI?
4. Do you include a course policy statement about student use of GenAI in your syllabi? If yes, does it explicitly address GenAI use, or is it designed to be "AI-resistant" by making it difficult to rely solely on GenAI?
5. Is there anything else you would like to share about students' use of GenAI?

Data Analysis

All interview recordings were professionally transcribed verbatim. The researcher reviewed each transcript while listening to the corresponding audio recording to ensure transcription accuracy and to add contextual notes regarding tone, emphasis, and significant pauses that could inform interpretation. Deidentification occurred during this review process, and all identifying information was systematically removed. To ensure participant confidentiality, each faculty member was assigned a pseudonymous identifier.

This study employed reflexive thematic analysis following Braun and Clarke (2006, 2019). The analysis proceeded through six phases. First, the researcher engaged in repeated reading of all 15 transcripts to develop deep familiarity with the data before coding began. Second, inductive coding was conducted in NVivo 15, with codes generated directly from the data while

remaining attentive to the research question. Third, codes were systematically refined by merging semantically similar codes and reducing redundancies to produce a set of analytically distinct categories. Fourth, candidate themes were developed by grouping related codes into broader patterns of meaning, with coded extracts examined for internal coherence and conceptual alignment. Fifth, themes were iteratively reviewed against both the coded extracts and the full dataset to ensure they accurately represented the data and remained meaningfully distinct from one another. Finally, themes were defined and named to capture their analytical essence. This iterative process resulted in four final themes representing distinct factors shaping faculty decision-making regarding student GenAI use. Table 3 illustrates how the initial codes developed into subthemes and final themes.

Several strategies were used to enhance the trustworthiness of the findings. First, a detailed audit trail was maintained to document methodological decisions, code development, and theme refinement, including instances where codes were merged, reassigned, or renamed across coding cycles. Second, reflexivity was practiced throughout the study, with the researcher documenting the analytic process, reflecting on potential assumptions, and considering alternative interpretations of the data. Member checking and peer debriefing were not employed in this study. This decision was consistent with Braun and Clarke's reflexive thematic analysis approach, which emphasizes the researcher's active interpretive role, reflexive engagement, and transparency in analytic decision-making rather than treating participant verification or interrater agreement as required markers of quality (Braun & Clarke, 2019, 2021). Because this study was undertaken independently, trustworthiness was strengthened through reflexive memoing, iterative engagement with the data, and maintenance of a detailed audit trail.

Table 3: Qualitative coding table illustrating theme and subtheme development

Interview Excerpt	Initial Code	Subtheme	Theme
'Your answer can be wrong, but I want to see your effort.' (A)	Valuing effort over output	Cognitive effort as evidence of learning	Student Meaning-Making and Cognitive Engagement
'The process of deciding what to write is the process of learning.' (A)	Editing AI-generated content is not learning	Cognitive responsibility for core tasks	
'Students should first learn foundational concepts before introducing GenAI.' (D)	Foundational concepts first	Sequencing GenAI with skill development	

'They should acknowledge what has been created by AI. If you use that, you need to mention it.' (B)	Mandatory GenAI attribution	Disclosure as an ethical expectation	Transparency and Disclosure of AI Use
'Back in the day, did we have to let people know how we brainstorm ideas?' (C)	Disclosure burden as overwhelming	Paradox of enforcing transparency	
'Trust goes both ways. If I want them to trust me, I need to trust them.' (I)	Mutual trust as a basis for disclosure	Transparency as a classroom value	
'I encourage students to use GenAI to brainstorm, understand difficult concepts, and organize their thoughts.' (D)	Productive/supportive GenAI use	AI as scaffolding for learning	AI's Role in the Student Learning Process
'It's just a tool. It shouldn't be a replacement for your thinking.' (F)	AI as a tool, not a substitute for cognition	Risk of cognitive bypass	
'I pull apart the process and guide them through rather than having them write a paper AI could generate.' (A)	Staged assignment design	Assessment design as bypass prevention	
'There are no AI detectors we can have confidence in, so we have to think differently about assessments.' (K)	Detection unreliability reshaping design	Policy gaps and detection limits	Institutional Policies and Disciplinary Norms
'Students will be using AI in their job places... they will guide other users using AI tools.' (B)	Professional preparation rationale	Disciplinary norms and workforce expectations	
'We're still working it out.' (O)	Norms still in flux	Evolving institutional expectations	

Note. Interview excerpts are representative examples drawn from across the 15 participant transcripts. Participant identifiers are pseudonymous (A–O). Theme labels are shown only in the first row of each thematic grouping.

RESULTS

The thematic analysis identified four interconnected factors that shaped how faculty interpreted and made decisions regarding students' use of GenAI: (1) student meaning-making and cognitive engagement, (2) transparency and disclosure of AI use, (3) AI's role in the student learning process, and (4) institutional policies and disciplinary norms, as discussed below.

"I Want to See Your Effort": Student Meaning-Making and Cognitive Engagement as a Faculty Decision-Making Factor

When evaluating student work in AI-mediated contexts, many faculty members emphasized that their primary concern was students' cognitive effort and how they meaningfully engage with the learning process. Across interviews, participants repeatedly framed their decisions about GenAI use around a central question: Did this work reflect the student's own thinking and learning? From this perspective, GenAI was viewed as appropriate when it supported the skill being assessed; however, it would be inappropriate when it replaced the intellectual work students were expected to perform. For instance, using GenAI for grammar correction or outlining was often seen as acceptable, whereas using AI to generate interpretations or arguments was considered inappropriate because it obscured the student's own meaning-making and cognitive reasoning. One faculty member explained: "For a literature review, I encourage students to use AI to help organize sources or identify themes they might have missed. However, for a reflective paper where I'm assessing their personal synthesis and critical thinking, AI-generated content would bypass the very process I'm trying to evaluate." Another faculty member articulated this distinction: "The process of deciding what to write is the process of learning. The process of editing someone else's writing is not a learning process in the same way. If they're just taking what AI generates and tweaking it, they're not truly learning."

These reflections indicate that faculty decisions about GenAI use were grounded in whether students remained cognitively responsible for core learning tasks. Faculty, therefore, valued students' cognitive engagement with the learning processes they needed to experience to demonstrate mastery and achieve expected learning outcomes. One participant illustrated this with a programming example: "Students should first learn foundational concepts of programming [Basic programming course] before introducing GenAI for more advanced tasks." Similarly, several participants mentioned that GenAI may help with structuring or organizing content, but it cannot replace students' content mastery. Additionally, the faculty considered whether the submitted work demonstrated evidence of student cognitive effort when assessing student learning rather than relying on GenAI. One faculty member emphasized, "Your answer can be wrong, but I want to see your effort. You need to show me that you truly worked on it."

“Transparency is a Paradox”: Disclosing Student Use of AI as an Essential Practice

Transparency emerged as a key factor in how faculty understood and evaluated student learning in AI-mediated contexts. Faculty members consistently described transparency and disclosure of GenAI use as ethical expectations closely tied to long-standing principles of academic integrity. Just as students are required to cite external sources, faculty expect them to acknowledge AI assistance.

Beyond its ethical dimension, disclosure also played a critical role in assessment. Disclosure, therefore, functioned not only as a matter of transparency but also as a mechanism for making invisible labor visible. In this sense, the faculty emphasized that appropriate AI use was not defined solely by how students used these tools but also by whether they were transparent about their use. As one faculty member explained, “They [students] should acknowledge what has been created by AI. If you use that, you need to mention it.”

At the same time, the faculty highlighted that enforcing transparency in practice was highly challenging. They described disclosure as paradoxical, as GenAI use is often invisible, difficult to verify, and embedded in multiple stages of academic work, such as generating ideas, drafting outlines, refining language, or editing code. One participant reflected on this tension: “Back in the day, did we have to let people know how we brainstorm ideas? Now it appears to be we have to tell everybody I used this AI tool to brainstorm, and it’s getting overwhelming.” Another added: “Do I truly want students writing detailed AI use logs for every assignment? At some point, the documentation becomes more work…” These reflections illustrate faculty uncertainty about where meaningful transparency ends and excessive documentation begins.

Therefore, while transparency was an essential practice in determining appropriateness, deciding how much disclosure was sufficient remained an open question in practice. The majority of faculty members had developed AI policies and communicated them to students as necessary, emphasizing the importance of acknowledging AI use and disclosing evidence of use. Many faculty experimented with middle-ground approaches: requiring AI disclosure for specific high-stakes assignments, using reflective prompts that asked students to explain their AI use decisions, or integrating AI use documentation into assignment rubrics rather than treating it as a separate requirement. Furthermore, the faculty emphasized that transparency is closely tied to classroom values in the era of GenAI, including trust and respect. Across these practices, faculty framed transparency as a trust-based mechanism that supported meaningful assessment, accountability, and shared classroom values. In this way, disclosure functioned as both an ethical practice and a practical tool for understanding student learning in AI-mediated environments.

"GenAI is Just a Tool. It Shouldn't Be a Replacement for Your Thinking": Making Sense of AI's Role in Student Learning

In determining appropriate student use of GenAI, faculty emphasized that understanding GenAI's role in the learning process was essential. This theme aligned closely with the previous themes but emerged as a distinct factor, highlighting the importance of students' learning processes. In this context, a recurring tension emerged in the interviews: "brainstorming versus bypassing learning." In other words, this tension centered on whether students used GenAI tools for brainstorming or for bypassing the learning process by relying on AI-generated content. Faculty emphasized that appropriate use occurs when students maintain intellectual control and use AI as a tool to enhance their thinking. If AI did the intellectual work on behalf of students and they passively consumed that content, it could hinder their learning. One faculty member described appropriate use as follows: "I do encourage students to use GenAI tools as a tool to support learning. For instance, helping them to brainstorm, understand difficult concepts, organize their thoughts, provide feedback on a draft, grammar check, those kinds of support." Several faculty members echoed this, emphasizing, "It's just a tool. It shouldn't be a replacement for your thinking," and "students can use [AI] just as a tool, like using a calculator."

"We're Still Working It Out": Interpreting Institutional Policies and Professional Expectations

The fourth factor reflected how institutional policies and disciplinary norms shaped faculty decision-making about student use of GenAI. Rather than relying on fixed rules, participants described their decisions as emerging from ongoing efforts to interpret institutional guidance, professional expectations, and evolving academic practices. Faculty emphasized that they did not make decisions in isolation; rather, their decisions were influenced by institutional guidelines, policy frameworks, and emerging norms around AI use in academic and professional work environments. First, institutional policy frameworks provided varying levels of guidance. As GenAI evolved, institutions continued to refine and update their policies. Traditional policies regarding plagiarism, academic integrity, and original work have become more complex with the increasing use of GenAI.

As GenAI use became increasingly common, faculty also recognized the limitations of AI-detection technologies. These tools were not fully accurate, and AI-generated content could go undetected (Beale, 2025). One faculty member reflected on this challenge: "There are no AI detectors that we can have confidence in... so we have to think differently about how we design our assessments." The realization of detection limitations influenced how faculty approached appropriateness, designed assignments, and established expectations for the responsible integration of GenAI.

Second, disciplinary norms also shape determinations of appropriateness. Different fields (i.e., information science, education) have distinct professional expectations regarding technology use. The faculty emphasized that prohibiting students from using GenAI would be disadvantageous, as graduates would need to use these tools in their workplaces and, critically, guide others in responsible AI use. Participants articulated this professional responsibility: "Students will be using AI in their job places... they will probably be the people who will guide other users using AI tools." Furthermore, faculty also referenced professional standards and ethical frameworks established by the discipline as factors. The emphasis on transparency and disclosure, discussed in the second theme, was directly connected to these professional ethics around proper attribution and academic integrity. Importantly, faculty recognized that norms were still in flux. What currently counts as appropriate AI use might differ from expectations in subsequent years as both the technology and academic conventions evolve.

Faculty recognized that determining what constitutes appropriate student use of GenAI would continue to evolve alongside institutional policies, disciplinary norms, technological capabilities, and workplace expectations. Faculty also noted the influence of emerging norms from the broader higher education community. Through professional development workshops, conferences, and informal collegial conversations, faculty were exposed to evolving practices and perspectives from across disciplines and institutions. Many faculty members mentioned attending institutional workshops or reading guidance documents on AI in education, which informed their thinking about its appropriate use, even when formal policies remained vague.

DISCUSSION AND CONCLUSIONS

Interpretation of Findings

This study addressed the research question: What factors do faculty consider when making decisions about student use of GenAI in graduate-level courses? The findings revealed four interconnected factors that shaped faculty determinations: (1) student meaning-making and cognitive engagement, (2) transparency and disclosure of AI use, (3) AI's role in student learning, and (4) institutional policies and professional expectations. Across the four considerations discussed above, faculty did not rely on fixed rules when responding to students' use of GenAI. Instead, they engaged in ongoing sensemaking as they interpreted novel classroom situations and evaluated incomplete or ambiguous information. Consistent with Weick's (1995) conceptualization of meaning-making in uncertain and evolving contexts, faculty members continuously negotiated meanings around AI use through reflection, discussion, and classroom experimentation. These considerations were closely interconnected and often examined simultaneously, reflecting the complex, situational nature of faculty decision-making in

sociotechnical learning environments. For instance, decisions about transparency were tied to judgments about cognitive engagement, while institutional and disciplinary expectations shaped how faculty interpreted AI's role in student learning.

Faculty emphasis on students' cognitive engagement reflected deeper efforts to preserve constructivist learning principles (Jonassen, 1999) in the face of technological change. The recurring concern that learning processes cannot be outsourced aligns with what researchers have described as cognitive offloading, whereby repeated delegation of intellectual work to AI may progressively weaken students' capacity to engage in cognitive processes independently (Jose et al., 2025). The findings repeatedly emphasized that GenAI should be considered a "tool" that should not replace the student learning process. From a sociotechnical perspective, this reflects faculty efforts to maintain joint optimization, which AI tools support rather than replace the cognitive work students must perform to develop meaningful understanding.

The paradox of transparency identified in the findings reflected a structural gap between institutional expectations and the realities of student behavior. Faculty viewed disclosure as essential for accountability and for making students' learning processes visible, yet they also recognized the practical challenges of documenting every instance of AI use. This tension mirrors research showing that students often avoid disclosure due to concerns about judgment rather than lack of awareness (Jiang et al., 2025). Faculty efforts to establish disclosure as a classroom norm illustrate how sensemaking operates around emerging practices that lack established precedent. In this context, transparency becomes a relational practice that supports trust, accountability, and shared responsibility in the classroom.

The brainstorming-versus-bypassing tension identified in this study reflects the nuanced nature of faculty decision-making about student use of GenAI. Faculty recognized that students need to learn to use AI effectively while also remaining committed to preserving students' independent reasoning and meaning-making capacities. This balance signals a shift toward pedagogical innovation. The unreliability of AI detection tools played an important role in this shift, prompting faculty to redesign assessments and move away from policing AI use toward creating learning experiences that emphasize process, reflection, and higher-order thinking. This finding aligns with research showing that limitations in detection technologies function not only as constraints but also as catalysts for more authentic and pedagogically grounded assessment practices (Kofinas et al., 2025; Farazouli et al., 2023).

Beyond course-level decisions, the findings highlight that faculty members consider the broader AI-driven work environments students are likely to enter. This future workforce requirement aligns with research showing that as AI technologies continue to integrate across industries, the skills required of the future workforce are evolving in parallel (Hashmi & Bal, 2024). Scholars have also

emphasized that avoiding AI in higher education may leave students underprepared for real-world practice (Lee et al., 2025). Faculty, therefore, balanced two commitments. They sought to preserve students' independent reasoning while also preparing them to work responsibly with AI in their future professions. This dual orientation reflects a forward-looking form of sensemaking in which faculty interpret appropriateness not only through current academic norms but also through anticipated workforce expectations.

IMPLICATIONS

Practically, this study extends current research, specifically in AI policy, assessment design, and academic integrity, in multiple ways. By examining how faculty engage in ongoing sensemaking in response to student use of GenAI tools, this study identifies key factors that inform their decision-making practices. These findings offer educators and researchers practical guidance for designing AI integration strategies that are flexible, context-sensitive, and responsive to disciplinary and institutional realities rather than universally prescriptive. Furthermore, this study advances the understanding of the "awareness-to-practice gap" identified in recent literature (Almisad & Aleidan, 2025; Sutedjo et al., 2025), providing empirical evidence of the pedagogical reasoning that underlies how faculty translate their awareness of GenAI into everyday decisions about student use of GenAI in their courses. These insights point to the importance of educator capacity building, calling for targeted training opportunities that strengthen faculty confidence and competence across diverse institutional contexts, alongside educational technology platforms that incorporate transparency features, making AI contributions more visible and easier to monitor within learning environments.

Theoretically, this study contributes to educational technology theory by demonstrating the value of a sociotechnical perspective for understanding GenAI integration. By positioning AI as embedded within the social, cultural, and technological contexts in which learning occurs rather than as an external tool to be permitted or banned, this research reframes fundamental questions about technology in education. This theoretical contribution extends beyond GenAI. This suggests that educators, researchers, and educational technology designers should approach emerging technologies not as isolated tools but as systems shaped by technical capabilities, pedagogical goals, institutional contexts, and disciplinary practices.

Limitations of the Study

Several limitations should be acknowledged. First, this study captured faculty perspectives at a particular moment (August to October 2025) when AI technologies and institutional policies were rapidly evolving. What constitutes appropriate use then may differ from current or future determinations as both

technologies advance and academic conventions develop. Second, the study relied on faculty self-reports of their decision-making processes and examined only educator perspectives. Students may hold different views on appropriate AI use. The findings should also be interpreted within the context of the sample characteristics and professional backgrounds represented in this study, as participants' substantial teaching experience may have shaped how they interpreted and evaluated students' use of GenAI. Finally, this study was conducted by a single researcher, which may have influenced coding and theme development. Although trustworthiness was supported through a detailed audit trail and analytic memoing, the absence of collaborative coding or interrater reliability checks remains a limitation that should be considered when interpreting the findings.

Future research directions

Several directions warrant further investigation. First, longitudinal research should examine how faculty AI policies, assignment designs, and judgments about appropriate student GenAI use change across multiple academic years as AI tools and institutional guidelines evolve. Second, student-focused studies should examine how learners interpret faculty AI policies, decide when to disclose AI use, and experience different AI-integrated assessment designs. Such work could clarify how AI use affects learning outcomes, self-regulated learning, and academic integrity in practice. Third, comparative research across disciplines should examine how professional standards, accreditation expectations, and disciplinary knowledge practices shape what counts as appropriate GenAI use. Finally, design-based research should test specific transparency and scaffolding features in learning management systems.

Conclusions

This study explored the factors that faculty members consider when making decisions about students' use of GenAI. Four interconnected factors emerged: student meaning-making and cognitive engagement; transparency and disclosure of AI use; AI's role in the learning process; and institutional policies and disciplinary norms. These findings demonstrate that faculty decision-making around GenAI is contextual, relational, and continuously negotiated rather than guided by fixed rules. Consistent with sociotechnical and sensemaking perspectives, faculty make decisions about student use of GenAI through ongoing interpretation of ambiguous situations, evolving technologies, and shifting academic expectations.

The significance of these findings extends beyond a descriptive understanding of faculty perspectives, as the factors identified in this study provide practical guidance for educators and institutions navigating AI integration. As AI technologies continue to evolve and student use becomes increasingly ubiquitous,

the factors identified in this study provide a foundation for institutional policies, pedagogical practices, and future research. However, what constitutes appropriate use will continue to evolve alongside technological capabilities, academic conventions, and societal and professional expectations. Hence, determining the appropriate use of GenAI in student learning remains an ongoing challenge.

Furthermore, GenAI raises concerns about biased data, privacy, reliability, socioethical issues, hallucinations, the digital divide, and equity in learning opportunities. Thus, determining what constitutes appropriate or inappropriate student use of GenAI cannot be based on a single judgment but rather requires contextual evaluation. Ultimately, preparing students with the knowledge, skills, and judgment they need to thrive in AI-integrated professional environments while preserving the cognitive engagement essential to learning represents the central challenge and opportunity for educators navigating this technological transformation.

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