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GenAI in Course Materials: Faculty Use and Perceptions

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Abstract: As generative artificial intelligence (GenAI) becomes increasingly relevant in higher education, faculty face growing pressure to integrate it ethically and effectively into teaching. While students are already using GenAI and seek faculty guidance, course materials often lack clear policies or instructional support. This study surveyed faculty and analyzed syllabi at a large public Midwestern research university to examine how GenAI is addressed in instruction. Findings reveal that faculty generally view GenAI as a potentially useful learning tool but report limited institutional guidance and inconsistent classroom practices. Despite some departmental efforts to establish GenAI policies, consensus on best practices is lacking. These results underscore the need for clearer institutional frameworks and faculty development to support ethical, pedagogically sound use of GenAI.

Keywords: generative artificial intelligence, higher education, faculty guidance, classroom practices

Popular discourse surrounding generative artificial intelligence (GenAI) has been marked worldwide throughout higher education with excitement over the potential for efficiency and analysis as well as unease over the implications for authorship and accuracy. In the context of pedagogy, this tension has translated to uncertainty among teaching faculty contending with applications of this technology. Professional organizations, artificial intelligence (AI) enterprises, and, perhaps mostly critically, universities have offered guidance on integrating GenAI into classrooms and other learning spaces, but the labor of implementing this guidance is frequently undertaken by individual faculty members.

We examined how faculty at a large public Midwestern research university have integrated policies and guidelines from their institution into their syllabi and other course documents. In addition to analyzing course documents, we collected survey data on faculty perceptions of the institution's guidance and the pedagogical utility of student AI use. Limited data on faculty AI use and demographics were also collected. The goal of this research was to collect information on faculty experience to make curricular recommendations based on these data.

Background Information

Institutions of higher education can be slower to adopt emergent, potentially disruptive digital technologies—particularly when compared to the speed at which industry adopts such technologies (Singun, 2025). In part, this slower adoption may be attributable to faculty preference for accepted approaches to teaching and research that are perceived to be successful (Feng et al., 2025; McGehee, 2024). This belief can lead to faculty skepticism and sometimes resistance to rapid transformation involving disruption of existing systems (Li, 2019; Rosenberg, 2023; Valtonen & Holopainen, 2025). Despite these attitudes, recent decades have seen colleges and universities adopt emergent digital technologies in ways that have fundamentally transformed the core work of these institutions. Recent adoptions/transformations include the microcomputer wave of the 1970s and 1980s and the introduction and rapid growth of the internet and online learning in the 1990s and 2000s. In both the microcomputer wave and the internet and online learning period, technology arrived without faculty preparation, which led to an initial resistance until early adopters began to identify advantages and opportunities for effective integration of the technology into the academy. To some extent, GenAI is following this same trajectory, but the rapid pace of the innovation exceeds the pace of previous technological emergences in the academy. As Schwab and Davis (2018) pointed out, GenAI affects "norms, rules, expectations, goals, institutions, and incentives that guide our behavior every day" (p. 8). GenAI, the latest of these technologies, has been defined by its rapid development and increasing presence in institutions. According to Duane and Fisher (2025), we are experiencing "techceleration … exponential technological acceleration that is transforming our world unprecedently" (p. 89). This accelerated change may require greater adaptability and experimentation among faculty, staff, and students.

As they did for the technologies noted above, colleges and universities have been responding to the perceived possibilities and risks associated with integrating GenAI tools into their routine function. Arguably, these institutions have adopted GenAI more slowly than private industry (Hutson et al., 2022; Slimi & Villarejo-Carballido, 2024; Tobenkin, 2024). Many factors exist that might account for this slower pace. Most relevant to our study are those factors related to the pedagogical implications of GenAI. These implications have received significant scholarly attention across disciplines (Wu et al., 2025). Broadly, this scholarship suggests that faculty are interested in the potential of GenAI to automate tasks, assist in data analysis, and support student learning but are wary of the risks GenAI poses to academic integrity, data privacy, and postsecondary education generally (Hamid & Schisgall, 2023; Robert & McCormack, 2025; Wu et al., 2025).

A more specific factor delaying GenAI use might be a lack of faculty training. Ruediger et al.'s (2024) recent national survey found that a majority of the faculty surveyed were not confident in their ability to use GenAI in their teaching. Another potentially contributing factor might be the perception that use of GenAI is unethical. Chan and Hu (2023) noted student concerns about the use of GenAI regarding privacy, ethics, threats to intellectual development, and career outcomes. Farrelly and Baker (2023) discussed the ethical implications of GenAI in a classroom environment, specifically concerning academic integrity. However, the authors also noted that GenAI is likely to persist and further develop, suggesting that academic units should "prioritize ethical [Gen]AI usage, cultivate [Gen]AI literacy, and develop frameworks that empower students and educators to safely harness the full potential of these technologies" (p. 10). A negative view of the ethics of GenAI use has led some faculty to adopt a surveillance approach to these tools. Petricini et al. (2025) found a trend among faculty toward compliance-oriented frameworks, which can create relational frictions between faculty and learners and hinder learner adoption of GenAI skills. Additionally, a compliance-oriented approach may discourage the use of GenAI among faculty because of concerns about accusations of academic misconduct (Muscanell & Gay, 2025).

A final potential factor affecting faculty adoption of GenAI tools is the perception that institutions should develop policies around the proper use and application of GenAI. We were particularly interested in this factor. Our institution has one policy that describes acceptable use of GenAI software (Indiana University [IU], 2025e). By *policy*, we mean "a formal, high-level directive that provides direction" and "establishes principles, standards, or requirements" (Indiana University [IU], 2025d). The policy in question does not explicitly mention AI; instead, it identifies four different categories of institutional data (IU, 2025e): public (e.g., employee names); university-internal (e.g., employee identification numbers); restricted (e.g., employee home addresses); and critical (e.g., employee social security numbers). Another webpage lists GenAI programs and specifies which category of data may be used with each program (Indiana University [IU], 2025b). For example, university-affiliated individuals are permitted to enter "public" and "university-internal" data into Google Gemini—assuming they are signed into their university Google account—because these data are not shared with Google. This document also states that GenAI software not appearing on the list is "not approved for any institutional data" at the institution, "even when data are anonymized" (IU, 2025b). In this way, the policy frames the use of GenAI software in terms of data security and privacy.

Some units and individuals at our institution have proactively produced guidelines for using GenAI software in teaching and research. By *guidelines*, we mean nonbinding recommendations typically produced by subject-area experts and intended to assist individuals. The most prominent GenAI-related guidelines are from Hodgson's (2023) *Generative AI, ChatGPT & Syllabi: An Ethics of Practice*. This document provides suggestions for constructing syllabi as well as an "ethics of practice" that addresses plagiarism, intellectual property, and other faculty concerns identified in the literature (Hodgson, 2023). As described in our Method section, we used Hodgson's (2023) document to guide our analysis of the educational materials collected for this study.

Study Design

In 2023, our institution convened several faculty learning communities to explore the role of GenAI within the university. This research study was the result of one of those communities. All authors participated in early discussions regarding the role of faculty perceptions of GenAI policy and adoption into courses. Faculty members in the group had varied disciplinary backgrounds, yet we all agreed that our anecdotal experience indicated a need for additional institutional guidance. With that concern in mind, we undertook this study with the following research question: How are faculty at our university adopting rules, guidelines, or other frameworks within their syllabi or other course materials to help students navigate the rules of engagement concerning GenAI?

Method

Review of the emerging literature in this new field and discussion regarding the most useful GenAI information to faculty at-large led us to a mixed-methods approach (Creswell & Clark, 2018) to investigate faculty attitudes toward GenAI in higher education, associated teaching and learning policies, and the extent to which GenAI had been incorporated into instructional materials at our institution, a large public Midwestern research university. The study combined quantitative survey data with qualitative content analysis of course documents submitted confidentially by faculty participants to provide a comprehensive understanding of how instructors conceptualized and integrated GenAI into their teaching.

Sampling and Recruitment

Participants were recruited through a multipronged combination of convenience and snowball sampling methods (Cresswell & Clark, 2018). Eligibility was restricted to currently teaching instructors of record at the university between September 2023 and May 2025. Faculty across all ranks, appointment types (e.g., tenured, clinical, lecturer, adjunct), and disciplinary homes were invited to participate via email, the university's learning management system (Canvas), newsletters, and face-to-face outreach in faculty governance bodies, and through faculty networks. The invitation directed participants to an online survey using Qualtrics survey software (Qualtrics, Provo, Utah), which included a study information sheet and consent process, all of which were approved by our Institutional Review Board. Recruitment messaging emphasized the voluntary nature of participation, the faculty-led nature of the study, and the brief time commitment required—approximately 10 min to complete the survey and upload relevant course materials such as syllabi or assignments that addressed GenAI policies, guidelines, or usage.

Data Collection

Participants completed a short online survey that gathered demographic data (e.g., faculty track, academic discipline, decade of birth), frequency and context of GenAI use, perceptions of the ethical implications of GenAI in student work, and satisfaction with institutional guidance on GenAI. Participants were also asked to upload between one and four course documents (syllabi, assignments, or policy statements) from the 2023–2024 and 2024-2025 academic years that addressed the use of GenAI. The scope of what and how GenAI was addressed was left to the participants to decide. The survey instrument was designed to capture both the prevalence and nature of GenAI-related content in instructional materials, as well as faculty attitudes toward its use in academic settings.

Data Analysis

Survey responses were analyzed using descriptive statistics to summarize faculty demographics, attitudes, and behaviors regarding GenAI. Document analysis was performed on 16 course artifacts submitted by participants. These artifacts were categorized by type (e.g., syllabus, assignment, policy statement) and then systematically coded using a predefined rubric. The rubric was designed by the authors and included criteria from our university's official data privacy and GenAI statements (IU, 2025b; 2025e), guidance from the university's teaching website (Indiana University, 2025c), and ethical frameworks articulated by Hodgson (2023) and others.

To ensure reliability and minimize bias, each author independently coded the documents. Each rater was trained in the coding scheme and conducted a pilot round of coding to calibrate interpretations. Codes were applied to identify the presence and depth of content in the following thematic areas: (1) acceptable AI use, (2) repetition of AI policies as stated in the documents, (3) ethical dimensions of AI use, (4) possibility for policy revision, (5) AI's relationship to plagiarism, (6) rules for citing AI use, (7) data privacy broadly, and (8) data privacy at the university. For each thematic area, documents were classified as "present robust," "present limited," or "completely absent." Discrepancies in coding were resolved through collaborative discussion and consensus among raters. Interrater reliability was assessed using a percentage agreement. The coding process emphasized transparency and rigor, with raters documenting their decisions and justifications for each code assigned.

The results of the coding process were compiled into frequency tables to illustrate the distribution of themes across the collected materials. We used this dual approach—survey and document analysis—to gather data for a richer, triangulated understanding of faculty perspectives and practices regarding GenAI in higher education.

Results

Participants

Fifty-six responses to the survey were collected regarding GenAI use, perceptions of ethical considerations, and satisfaction with institutional guidance. Participants varied in terms of gender, academic track, and discipline, with less variability in terms of race and ethnicity. Most responses came from faculty in liberal arts (n = 16, 34%), medicine (n = 9, 19%), and business (n = 8, 17%). Participants' demographic and academic characteristics are presented in Tables 1 and 2.

Table 1. Demographic characteristics.

Item	*n*	%
Race		
White	35	74
Black or African American	1	2
Asian	4	8
Other	2	4
Prefer not to say	5	10
Spanish, Hispanic, or Latino origin?		
Yes	1	2
No	45	98
How do you describe yourself?		
Male	22	47
Female	22	47
Prefer not to say	3	6

Note. Forty-seven of the participants answered demographic questions. One participant skipped the question about Spanish, Hispanic, Latino origins but answered the other questions.

Table 2. Academic characteristics.

Item	*n*	%
Faculty track		
Clinical	6	13
Tenured/tenure-track	30	64
Lecturer	9	19
Associate or volunteer faculty	2	4
In which school do you conduct most of your teaching?		
Art and design	2	4
Business	8	17
Dentistry	1	2

Item	*n*	%
Health and human sciences	2	4
Informatics, computer science, and engineering	1	2
Law	1	2
Liberal arts	16	34
Medicine	9	19
Nursing	3	6
Public health	1	2
Science	3	6

GenAI Use and Perceptions of Institutional Guidance

Thirty-eight percent (*n* = 21) of participants indicated that they "never" used GenAI for work or personal purposes (Table 3). The remaining 62% (*n* = 35) indicated that they used this technology at least weekly with 12% (*n* = 7) reporting that they used it most days of the week. Among those that used GenAI, the most common application was "administrative work" (*n* = 26), followed closely by "teaching" (*n* = 25) and "research" (*n* = 18).

The survey suggests that use of GenAI in the context of teaching did not seem to be informed by the institution's guidelines; when asked "to what extent [do] the institution's guidelines on AI shape your course materials?" well over half of participants (71%) answered either "none" (*n* = 22) or "a little" (*n* = 18). Regardless of whether they used them, most participants (52%, *n* = 29) indicated that they were "neither satisfied nor dissatisfied" with the institutional guidelines. An additional 20% of participants (*n* = 11) answered that they were "somewhat dissatisfied" and 16% (*n* = 9) answered that they were "somewhat satisfied" (Table 4).

Table 3. Generative AI use.

Item	*n*	%
How often do you use generative AI for any purpose (work or personal)?		
Never	21	38
Once a week	16	29
2 or 3 times a week	12	21
4–6 times a week	3	5
Daily	4	7
In which contexts do you use AI?		
Teaching	25	45
Research	18	32
Service	13	23
Administrative work	26	46
I don't use AI	18	32

Note. AI = Artificial intelligence.

Table 4. Satisfaction with institutional guidance.

Item	*n*	%
To what extent did the institution's guidelines on AI shape your course materials (i.e., syllabi and/or other materials that explain course policies)?		
None	22	39
A little	18	32
Some	11	20
A great deal	5	9
How satisfied are you with Indiana University's institutional guidelines around AI?		
Extremely dissatisfied	6	11
Somewhat dissatisfied	11	20
Neither satisfied nor dissatisfied	29	52
Somewhat satisfied	9	16
Extremely satisfied	1	2

Ethics of GenAI Use

The ambivalent response to the institutional guidelines is mirrored in participants' perception of the ethical and educational implications of GenAI (Table 5). The survey presented a scenario in which "no explicit rules are given to the student" regarding GenAI and asked participants if they "think student use of AI in instructional contexts (i.e., to complete assignments in class) is ethical?" Sixty-six percent of participants ($n = 37$) answered that this use would be ethical "in certain scenarios" while 29% offered an unqualified "yes" or "no" (16% yes, 13% no). The following question again asked participants to imagine a situation in which "no explicit rules are given to the student" and asked if they "think student use of AI supports learning outcomes?" As with the previous question, most participants (77%, $n = 43$) indicated that GenAI use supports learning outcomes "in certain scenarios" while 18% answered with a definitive "yes" or "no" (both 9%).

Table 5. Perceptions of Generative AI in learning.

Item	*n*	%
Assuming no explicit rules are given to the student, do you think student use of AI in instructional contexts (i.e., to complete assignments in class) is ethical?		
Yes	9	16
In certain scenarios	37	66
No	7	13
I'm not sure	3	5
Assuming no explicit rules are given to the student, do you think student use of AI supports learning outcomes?		
Yes	5	9
In certain scenarios	43	77
No	5	9
I'm not sure	3	5

Document Analysis

In the survey, we invited participants to upload course documents related to GenAI. Table 6 presents the results of our document analysis. In sum, 16 course documents were uploaded: nine syllabi, six policy statements, and one assignment.[1] Perhaps unsurprisingly, most of these documents included a statement describing acceptable use of GenAI, what Hodgson (2023) called a "permission and acknowledgement disclaimer." Raters coded the presence of this disclaimer as "robust" in 59% of documents (n = 8) and as "limited" in an additional 25% of documents (n = 4). Other themes were more diffuse, appearing in at least limited form in most documents. Instructions for citing GenAI use, for example, were present in "robust" form in 19% of documents (n = 3) and in "limited" form in 38% of documents (n = 6). A notable outlier in the coding is the paucity of data privacy guidance. As noted earlier in this article, the institution's most direct guideline regarding GenAI is related to data management. Raters agreed that a general discussion of GenAI and data privacy was present in a "limited" way in 25% (n = 4) of documents and was "completely absent" from the remaining 75% (n = 12). Raters also found that only one document mentioned the university's data privacy policy. It is possible that underrepresented themes such as "data privacy" might be present in presentations, in-class activities, and other curricular products that were not collected. Nonetheless, these results suggest an uneven relationship between institutional guidelines and the implementation of those guidelines in course documents.

Table 6. Results of data analysis of AI use.

Document feature	Present robust		Present limited		Completely absent	
	n	%	*n*	%	*n*	%
Permission and acknowledgment disclaimer	8	59	4	25	4	25
Repetition of AI policies	5	31	6	38	5	31
Discussion of AI ethics	3	19	6	38	7	44
Potential for policy revision	2	13	1	6	13	81
AI relationship to plagiarism	3	19	7	44	6	38
Citation rules for AI	3	19	6	38	7	44
AI data privacy	0	0	4	25	12	75
University data privacy	0	0	1	6	15	93

Discussion

The findings of this study suggest that faculty members at our institution would benefit from clearer guidance on how to integrate GenAI into their teaching. Data indicate that many instructors were experimenting with GenAI tools but were doing so in markedly different ways—particularly in course materials and syllabi. Some of these differences might be attributable to disciplinary differences (e.g., different styles of citation for student GenAI use); others reflect an uncertainty about best practices (e.g., limited or absent discussions of what uses constitute plagiarism). This uncertainty is compounded by a notable absence of information shared with students regarding data

[1] An image of a room was also uploaded but not included in the data analysis.

privacy. Few instructors explicitly addressed how GenAI tools collect or store data, underscoring a significant gap in faculty knowledge or confidence about privacy considerations. Fewer still referenced the university's management of institutional data policy (IU, 2025e). This omission signals the need for more targeted research and educational resources that clarify the implications of data privacy in the instructional environment.

In addition to these practical concerns, participants expressed ambivalence about the ethics and utility of student use of GenAI. Unlike more established technologies such as search engines, spreadsheets, calculators, or word processors, the pedagogical implications of GenAI have not been clearly established within disciplines or institutions. This uncertainty reinforces the need for clearer guidelines, as well as faculty development programs that explore both the pedagogical possibilities and limitations of GenAI technologies. Such programs should support instructors in identifying discipline-specific use cases, evaluating the credibility and transparency of AI-generated content, and developing ethical frameworks for responsible use. Faculty need opportunities to discuss scenarios, consider policy implications, and align their instructional strategies with both institutional values and student learning goals.

At Indiana University, a task force was convened by the university's faculty governance body in the spring of 2024 in an effort to address some of these challenges, though not as a direct result of this survey. The Indiana University *Generative AI Task Force Report* (Indiana University, 2025a) offered a series of recommendations in concurrence with some of the outcomes of the survey, including: creating a university ethics policy framework for GenAI; recommending a research data policy to manage data used in AI training; and review and revision of the student code of conduct, course syllabi, promotion and tenure guidelines, and data management and privacy protocols. As illustrated by the previous references to institutional policies (IU, 2025b, 2025c, 2025d), only some of these recommendations have been implemented. As Dubois (2024) indicated, simply implementing policies will likely not result in the kind of organizational behavior change required to address the complex issues raised by GenAI. The author concluded there is a "need for more complete organizational routines to foster stability while adapting to technological change, which challenges educational practices and raises concerns about academic freedom" (Dubois, 2024, p. 8). Thus, considering how challenging it has been for many institutions to fully address this issue (See McCarthy, 2025), we offer strategies for future research at our own and other institutions.

Future research could examine the specific concerns faculty members and students have regarding pedagogical, ethical, and technical dimensions of GenAI use in higher education at institutions broadly. This research should attend to faculty use of GenAI—the primary focus of this study—as well as student and staff use. More specifically, longitudinal studies across academic disciplines might examine how institutional policies and guidelines develop in response to student, faculty, and staff perceptions of GenAI. Additional investigations could build on existing research focused on students' understanding of and expectations around GenAI use in higher education and draw on the technological pedagogical content knowledge (TPACK) framework (Koehler & Mishra, 2005) or other, similar frameworks to seek more generalizable findings. Ultimately, negotiating among institutional values, faculty readiness, staff adoption, and student perceptions is critical to working toward an equitable and ethical integration of GenAI in higher education.

Limitations

Our study offers an important snapshot of how faculty members have responded to the emergence of GenAI in higher education, but it is not without limitations. First, the research was conducted at a single large public Midwestern research university, which may limit the generalizability of the findings to other institutional contexts. Policies, resources, and cultural attitudes toward GenAI can vary significantly between institutions, especially between public and private universities, or those with different levels of technological infrastructure. It should be noted that given the mixed methods approach used in the study, the qualitative data are not focused on generalizability (Herndon & Kreps, 1993; Merriam, 1998). Rather, the insights gained from the exploration enable an understanding of a somewhat idiosyncratic case. The value of this approach is that learning from this qualitative study creates an opportunity for understanding meaning that could not be planned or expected.

Second, the sample underrepresents faculty from certain disciplines—particularly those in education and allied health professions. These areas are likely to engage with GenAI in unique ways given their focus on professional ethics, clinical simulation, and pedagogical innovation. Their limited participation restricts the breadth of disciplinary perspectives captured in this study.

Third, the voluntary nature of the survey may have introduced selection bias. Faculty members most comfortable or enthusiastic about discussing GenAI may have been more likely to participate. Conversely, those who harbor skepticism or fear institutional consequences for expressing concern may have chosen not to respond. This self-selection could have skewed the data toward more favorable or neutral perceptions of GenAI use in academic settings.

Fourth, ongoing development of GenAI technology is occurring at a rate that likely exceeds the traditional rate at which university administrations have been accustomed to setting policy or developing guidelines. Findings from our study suggest faculty and students would appreciate clearer guidance and quicker policy updates to accommodate further advances in GenAI tools.

Finally, the reliance on self-reported data and submitted documents means that the findings reflect participants' willingness to share rather than a comprehensive view of all instructional uses of GenAI across the institution. Despite these limitations, this study offers a timely and valuable contribution to understanding faculty perceptions and practices at a critical inflection point.

Conclusion

GenAI is shifting traditional pedagogy within higher education, and faculty, students, and institutions must adapt. Our study highlights both opportunities and challenges faculty face in responding to the rapid adoption of GenAI tools by students and their future employers. While many instructors at our university viewed GenAI as a potentially valuable educational toolset, they did so without consistent institutional guidance and with varying levels of confidence in best practices. Course materials reflected this variability, demonstrating uneven attention to core issues such as data privacy, ethical GenAI use, and plagiarism. Developing new GenAI policies and guidelines for faculty does not come without challenges. The rapid evolution of the technology, combined with concerns about student skill development, the integrity of learning, the effectiveness of curriculum design, and grading practices, underscore the need for continued research.

Ultimately, this moment presents an important opportunity for institutions of higher education such as ours to lead in shaping thoughtful integration of GenAI into overarching pedagogical infrastructures. Given the transformative nature of GenAI on teaching and learning, faculty might be well-served to strengthen their own GenAI capabilities, to explore the origins of students' fears and concerns, and to provide policy-based or at least guidelines-based scaffolding to allow students to develop GenAI fluency. As the use of GenAI by students accelerates, it is vital to document how instructors are navigating this shift—even within the constraints of a single institutional setting—to inform future policy, pedagogy, and research across the higher education landscape.

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