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Faculty Strategies for Integrating Generative AI Across Disciplines: Emerging Practices, Policies, and Pedagogical Insights

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Introduction

Since the public release of ChatGPT in late 2022, generative AI (GenAI) tools have rapidly permeated higher education, prompting debate about their role in teaching and learning [1]. Educators across disciplines are navigating how to leverage GenAI's potential benefits while managing risks related to academic integrity, bias, reliability, and the authenticity of student work [2]. In response, many universities have issued guidance emphasizing ethical use and academic honesty, often encouraging instructors to articulate course-level policies and redesign assessments to reduce plagiarism or over-reliance on AI-generated outputs [3]. At the same time, early-adopting instructors have begun experimenting with GenAI to support instruction—for example, generating practice questions, producing alternative explanations, or developing cases and scenarios—thereby increasing instructional efficiency and expanding pedagogical options [4]. These divergent responses underscore the need to better understand how faculty are making instructional decisions about GenAI within real courses.

Despite the rapid growth of scholarship on GenAI in higher education, existing work has focused primarily on student use, broad institutional perspectives, and policy discourse, with comparatively limited empirical attention to how faculty make course-level decisions in practice [1–4]. In particular, there remains a need for discipline- and course-sensitive accounts of how instructors integrate, constrain, or deliberately exclude GenAI based on learning objectives, assessment validity, and disciplinary norms [3,4]. Without such evidence, guidance on GenAI adoption can implicitly assume a uniform instructional context, obscuring meaningful variation across technically intensive, applied, and policy-oriented courses.

To address this gap, we conducted a multi-case qualitative study spanning four disciplinary contexts—engineering, project management, computer science, and public administration—to capture variation in faculty practices and rationales. A multiple-case design supports examination of a phenomenon across contrasting settings and enables cross-case comparison to identify patterns that may not be visible within a single context [5]. Each case represents an instructor–course policy configuration and draws on multiple sources of qualitative evidence: reflective narratives describing instructors' approaches and rationales; course- and institution-level policy documents specifying acceptable AI use; and instructional artifacts (e.g., assignment prompts, rubrics, templates, or disclosure forms) demonstrating how policies and teaching strategies are enacted in practice. Using multiple data sources enables triangulation and supports a more grounded interpretation of instructors' decisions.

In addition to documenting practices across cases, this study uses Rogers' Diffusion of Innovations (DOI) as an interpretive lens to contextualize differences in GenAI adoption and regulation [6]. DOI theory suggests that adoption of an innovation is influenced by perceived attributes such as relative advantage, compatibility, complexity, trialability, and observability [6]. Prior work applying diffusion concepts to GenAI in academic settings suggests that instructors' perceptions of instructional value, alignment with disciplinary expectations, and the visibility of meaningful outcomes can shape whether and how GenAI is adopted [3,4]. In this study, diffusion concepts are used to support interpretation of heterogeneous faculty responses—ranging from deliberate restrictions in some courses to structured integration in others—without assuming a single linear pathway of adoption.

This collaborative study examines faculty strategies for integrating, regulating, or restricting GenAI across multiple disciplines and four institutions: a primarily undergraduate, teaching-focused institution; an HBCU R2 university; and two large R1 universities. Responding to calls for clearer guidance and faculty development related to ethical GenAI use in higher education [7], the study pursues three objectives:

1. Document faculty GenAI practices across disciplines: Provide comparative accounts of how instructors integrate GenAI into coursework or regulate its use, including examples of assignment designs, classroom activities, and assessment policies.
2. Identify shared pedagogical strategies and concerns: Distill common approaches, perceived benefits, and recurring concerns across cases, including strategies for academic integrity, transparency, and managing over-reliance.
3. Develop a transferable, evidence-informed framework: Synthesize cross-case insights, supported by diffusion concepts, into guidance that other educators can adapt when designing course-specific GenAI policies and instructional uses.

By combining multi-case qualitative evidence with an established interpretive framework, this study contributes practical insight into course-level GenAI decision-making while extending emerging scholarship on how educational innovations diffuse across disciplinary and institutional contexts [6].

Methodology

This study employed a multi-case qualitative research design to examine how faculty across disciplines integrate, regulate, or deliberately restrict the use of Generative Artificial Intelligence (GenAI) in teaching and assessment as shown in Figure 1. The purpose was to document current practices, policy rationales, pedagogical strategies, and observed benefits and limitations, rather than to test hypotheses or establish causal relationships. A qualitative, descriptive–interpretive approach was selected because faculty uses of GenAI represent a rapidly evolving phenomenon characterized by contextual variation, emergent norms, and institutionally mediated constraints [8,9].

Case Selection and Units of Analysis

Participants were ten faculty collaborators drawn from multiple disciplines and course contexts who were actively teaching during the recent emergence of Generative Artificial Intelligence (GenAI) tools. Purposeful sampling was used to ensure representation across undergraduate and graduate courses, technical and non-technical disciplines, and a range of GenAI policy stances, including prohibition, restricted use, and guided integration.

The unit of analysis was defined as an instructor–course policy configuration rather than the individual instructor alone. Several participants contributed more than one case when their GenAI practices differed across courses or assessment regimes. This approach allowed course-specific instructional decisions to be examined without collapsing distinct pedagogical contexts.

Some contributors provided extensive narrative responses and instructional artifacts without completing the structured survey. These narrative-only cases were retained as qualitative cases and included in thematic and artifact-based analyses, consistent with qualitative case study guidance that emphasizes analytic depth over uniform data completeness [8]. They were excluded from survey-based summaries and descriptive comparisons. No attempt was made to reconstruct or infer missing survey data.

Data Sources

Data were drawn from three complementary sources to support triangulation:

1. Structured AI Practice Profile Survey
   A custom survey captured instructor self-reported GenAI use, perceived student use, policy stance (AI zones), adoption stage, training background, familiarity with GenAI techniques, and instructional use categories. The instrument included closed-ended items and targeted open-ended prompts.
2. Narrative Responses
   Faculty provided open-ended narrative descriptions of their GenAI practices, policy rationales, perceived benefits and risks, and reflections on student use. In several cases, narratives served as the primary data source.
3. Instructional and Policy Artifacts
   Artifacts included syllabi, assignment prompts, reflection templates, disclosure or consultation forms, policy statements, and examples of AI-supported or AI-restricted assessments. Artifacts were treated as primary qualitative evidence.

   Survey responses were submitted in varied formats, including highlights, annotations, and color coding. All survey entries and artifacts were reviewed, reconstructed where necessary, and explicitly verified prior to analysis. Only finalized and confirmed materials were included in the dataset.

Analytic Approach: Thematic Analysis

Data analysis followed an iterative thematic analysis process across survey open-ended responses, narrative submissions, and artifacts [10,11]. Initial inductive coding focused on identifying recurring patterns in:

- faculty rationales for GenAI policies,
- instructional uses and non-uses of GenAI,
- perceptions of student engagement and misuse,
- and alignment between stated policies and enacted practices.

Codes were refined through cross-case comparison and organized into higher-order themes that captured both convergence and divergence across contexts. Artifacts were used to validate and contextualize themes, enabling analytic triangulation.

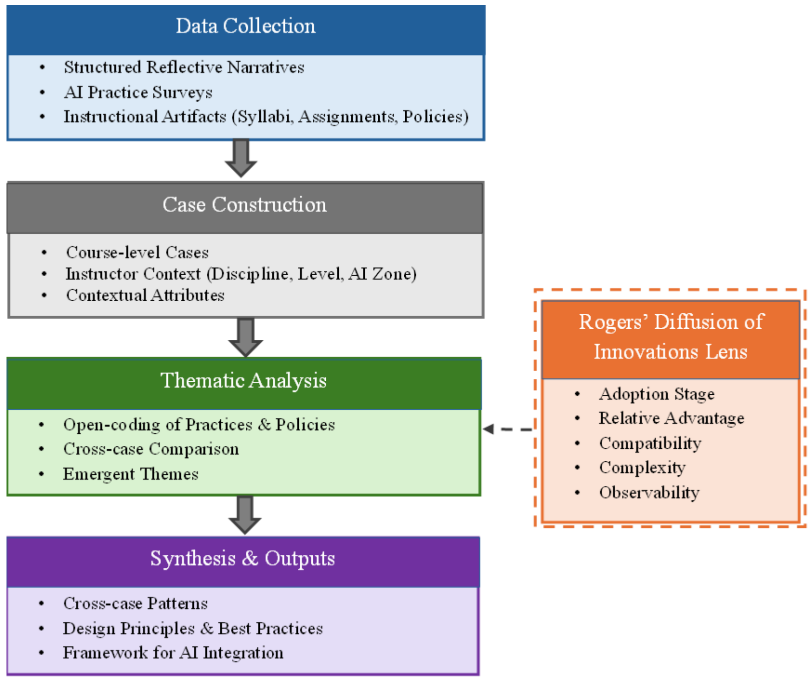

Figure 1: Overview of study methodology and analytic framework

Use of Rogers' Diffusion of Innovations

Rogers' Diffusion of Innovations framework [6] was employed as a secondary interpretive lens to contextualize variation in faculty adoption stages and policy stances. Diffusion concepts were used descriptively to support sense-making (e.g., experimenting, piloting, integrated use), not as a predictive or evaluative model. Narrative-only cases were not forced into diffusion categories unless explicitly supported by participant statements. The framework served to interpret heterogeneity in practice rather than to imply linear or normative adoption trajectories.

Cross-Case Comparison

Cases were compared across discipline, course level, policy stance, and adoption stage to identify patterns, contrasts, and boundary conditions. The analytic emphasis remained on understanding *why* different strategies emerged in different instructional contexts, rather than ranking or evaluating faculty practices.

Ethical Considerations and Limitations

All contributors were coauthors and were fully aware of the use of their data and artifacts. No student-identifiable data were analyzed. As a qualitative study with purposeful sampling and self-reported data, findings are not intended to be statistically generalizable. Instead, results provide transferable insights into faculty decision-making around GenAI in higher education.

Results

This section presents findings from the multi-case qualitative analysis, organized into four parts:
(1) descriptive characteristics of cases and instructional contexts,
(2) survey-based patterns across verified cases,
(3) cross-case qualitative themes grounded in narratives and artifacts, and
(4) interpretive synthesis using Rogers' Diffusion of Innovations as a secondary lens.

Narrative-only cases are included in thematic and artifact-based analyses but excluded from survey-based summaries.

Case and Course Context

Table 1 situates each case within its instructional context, while Table 2 summarizes faculty background and adoption characteristics. Across cases, restrictive AI policies appear in both undergraduate and graduate courses and across faculty ranks and expertise levels. This pattern indicates that policy stance is not a simple function of seniority or GenAI familiarity, but reflects course-specific instructional considerations.

Survey-Based Descriptive Patterns

Across cases, AI policy stances varied widely and did not align linearly with faculty rank or self-reported GenAI expertise (Tables 1–2). Instead, policy choices were closely associated with course role and learning objectives.

Notably, several Red and Orange cases corresponded to technically intensive or foundational courses (Table 1), including laboratory-based and prerequisite engineering courses, even when taught by faculty reporting advanced GenAI expertise (Table 2). This pattern indicates that policy restrictiveness reflects intentional pedagogical design rather than lack of familiarity or openness to AI.

Most instructors reported moderate personal use of GenAI while perceiving equal or greater levels of student use, particularly in courses where AI was permitted or conditionally allowed. In courses with explicit disclosure requirements or structured AI assignments (predominantly Green and Orange cases in Table 1), instructors described student AI use as more transparent and intentional. By contrast, in Red-zone cases—especially those classified as technically intensive—perceived student AI use was reported as low, but accompanied by heightened concern regarding inappropriate reliance on AI outputs and erosion of foundational skills. These concerns were articulated even by instructors with advanced GenAI expertise (Table 2).

Self-reported adoption stages ranged from occasional experimentation to AI as a core feature of course design (Table 2). Many cases clustered around piloting structured AI use, reflecting deliberate, bounded experimentation rather than wholesale adoption. Instructors frequently adopted different adoption stages across courses, reinforcing the importance of course-level analysis.

Across survey-verified cases, familiarity with GenAI techniques was highest for basic prompting and prompt engineering, with fewer instructors regularly employing more advanced approaches such as multimodal or batch prompting. Advanced techniques were primarily used in courses where instructors explicitly designed assignments around AI use rather than allowing AI as an unrestricted study aid.

Instructor use of GenAI clustered into three primary categories:

1. Course and content creation (e.g., examples, rubrics, syllabus refinement),
2. Assessment and feedback support (e.g., intentionally flawed solutions, feedback drafting),
3. Student learning support (e.g., visuals, simulations, explanatory scaffolds).

Use of GenAI for policy analysis or role-play appeared in a smaller subset of cases, typically in applied or policy-focused courses rather than technically intensive foundational courses (Table 1).

Cross-Case Qualitative Themes

Theme 1: AI Policy as Pedagogical Design:

Across cases, AI policies functioned as intentional instructional design decisions, not binary permissions or prohibitions. Instructors articulated clear rationales linking AI policy to course-specific learning outcomes, accreditation expectations, and assessment validity. This was especially pronounced in technically intensive or prerequisite courses (Table 1), where instructors emphasized the need for unaided problem-solving as a foundation for later learning.

Theme 2: Guardrails, Transparency, and Disclosure:

In Green and Orange cases, transparency mechanisms—including disclosure statements, prompt documentation, and reflective commentary—emerged as central pedagogical strategies. Rather than prioritizing detection of hidden AI use, instructors redirected effort toward making AI use explicit and discussable, thereby supporting metacognition and reducing adversarial dynamics.

Theme 3: AI as Cognitive Scaffold, Not Solution Replacement:

Instructors consistently framed GenAI as a cognitive scaffold rather than a substitute for disciplinary reasoning. Several cases incorporated assignments requiring students to critique, revise, or identify limitations in AI-generated outputs. This design choice was particularly salient in technically intensive courses, where instructors expressed concern that uncritical AI use could bypass essential reasoning processes.

Theme 4: Discipline- and Course-Specific Risk Sensitivity:

Perceived risks of GenAI varied systematically with course role. In technically intensive or foundational courses (Table 1), instructors emphasized risks related to loss of core competencies, over-reliance on AI outputs, and diminished problem-solving fluency. In contrast, courses emphasizing synthesis, policy analysis, or professional reflection demonstrated greater openness to structured AI integration, often accompanied by explicit guardrails.

Theme 5: Student Use Remains Largely Instrumental:

Even in courses where AI use was explicitly permitted, instructors observed that many students used GenAI in limited, instrumental ways, analogous to search engines or grammar tools. This mismatch between instructor intent and student practice motivated the creation of reflective assignments and guided prompting activities aimed at elevating cognitive engagement beyond surface-level use.

Artifact-Based Exemplars

Instructional and policy artifacts provided concrete evidence of how stated policies were enacted, including AI reflection templates, disclosure forms, Red-zone policy statements with explicit pedagogical rationale, and critique-based assignments. These artifacts corroborated survey and narrative findings and highlighted alignment, as well as occasional tension, between policy intent and instructional practice.

Table 1. Case and Course Context Summary

Case ID	Discipline	Course(s) Included in Case	Level (UG/G)	Required / Elective	Course Role in Curriculum	AI Policy Zone	Data Source
C1	CE	Statics	UG	Required	Foundational, technically intensive	Yellow	Survey + Artifacts
C2	CE	Engineering Probability & Statistics	UG	Required	Foundational, quantitative	Yellow	Survey
C3	CE	Statistics for Civil & Construction Eng.	UG	Required	Foundational, quantitative	Yellow	Survey
C4	ST&S	Science and Technology Studies & Eng. Practices	UG	Elective	Writing-intensive, synthesis-focused	Green	Survey + Artifacts
C5	ME	Energy Sources, Technology, and Policy	G	Required	Core technical sequence	Orange	Survey + Artifacts
C6	PA	Introduction to Public Policy	UG	Required	Policy analysis, applied reasoning	Orange	Survey + Artifacts
C7	ELPM	Undergraduate Project Mgmt course	UG	Elective	Applied, professional skills	Green	Survey + Artifacts
C8	ELPM	Technical Project Planning & Scheduling	G	Required	Advanced applied/analytical	Green	Survey + Artifacts
C9	CE	Geotechnical Earthquake Engineering	G	Required	Advanced technical, design-oriented	Orange	Survey + Artifacts
C10	CE	Multiple Civil Eng. Courses	UG	Required	Foundational & lab-intensive technical courses	Red	Survey + Artifacts
C11	CS	Multiple CS/AI-related courses	UG/G	Mixed	Technically intensive, AI-centered	Green	Narrative + Artifacts
C12	PA	AI in Local Government Administration	G	Elective	Policy, ethics, reflection-focused	Green	Narrative + Artifacts
C13	CONE	Multiple Construction Eng. & Management Courses	UG	Required	Applied technical & managerial	Green	Survey + Artifacts

Table 2. Faculty Background and Adoption Characteristics

Case ID	Faculty Rank	Discipline	Teaching Emphasis	GenAI Expertise (Self-Reported)	Adoption Stage	Survey-Based?
C1	Asst Prof	Civil Eng	Core technical foundations	Intermediate	Piloting	Yes
C2	Prof	Civil Eng	Quantitative foundations	Intermediate	Integrated	Yes
C3	Prof	Civil Eng	Quantitative foundations	Intermediate	Integrated	Yes
C4	Asst Prof	STS	Writing & synthesis	Very comfortable	Piloting	Yes
C5	Asst Prof	Mech Eng	Core technical sequence	Novice	Experimenting	Yes
C6	Asst Prof	Public Admin	Policy analysis	Intermediate	Experimenting	Yes
C7	Asst Prof	Engineering Leadership	Applied professional skills	Expert	Piloting	Yes
C8	Asst Prof	Engineering Leadership	Advanced PM analytics	Expert	Piloting	Yes
C9	Prof	Civil Eng	Advanced technical design	Advanced	Piloting	Yes
C10	Prof	Civil Eng	Foundational & lab-based technical	Advanced	Experimenting	Yes
C11	Prof	Computer / Data Science	AI, ML, programming	Advanced	Integrated	No (Narrative-only)
C12	Asst Prof	Public Admin	AI policy & ethics	Intermediate	Integrated	No (Narrative-only)
C13	Assoc Prof	Construction Eng	Applied technical & managerial	Expert	Core feature	Yes

Interpretive Synthesis

Viewed through Rogers' Diffusion of Innovations as a secondary interpretive lens, the cases reflect heterogeneous and non-linear adoption pathways rather than convergence toward a single model of AI integration. Experimentation, piloting, integration, and deliberate non-adoption coexist across instructional contexts. Importantly, restrictive policies often reflected deliberate, mature pedagogical decisions, particularly in technically intensive or foundational courses, rather than resistance or lack of expertise.

Together, the results demonstrate that faculty responses to GenAI are contextual, intentional, and course-specific. Variation in AI policy stance and adoption stage is best explained by differences in course role, disciplinary expectations, and assessment design (Table 1), rather than faculty rank or technical competence (Table 2).

Conclusion

This study examined how faculty across disciplines are responding to Generative Artificial Intelligence (GenAI) through instructional practice, policy design, and assessment strategy using a multi-case qualitative approach. Across cases, variation in GenAI policy stances and adoption strategies was shaped primarily by course role, learning objectives, and disciplinary expectations rather than by faculty rank or technical expertise. Restrictive policies were most common in technically intensive or foundational courses, while greater openness to structured GenAI use appeared in courses emphasizing synthesis, policy analysis, or professional reflection.

Across policy stances, instructors consistently framed GenAI as a pedagogical design problem rather than a binary permission issue. Disclosure requirements, reflective assignments, and critique-based activities emerged as common strategies to align GenAI use with learning goals while mitigating academic integrity concerns. Notably, even when AI use was permitted, instructors observed that student engagement often remained instrumental and surface-level, motivating instructional interventions aimed at fostering more intentional and higher-order use.

Implications for Engineering and Interdisciplinary Education

The findings suggest several implications for educators and institutions navigating GenAI integration:

1. Policy should be course-specific rather than uniform. Institution-wide AI policies may benefit from allowing flexibility at the course level, particularly for foundational or accreditation-sensitive courses.
2. Restrictive AI policies can reflect pedagogical maturity. Deliberate non-adoption or limited adoption should not be interpreted as resistance or lack of competence, especially in technically intensive contexts.
3. Transparency and reflection are more productive than detection. Instructional designs that require students to disclose and reflect on AI use may reduce adversarial dynamics and support metacognitive learning.
4. Artifact-based guidance matters. Concrete instructional artifacts—such as reflection templates, disclosure forms, and critique-based assignments—play a critical role in translating policy intent into practice.

For engineering education specifically, these findings highlight the need to align GenAI use with the development of foundational problem-solving skills while still preparing students to engage responsibly with emerging tools in professional contexts.

This study has several limitations. First, the sample was purposefully selected and relatively small, limiting statistical generalizability. Second, much of the data relied on self-reported practices and perceptions, which may not fully capture student behavior or long-term outcomes. Third, the GenAI landscape is evolving rapidly; practices documented here represent a snapshot in time and may change as tools, policies, and norms mature. Finally, although narrative-only cases enriched the qualitative analysis, they were not included in survey-based summaries, which constrains quantitative comparison.

Future research could extend this work in several directions. Longitudinal studies could examine how faculty GenAI policies evolve over time and how student engagement changes with repeated exposure to structured AI use. Empirical studies linking specific instructional designs to learning outcomes would strengthen evidence-based guidance. Comparative studies across institutions or accreditation regimes could further clarify how disciplinary and institutional contexts shape GenAI adoption. Finally, student-centered investigations could complement faculty perspectives by examining how students interpret, navigate, and learn from GenAI policies and assignments.

Closing Remarks

As Generative AI continues to reshape higher education, the findings of this study suggest that meaningful integration depends less on technological enthusiasm and more on intentional instructional design. By grounding GenAI policies in course-specific learning objectives and making AI use transparent and reflective, educators can move beyond reactive responses toward more principled and pedagogically sound approaches.

References

1. Jin, Y., Yan, L., Echeverria, V., Gašević, D., & Martinez-Maldonado, R. (2025). *Generative AI in higher education: A global perspective of institutional adoption policies and guidelines*. Computers and Education: Artificial Intelligence, 8, 100348.
2. Mikroyannidis, A., Ekuban, A., Kwarteng, J., & Domingue, J. (2025). *Best practices for the responsible adoption of generative AI in higher education*. Proceedings, 114(1), 6.
3. Singh, S., & Strzelecki, A. (2025). *Academics as adopters of generative AI: An application of diffusion of innovations theory*. Education and Information Technologies (in press).
4. Mai, D. T. T., Da, C. V., & Hanh, N. V. (2024). *The use of ChatGPT in teaching and learning: A systematic review through SWOT analysis*. Frontiers in Education, 9, Article 1328769.
5. Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). Sage.
6. Sarıkahya, S. D., Özbay, Ö., Torpuş, K., Usta, G., & Özbay, S. Ç. (2025). *The impact of ChatGPT on nursing education: A qualitative study based on the experiences of faculty members*. Nurse Education Today, 152, 106755.
7. Coombs, H. (2022). *Case study research: Single or multiple* [White paper]. Southern Utah University. https://doi.org/10.5281/zenodo.7604301 .
8. Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. https://doi.org/10.1191/1478088706qp063oa
9. Braun, V., & Clarke, V. (2021). *Thematic analysis: A practical guide*. SAGE.
10. Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). SAGE.