Shaping AI Policy in Engineering Classrooms: A Qualitative Study of 17 Faculty Perspectives on Learning, Integrity, and Professional Preparation

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Abstract

The rapid emergence of generative artificial intelligence (AI) in higher education has reshaped how engineering faculty approach design-focused courses, where iteration, creativity, and ethical reasoning are central. Although institutional and national discussions about AI policy are expanding, scholars have not thoroughly explored how engineering design instructors, specifically, are enacting classroom-level policies.

This paper addresses that gap by presenting findings from 17 semi-structured interviews with engineering faculty from varied US institutional contexts. The study focuses on how instructors interpret and implement AI-related policies, and the implications of these choices for student learning, in addition to academic integrity and professional preparation. We address the following research questions: "What guidelines and policies do design instructors think should (and should not) be included in design courses or projects?" and "How can these guidelines and policies be organized into guiding paradigms?"

Using thematic analysis, we identified several recurring patterns which we then grouped into four "paradigms," or shared frameworks of assumptions, values, and approaches to AI integration in design teaching and learning. The four paradigms include Restrictive Use (limiting AI usage to human production alone), Ethical Use (prompting ethical and responsible AI usage), Guided Use (scaffolding AI usage), and Pedagogical Alignment (ensuring AI use aligns with sought objectives). We present paradigms discretely with exemplary quotes, but we recognize that instructors in our study enacted distinct paradigms based on varying instructional goals and contexts. In our discussion, we consider the interrelation between paradigms and offer an organizing model regarding how paradigms inform each other.

The paradigms and policies we identify in this study provide a conceptual framework to guide instructional approaches to AI use in engineering and engineering design curricula. This includes evidence-based insights for faculty, administrators, and policymakers seeking to develop AI policies aligned with instructional goals and towards the cultivation of critical and ethical capacities that engineers need to responsibly engage with AI in professional practice.

1. Introduction

ChatGPT can write code. GitHub Copilot can complete it. A student can generate design concepts in minutes that once took hours to sketch by hand. These tools have arrived, and engineering faculty are caught in the middle of a real dilemma: How do we let students benefit from what these tools can do while making sure students learn what they need to learn for their future careers?

Engineering faculty have been placed in a challenging position with the arrival of generative AI (GenAI) tools such as ChatGPT, Perplexity, Deepseek, and GitHub Copilot. Students can generate code, draft reports, and brainstorm design concepts in moments, tasks that once required hours of focused effort. While these tools offer clear benefits, they also threaten to shortcut the very learning processes that defines engineering education: creativity, iteration, and deep problem-solving [1]. Faculty face a pressing dilemma: how to allow students to leverage AI's potential without undermining the development of genuine competence and judgment [2].

Discussions of current policy occur in different areas, such as in committees who drafting guidelines for AI use in graduate curriculums or institutions who issue broad directives that apply throughout an entire university system. As these decisions may occur at a high-level, the voices of the instructors in classrooms and labs who implement these policies may not be heard [3]. Faculty make daily decisions about where GenAI fits into learning and are ultimately responsible for translating university policies around academic integrity and openness into practical pedagogy. Their experiences reveal tensions that top-down policies often miss, including concerns about student privacy, the credibility of AI-augmented degrees in professional settings, and how to teach ethical reasoning in an age of instant, machine-generated responses [4].

This paper draws on interviews with 17 engineering faculty to explore how instructors are navigating these challenges. Rather than asking whether GenAI should be banned or fully embraced, we investigated how faculty decide when and how to integrate GenAI into their courses. We focused on two core questions: How do engineering faculty think GenAI should be integrated in design education, if at all? And what values (e.g., integrity, learning) guide those decisions? Our findings revealed nuanced perspectives: faculty distinguished not between "good" and "bad" GenAI use, but between use that deepens learning and use that replaces it. Our study findings can help clarify why some instructors view and seek to promulgate AI-as-collaborator in their curricula while others adopt AI-as-threat restrictions, and how these patterns might inform more coherent, discipline-sensitive AI governance in engineering education [5], [6], [7], [8].

2. Background & Motivation

2.1. From Gen AI- in Education to Policy Concerns

The rapid diffusion of GenAI into society and industry has been accompanied by a parallel push to integrate GenAI into engineering education, both as a topic of study and as an infrastructure for teaching and assessment [9]. This has created an urgent need for coherent GenAI policies at institutional, program, and course levels.

GenAI in education is not entirely new. Since at least the 1970s, there have been applications, such as intelligent tutoring (or what was once often referred to as Intelligent Computer-Assisted Instruction), adaptive learning systems, and administrative tools [6], [9], [10]. While many may not have recognized the pervasive use of these tools in society, it is virtually impossible to ignore the impact of GenAI today. Each generation of AI technologies have brought their own policy debates, and policy discussions have expanded beyond technical effectiveness to questions of equity, ethics, and the role of human relationships in education. Accordingly, national and international agencies such as UNESCO are increasingly emphasizing GenAI literacy, digital inclusion, and the preservation of foundational educational practices and values, such as teacher-student interaction and academic integrity, respectively [9].

Concerns about powerful generative models intensified dramatically in recent years. With uneven infrastructure and digital divides, especially in educational systems, universities encountered many new questions regarding how to integrate GenAI in curricula, ranging from how GenAI changes assessment design, curriculum content, and access to learning support [9], [11], [12], [13], [14]. Policies are expected to increasingly address privacy, bias, and fairness in order to monitor or subvert the risk of GenAI deployment, particularly as GenAI is inreasingly driven by commercial incentives that may be misaligned with long-term educational goals [12], [13], [14].

Engineering is a focal point in this policy landscape because GenAI is both a subject engineers must understand and a tool that is transforming engineering work. GenAI a subject they must study to become AI literate, but GenAI is also a tool that is quietly rewriting the job description of an engineer. Employers want graduates who are fluent in AI, so curricula are being stretched and reshaped to include it [11], [15], [16], [17]. The problem, as several reviews have pointed out, is that this integration is often piecemeal. Reviews of engineering programs show growing inclusion of AI content, yet also highlight gaps in systematic integration and in preparing students to work responsibly with AI systems [11], [15], [16], [17], [18].

At the very same time, Gen-AI is sneaking in through the back door of the classroom itself, including as a component of auto-graders, code-completion plugins, and generative design software [6], [11], [15], [16], [19], [20]. This dual role of Gen-AI as both curricular content that students must learn and pedagogical infrastructure that instructors may use to assess student learning means that curricular policy must attend simultaneously to numerous factors, audiences, and the emergent and sometimes unexpected uses of GenAI in engineering curricula.

2.2. Emerging Policy Frameworks and Rationales

Recent work proposes explicit frameworks for AI education policy in higher education. Chan's AI Ecological Education Policy Framework organizes policy into three dimensions, focused on what we teach (i.e., a pedagogical dimension), how we manage risks associated with ethics and privacy (i.e., a governance dimension), and what support we provide for sustainable implementation (i.e., an operational dimension) [9], [14], [21].

Document analyses of university Gen-AI guidelines show that policies typically (1) begin with technology descriptions, (2) highlight the rapid pace of AI development, (3) specify target groups (students and staff), and (4) articulate institutional stances ranging from cautious encouragement to strong promotion of GenAI for future-oriented competence building [22]. These policies often acknowledge the need for frequent revision as technologies and regulations evolve [22].

International policy recommendations emphasize interdisciplinary planning, equitable and inclusive use of AI, comprehensive master plans for GenAI in management, teaching, learning, and assessment, as well as pilot testing with systematic evaluation [9]. In developing and emerging contexts, GenAI is linked to education for sustainable development and the broadening of access to high-quality learning. Despite existing international policy recommendations, significant policy challenges remain, particularly in higher education [6], [13].

Existing scholarship documents growing efforts to integrate GenAI into engineering curricula and to articulate institution-wide GenAI education policies, but these accounts tend to be either student-centered, system-level, or technology-driven. This has limited scholars' attention to how front-line engineering faculty themselves are making sense of GenAI when shaping concrete classroom policies [9], [13], [14], [16], [17], [19], [21], [23]. Studies of GenAI in higher education show that academics recognize both pedagogical benefits and serious concerns, especially around academic integrity, reliability, equity, and ethical use.

2.3. Paradigms and Policy Choices for AI Use

In public policy scholarship, a paradigm refers to a coherent framework of ideas that defines what problems are salient, what goals are legitimate, and what instruments are appropriate for addressing them [24] [25]. Paradigms bundle normative commitments (e.g., prioritizing efficiency versus equity), causal assumptions about how the world works, and epistemic criteria for what counts as valid evidence or sound reasoning [24], [25], [26]. In short, paradigms are shared frameworks of assumptions, values, and beliefs and in the context of higher education or a classroom, these are the assumptions, values, and beliefs that shape how educators define good learning, legitimate use of tools (GenAI or otherwise), and acceptable evidence of competence.

In the context of this study, paradigms represent and make visible the assumptions and values that drive instructors' policy choices regarding a GenAI use [24], [26]. In this context, naming paradigms can clarify (1) the role of GenAI in design teaching and learning (e.g., augmenting, replacing, or re-shaping teaching and learning [5], [8], [27]) and (2) appropriate human-user interaction (e.g., using AI as a tool that directs learning, as a learning collaborator, or as an infrastructure that empowers learner agency [5], [6], [8]); and (3) what values and responsibilities are necessary when students or instructors use AI in educational settings [5], [6], [28]. By naming the paradigms that emerged from our analysis of interviews with 17 engineering faculty, we offer a conceptual vocabulary for understanding why instructors facing similar challenges often arrive at very different classroom policies [26], [29].

While this study is exploratory, paradigms—including but not limited to those we identify in this study—can guide the creation and refinement of concrete policy, guidelines, and associated pedagogical choices pertaining to GenAI use, including but not limited to in engineering design curricula. For example, understanding paradigms can help instructors shape when and how to enact permissive, conditional, or prohibitive course policies [7], [9], [24], [29], [30]. In higher education, most policy discussion remain high-level, or at the program, institutional, or national scale. In addition, there are numerous frameworks and taxonomies for AI governance, pedagogy, and leadership [9], [14], [30], [31]. These accounts describe recommended principles (e.g., ethics, equity, privacy, sustainability) and macro-level "paradigm shifts" but rarely show how individual instructors translate such ideas into everyday course rules, assignment designs, and integrity expectations, especially in technically oriented fields like engineering [5], [6], [9], [24], [26], [30]. There is also limited qualitative evidence on how faculty understand AI's role in professional preparation and how competing imaginaries of future engineering work shape their decisions [7], [26], [29], [32]. This study seeks to provide such a contextual understanding.

2.4. Summary

Given the rapid emergence of GenAI, there is a need for clearer guidelines, training, and supportive policy frameworks for GenAI integration in engineering curricula [6], [11], [12], [15], [20], [23], [33], [34], [35], [36]. However, much existing scholarship aggregates perspectives across disciplines, focuses on GenAI in general, or treats policy at the institutional or national level, leaving a critical gap in understanding how engineering instructors interpret emerging GenAI policies, negotiate tensions between learning and integrity, and connect classroom rules to professional preparation in AI-mediated engineering practice [12], [13], [16], [17], [19], [20], [37]. This qualitative study of 17 engineering faculty members addresses that gap. By examining these instructors' perspectives, challenges, and context-specific strategies, we illuminate the situated reasoning that currently shapes GenAI policy *on the ground*. This grounded understanding is essential for developing more realistic, discipline-sensitive approaches to GenAI governance that truly align educational practice with the evolving expectations of the engineering profession.

3. Methods

3.1. Overview

In this study, we address the following research questions:

1. What guidelines and policies do design instructors think should (and should not) be included in design courses or projects?
2. How can these guidelines and policies be organized into guiding paradigms?

We began this study with the initial question, and the latter emerged during analysis as we began seeing commonalities across guidelines and practices. To address these questions, we employed an exploratory research approach, wherein we inductively interpreted and characterized phenomena based on the lived experiences and perceptions of engineering design instructors. More specifically, we explored semi-structured interview responses collected from experienced design instructors about their experiences with GenAI in their courses, coupled with their perceptions of GenAI, writ broadly. Through interviews, we sought to understand the content and context of the participants' perspectives. The contents of instructor-enacting policies are relevant for suggesting curricular adaptations for GenAI, while the instructional contexts provide important nuance regarding the transferability of these adaptations. By naming these paradigms based on how 17 engineering faculty articulate and enact AI's role in learning and instructional practice, the study makes visible the assumptions, values, and future imaginaries that drive divergent policy choices in the same institutional and technological environment [5], [7], [26], [30].

3.2. Data Collection

In this study, we analyzed a subset of a larger dataset to investigate engineering design instructors' experiences with GenAI, as described in [REDACTED]. Participants were recruited via a screening survey sent to various professional societies' email lists. Our survey gathered data on participants' teaching experiences, self-assessed proficiency with GenAI, and demographic details. In late 2024 and early 2025, we selected and interviewed 17 engineering design instructors, emphasizing those with high GenAI familiarity while ensuring diversity in gender, race, and institutional backgrounds. Appendix A provides a summary of participant pseudonyms alongside the number of years they have taught engineering design, how long they have introduced GenAI in their teaching, gender identity and racial or ethnic identity. Importantly, we prioritized recruiting instructors with high GenAI familiarity and prior experience, as we theorized that these faculty would have personal experiences from which to share thoughts, perspectives, and challenges. We recognize that this choice neglected many who have not used GenAI, including those who may be fundamentally opposed to GenAI usage. Importantly, most of our participants recognized challenges and limitations of GenAI integration. Our goal of naming paradigms emerged from this observation, which gave rise to our second research question.

During interviews, we solicited participants' insights on teaching engineering design, their use of GenAI, and their assessments of its advantages, disadvantages, opportunities, and challenges integrating GenAI in their curriculum. The interview included five sections: (1) background, (2) experiences teaching engineering design, (3) experiences prompting/using GenAI in engineering design teaching and learning, (4) strengths, weaknesses, opportunities, and threats of leveraging GenAI in engineering design teaching and learning, and (5) summarizing views on GenAI in engineering design teaching and learning. A small portion of the interview explicitly sought participants' perspectives on GenAI policy, including how it was enacted within their classroom, and this was the primary focus of this research study. In particular, Section 5 of the interview opened with the question, "Based on our discussion, what all should be integrated into a policy or guidelines for students' use of AI in engineering design courses and curriculum?"

Interviews were conducted by Author 2 via Zoom and the Zoom automated transcripts were later reviewed and anonymized by Author 1 and another graduate research assistant. Interviews typically lasted 90 minutes. Participants received a $100 gift card for participating in the study. Participants also chose their own pseudonyms at the end of the interview.

3.3. Data Analysis

We employed a reflexive thematic analysis approach [38] to identify, interpret, and characterize patterns in how engineering faculty understood, negotiated, and implemented GenAI policies in their classrooms. Thematic analysis was selected for its flexibility and ability to generate rich, detailed descriptions of participant experiences and values, which aligned with our goal of capturing the complex, contextual reasoning behind policy decisions.

Our analysis followed a recursive, phased process. The first author began by immersing in the data, reading and re-reading all 17 interview transcripts while noting initial impressions and recurring ideas. Following this familiarization, we first addressed a research question pertaining to key SWOT elements [Redacted]. While conducting that SWOT analysis, we noted the need for a more concerted focus on policy, both based on participant responses and our experiences teaching and observing GenAI use (or restrictions) in our curricular experiences as a student (Author 1) and instructors (Authors 2 and 3).

Driven by these experiences, we chose to focus on policy choices by participants. We conducted a systematic, inductive coding cycle across the parts of the interview dataset with this focus. Using qualitative data analysis software (NVivo), we manually generated initial codes that captured distinct concepts in the transcripts pertaining to policy or guidelines, focusing on segments where faculty explicitly described AI policies as well as any instances where participants named pedagogical strategies, decision-making rationales, and the challenges they encountered enacting key values and beliefs associated with GenAI in their courses or curriculum.

After this initial coding, we began developing initial themes by examining relationships, tensions, and patterns between codes, both within individual transcripts and across the participant pool. For example, we observed that instructors like Sven, who was a strong advocate for GenAI use in design, described experiences of AI misuse which motivated them to shift their policies regarding AI use. The relationship between these codes was captured in an early theme we termed "responsive restriction: policy as a reaction to observed misuse."

Initially, we prioritized semantic themes that stayed close to the explicit language of participants, such as *policy is a faculty preference* and *you have to be smarter than the AI*. Subsequently, we developed a set of latent themes that addressed deeper, often implicit connections in the data. For instance, while many participants valued *course-level policy,* their discussions also revealed frustration with institutional ambiguity and a desire for supportive frameworks. This led us to formulate the latent theme, "The Pedagogical Alignment Paradigm: Strategic Integration to Achieve Learning Outcomes." Themes were iteratively reviewed, named, and defined in relation to the coded data and the study's research questions.

This process culminated in the identification of four core analytic paradigms: Restrictive Use, Guided Use, Ethical Use, and Pedagogical Alignment. We structured our findings around these paradigms. In the discussion, we describe how paradigms can provide a framework for understanding the spectrum of faculty approaches to AI policy in engineering education, including but not limited to engineering design education.

3.4. Validation Approaches

We conducted this study within an interpretivist paradigm, where validity is established through rich description, procedural alignment, and relevance to instructional practice and literature [39]. Here, we describe how our strategies aligned with the Quality framework that was developed by Walther et al. [40]. Aligned with procedural validation, we used a qualitative software program (NVivo) to maintain the connections between codes and themes. Author 1 led all coding but engaged co-authors in peer review of emergent codes and themes to inform code and theme refinements. Towards communicative validation, or to ensure that results are understandable to readers in engineering education, we structured findings around participant voices and supported each theme with direct quotes that illustrate participants' reasoning and context. Towards process reliability, each author reviewed themes, associated passages, and the team collectively refined themes until we reached agreement. Towards pragmatic validation, we curated themes to highlight those most pertinent to both classroom decisions, and then we refined themes based on our teaching and learning experiences. Finally, towards theoretical validation, we sought to situate study findings in broader policy discussions in engineering education, ensuring our contributions connect meaningfully to existing scholarship and practice.

4. Results & Findings

In our analysis, we identified four paradigms that guide instructors' course-level policies for GenAI use: (1) Restrictive Use, which emphasizes core skill development through limited GenAI use, (2) Ethical Use, where instructors expect students to use GenAI ethically (e.g., with integrity), (3) Guided Use, where GenAI use must be coupled with instructor verification or scaffolding, and (4) and Pedagogical Alignment, where GenAI use must align with course learning outcomes. **Table 1** summarizes these policies, provides an example context for use, and example practices. While we recognize that there is overlap between these paradigms, naming discrete paradigms can provide clarity that then enables instructors to better understand their own approaches as well as the affordances and limitations of each. In the discussion, we consider the boundaries between paradigms as well as future work needed to substantiate these boundaries.

Table 1. Paradigms Guiding Course Level-Policies for GenAI Use

Paradigm	**Core Goal**	**Key Rationale & Typical Context**	**Example Practices Policies**
Restrictive Use	To safeguard foundational skill acquisition, to ensure authenticity, and to verify unaided student work.	Restrictive use aims to verify mastery of fundamental competencies (e.g., coding, core course concept) in a controlled environment where AI cannot substitute for learning. This is often used when assessing learning is the instructor's goal.	Mandatory in-person, handwritten exams.
			Prohibition of AI tools on core skill-building assignments.
			Physical separation from digital tools during assessment.
Ethical Use	To promote transparent and accountable usage of or engagement with GenAI.	Ethical use is applied in contexts where GenAI is permitted, provided students adhere to ethical principles, such as transparency and verification. The focus is on how tools are used, *not* the final product.	Mandatory vetting and critique of AI output.
			Transparency with disclosure includes prompt use and responses.
			Defensible ownership and documentation of the rationale of AI usage.
Guided Use	To scaffold GenAI as a tool while providing students with critical training and support.	Guided use aims to allow the productive use of GenAI as an assistant while learning or designing. GenAI can be applied to projects, homework, or design phases where process and critical thinking are learning objectives, albeit, with instructor oversight.	Conditional permission requires instructor oversight and guardrails.
			Structured just-in-time feedback to help with usage.
			Instructor-provided direct instruction on usage and AI literacy guidance.
Pedagogical Alignment	To strategically integrate GenAI to achieve specific or higher-order learning outcomes.	The Pedagogical Alignment prepares students for an AI-augmented workplace by making the tool a central part of the learning activity. Gen AI is used when the learning objective itself involves either interacting with or evaluating AI.	Direct training in prompt engineering for professional tasks.
			Gen-AI use is designed into assignments (e.g., role-playing negotiations, generating stakeholder perspectives).
			Focus on using Gen-AI to teach communication, ethics, or metacognitive skills.

4.1. The Restrictive Paradigm

The restrictive paradigm aims to create learning environments and opportunities that require students to engage in original thinking or showcase their knowledge without leveraging GenAI. Accordingly, the restrictive paradigm manifests though pedagogy and assessment choices where instructors can observe or evaluate students' own thoughts.

The restrictive paradigm is commonplace, when instructors prioritize the generation of authentic student work. Zeina explicitly designs tasks that are personal and informal, allowing responses in a student's native language or through drawings. Zeina emphasizes that "an AI cannot do a reflection for you" because "it can't have your thoughts." Titus similarly values reflection-based assignments for student learning. Titus describes the importance of designing rubrics that "reward authenticity" over well-structured or grammatically refined ideas. Leia similarly prioritizes student autonomy, such as by prompting students to take ownership of intellectual ideas. As she shares, "A student needs to leave their mark on everything that they have done and not turn in something that was completely done by an outside source." Accordingly, towards the goal of elevating student autonomy and personalization, Leia shares, "I don't let my students use AI to write their reports."

This paradigm can also guide assessment choices. Sven, a proponent of GenAI use in design, observed "disheartening" misuse of GenAI among his students in a course when he enabled open GenAI use on an exam. Afterwards, he went "the opposite direction" and implemented a restrictive policy of mandatory, in-person, handwritten exams. Potentially due to similar issues, Elizabeth noted that a colleague teaching an introductory Python course for mechanical and civil engineers "reverted to paper quizzes" and "paper exams," whereas other colleagues "are going back to Blue Books for exams rather than let students have a computer in front of them." Like these faculty, Zeina requires "programming exams on paper," but in addition to the exam, Zeina has students "grade their own [submissions] and do revisions in class right after taking it." Separately, Met continued to conduct online exams but in person. Met described how their smaller class size enabled them to employ this assessment strategy, as they felt confident monitoring the exam.

4.2. The Ethical Use Paradigm

The Ethical Use Paradigm emphasizes ethical values that are core to uphold and practice if and as students employ GenAI in design. Instructors operating within this paradigm do not necessarily provide extensive training on how to use AI but rather articulate guiding principles. After an instructor clearly specifies these values, including but not limited to in one's syllabus, the locus of responsibility rests primarily with the student, who must demonstrate said values.

A common principle emphasized by participants was transparency. Students must explicitly acknowledge when and how they have used GenAI. Maya succinctly stated, "AI is out there, please attribute it." Similarly, Morgan's overarching policy dictates that students must report GenAI use, and their failure to disclose such use is an academic integrity violation. Here, the instructor defines the expectations and the student executes them. Yet, others advocated that students be transparent regardless of course policies. For example, Morgan shared, "Unless you [an instructor] say that AI cannot be used on a certain portion, you [a student] should use it, but be transparent about it by providing the prompt and the response." Stevie similarly advocated for transparency regardless of course policy, but Stevie suggested students should consider their purpose of using GenAI through meta-cognitive reflection. As Stevie shared, "You can use it as long as you record why you're using it, what are you using it for." Given this goal, Stevie prompts students to not only be transparent but also to think about why they are using GenAI in their courses.

A second common ethical principle was accountability, which participants often defined in terms of verifiability and accuracy. According to this specification of accountability, permission to use GenAI is contingent on the student's commitment to critically evaluate its outputs. As Maya shared, if students "use AI, but don't check it, it might not be accurate." Chel similarly shared, "As long as they're [students are] critical and they know how to use it, and they are able to criticize it, then I'm okay with that." Leia similarly suggests that students must "evaluate what is given [by GenAI] and not just turn it in without thinking." Leia presupposes that GenAI may be faulty, so she further expects students to "fix what it has come up with." Leia elaborated:

> *[Students can] use it [GenAI] to help you along, and then you will have to fix what it has come up with or evaluate what is done... I think it is okay to use that AI more in those classes than you would in other classes. As long as the students are as long as the students evaluating what is given and not just turning it in without thinking.*

Maya emphasizes that students must verify the accuracy of GenAI references, sharing:

> *You have to be smarter than the AI. If you're going to use AI, great, but make sure that you're double-checking the information. If you're using AI to generate a literature review, actually click on the links and make sure that they go to a paper and the paper actually says the thing that AI said it was going to.*

The expectation is not that students are trained to fix AI outputs, but that they are *accountable* for the final product's accuracy.

A third set of ethical values are associated with *respecting intellectual ownership*, which aligns with the ethical principle of respect for autonomy. Here, students must respect the autonomy of the individual creators of intellectual property which informs Large Language Models, as well as what qualifies as their own intellectual knowledge or property. Ultimately, students must be able to claim the work they submit as their own. Rehaan articulates these aspects when they advise students:

> *I tell students, all right. there's this policy, right? The AI policy, again, different instructors have different policies. I tell them you can use it. But just don't… make sure that everything that you submit for this course, all the assignments, every assignment, you don't have to use sensitive AI and put everything from generative AI.*

Like Rehan, Chel emphasizes that students should be confident that they own their ideas. As she argues, students should "be able to present it and be confident that what they're presenting is their work." This may involve questioning GenAI outputs or comparing results across different AI models and versions.

These principles overlap. For example, integrity is often more than avoidance of plagiarism but also involve becoming accountable, transparent and respectful of the intellectual ideas that students share in their coursework. Encapsulating these ideas, Rehaan shared, "I would just say, use it wisely." For some instructors, this involves clearly defining boundaries within a course setting or defining ethical principles that go beyond a single course setting. defines the boundary; the student exercises judgment within it. Thus, collectively, the Ethical Use paradigm prioritizes critical engagement and personal accountability over technical proficiency. Students must be "able to criticize" the output (Chel) and understand "what you've actually done" in the process (Zeina). It requires using AI "as a tool and not as a crutch" (Leia), ensuring students never simply "paste the information generated as is" (Rehaan).

Importantly, this paradigm does not assume that students enter the classroom already knowing how to use GenAI ethically, nor does it require instructors to teach effective use of GenAI. Rather, it establishes an ethical foundation from which to use GenAI, wherein students may use GenAI, but they bear full responsibility for the accuracy and ownership (or lack of accuracy or ownership) of what they submit.

4.3. The Guided Use Paradigm

The Guided Use Paradigm moves beyond rule-setting to active instructional scaffolding. The defining feature of this paradigm is the instructor's purposeful involvement through direct or indirect scaffolding in building students' capacity to use GenAI effectively and critically. Here, the instructor acts as a coach and guide, not merely a rule-setter. It reflects a commitment to treating GenAI as a tool for enhancing learning coupled with intentional support. This paradigm is characterized by three signature practices expanded below.

First, instructors provide guardrails and structured experimentation spaces. Here, the instructor defines not just what is forbidden but what productive experimentation looks like. For instance, Stevie described the importance of developing "guardrails" and a clear "box" for experimentation and "play." Such guidance can be helpful for students who struggle with open-ended ambiguity. Stevie elaborated that this approach can be particularly helpful for engineers:

> *Having at least some guardrails, I think, is useful for students, particularly [if] they do not deal well with, especially engineers, with a lack of structure and being told what to do. So saying, "Okay, you have this, here's your box, go play in it," I think can be helpful and then continual kind of coaching.*

The second signatory practice is offering situated guidance and modeling, where instructors actively coach students on how to interact with GenAI tools and outputs. Zeina described this as requiring direct instruction: "I may want to do more or just point to a resource [but rather provide] examples of, here are productive things you can do." Zeina views her role as providing reminders to situated GenAI use, such as "don't forget to provide context, share some of your own writing. Ask the AI to respond to you in a very particular way." The instructor then models effective prompting strategies and provides just-in-time feedback.

The third signatory practice involves guiding students to use GenAI in certain ways and for certain tasks. In this paradigm, helping students learn when and how to use GenAI requires curricular time and instructional attention. For example, Met described leveraging GenAI as a dedicated writing coach to "refine your writing," directly targeting the development of students' writing skills. Met suggested that instructors could direct students to "take your paragraph you just wrote and throw it into Chat GPT and tell it to refine your writing." This is not a rule about attribution but is a *learning activity* designed to build skill. For Maya, the tool itself became the subject of study through prompt engineering lessons. In each case, AI is not merely *allowed*; it is intentionally designed into the learning process to achieve a specific, high-level outcome. Maya shared:

> *That's more like a lesson on how to use AI. Like here, here is a prompt, for example, that I've used in the past that effectively answered the question I wanted it to. But I don't really*

> *have a lot of those because I haven't super played around it but again. So what I really wanted was students to generate those examples.*

Alvin similarly described developing tools that help students learn to interact with Gen-AI effectively, framing it as a way to provide just-in-time support without replacing student thinking. As Alvin shared the ideal user-GenAI interaction for learning:

> *I think there's this amazing thing where AI can do this work, right? Just-in-time principles. This is often what the TA or the instructor has to provide. But now we have this other tool that can be like, as I start to get anxious. I turned to AI. It gives me a little bit of a hint and brings me back in… And can pretend to be, and can be a TA, and can lead students in these processes.*

In each case, the instructional goal is to build students' capacity to use GenAI effectively, distinct from using GenAI to guide learning specific learning objectives.

4.4 The Pedagogical Alignment Paradigm

The Pedagogical Alignment Paradigm emphasizes aligning GenAI Use with course learning objectives. The central policy question in this paradigm is how GenAI can be used to achieve a defined educational outcome, making the tool a deliberate component of the pedagogy itself.

This paradigm is defined by a core principle: that policy must be subordinate to the intended learning experience. Alvin articulates this most clearly, stating that "context matters." Instructors make distinct choices based on the core competency a course or assignment aims to develop. Alvin exemplifies this, noting, "My policies are very different" between courses. He encourages AI in his design course to help students be "more adventurous" and do "really cool stuff," seeing it as a catalyst for creativity. Alvin shared

> *…in my engineering design. I believe that it's smoothing out the friction and getting them to do the engineering design better and faster and more adventurous and sort of everything else. So I encourage it as much as possible because I know, and from evidence, that they're still engaging in the work and doing really cool stuff, and it's valuable*.

Conversely, Alvin restricts GenAI use in his computing course because, at the introductory level, "it could do all of my assignments quickly," and thus destroys the essential, low-level struggle of learning to code, which is the primary goal. Alvin shared, "I have basically banned it in my computing course because we're just doing low-level computing, and it could do all of my assignments quickly." This demonstrates that the policy is not about the tool, but about protecting or enabling the intended learning experience. Additionally, the choice is not about AI's capability, but about guarding the integrity of the specific educational journey he has designed for each course.

Crucially, this paradigm is often explicitly grounded in educational theory, framing GenAI as a strategic scaffold within the learning process. Alvin structures his entire course around learning theories, and he explains the importance of wrestling with hard concepts. However, he also recognizes that when students struggle with concepts, they may give up: "If you spend too long in the bottom of the learning pit... that's when you quit engineering." In this framework, the purpose of GenAI policy is to act as a responsive interface to monitor where a student is, understand their history of struggle, and "edge them on a little bit" to maintain productive challenge and prevent debilitating frustration. This transforms GenAI from a simple answer-generator into a metacognitive tool for curating the cognitive journey. Alvin Shared:

> *I actually… Show this. In my classes, I actually show Vygotsky's zone of proximal development to my freshmen. And most of them are like, what the hell is going on? I don't really care or whatever. But I do a thing where I actually show it on day one and then I show it again on the last day because I want them to say like. I designed my course in a certain way… James Nottingham from the UK has this concept called the "learning pit…If you spend too long at the bottom of the learning pit, doing " I don't get it", that's when you fall out, right? That's when you quit engineering. That's when you give up on the problem… I think interface development is super interesting in these spaces of monitoring where is the student, what has the history been? What have I historically seen them struggle with or had success with? How do I edge them on a little bit? And how? I do it in a way that's not patronizing or sort of talking down to the student or being like.*

Thus, for instructors like Alvin, policy is an exercise in reflective and adaptive course design. It demands "reinventing assignments," as Alvin notes, to ask better questions and conceive of AI's role as a partner for "debugging, not for doing." It requires building "*guardrails,*" as Stevie emphasizes, specifically to ensure that GenAI integration in design class aligns with the learning outcome and also the professional preparedness of the students. Stevie shared.

> *In their design processes, and so I think having almost like these guardrails is like really, really important to making sure it aligns with what you're trying to get them to learn, how it can help support their work, and ultimately prepare them for Industries that are rapidly evolving with this technology because they will probably be expected to use it.*

It is motivated by a fundamental commitment to student learning as the primary value. As Casey argues, the real failure lies when students miss learning what they need to learn, thereby losing the value of the money spent on education. Additionally, she noted that not only will students not get their money's worth, but they will also miss out on acquiring essential life skills and goals:

> *A lot of these students are paying a lot of money to go to school. And they don't think about that very often. How every time they don't learn, they're losing money… When really what's bad is that students aren't learning, and they're not getting their money's worth, and they're hindering their ability to progress in life and achieve their life goals and whatnot.*

This reflects the paradigm's ultimate and distinct value: a profound commitment to learning itself. It is the conviction that the highest purpose of educational technology is to cultivate learners' educational journeys. The policy, therefore, is not a set of rules about a tool, but the blueprint for its pedagogical integration, ensuring its power is harnessed exclusively to serve the fundamental goals of human learning and professional formation.

5. Discussion

The analysis of instructor interviews revealed a complex landscape where faculty are actively constructing the rules of engagement for generative AI (GenAI) in engineering design classrooms. In the absence of strong institutional mandates, engineering faculty independently create and implement generative AI policies at the course level. The findings reveal that engineering design faculty are not passive recipients of institutional AI policy but are active, pragmatic policy entrepreneurs operating in a decentralized landscape, wherein they have already developed a nuanced, interconnected spectrum of approaches. In this discussion, we summarize the four paradigms we defined in this study, situate these paradigms within the literature on educational technology adoption, and then explore implications for the future of engineering education.

5.1. Paradigms and Instructional Choices

In our study, we identified four paradigms guiding the integration of GenAI into design teaching and learning contexts: Restrictive Use, Ethical Use, Guided Use, and Pedagogical Alignment. In this section, we highlight how these paradigms support distinct instructional goals and, in turn, how paradigms might guide instructional choices to obtain these goals.

First, each paradigm affords the pursuit of instructional goals (see **Table 1**). If an instructor aims to verify students' attainment of a core skill, instructors may employ the Restrictive Paradigm. Here, control lies with the instructor, who designs assessments (e.g., handwritten exams, physical separation from technology) that preclude AI use entirely, ensuring students demonstrate unaided understanding. If one's goal is to develop students' ethical dispositions and behaviors, instructors may adopt the Ethical Use Paradigm. As a first step, an instructor must define guiding ethical principles (e.g., transparency, accountability, respect for autonomy) and then discern how students must act accordingly. The emphasis is here on ethical behavior, and depending on the instructor, levels of guidance may be more or less concrete. If aiming to build support students as they learn to use AI, instructors may then design guardrails or "hard scaffolds" that model effective prompting or "soft scaffolds" such as dedicated class time to GenAI use. The goal is proficiency with the tool itself. When the primary value is achieving course learning outcomes (e.g., content, skills), instructors may emphasize the Pedagogical Alignment Paradigm. GenAI is strategically designed into the learning experience as a cognitive scaffold, a simulator of professional contexts, or a catalyst for metacognition. The locus of control remains with the instructor as curriculum designer, but the aim is not Gen-AI literacy per se; it is enhanced learning of engineering concepts and practices.

Second, the paradigms we have highlighted emphasize distinct aspects of the educational experience. Each paradigm provides guidance for GenAI use with a focus on specific concerns, including assessing learning (Restrictive Use), upholding ethical values (Ethical Use), scaffolding learning (Guided Use), or achieving learning objectives (Pedagogical Alignment). Across all paradigms, the underlying logic provides a decision-making heuristic for faculty. By asking, "Which paradigm best serves my goals for this assignment?", instructors can move beyond reactive or arbitrary policy-making toward intentional policy choices. This paradigm-based approach not only clarifies policy rationales for students but also fosters curricular coherence, supports professional socialization, and ensures that GenAI integration advances, rather than undermines, the core mission of engineering education. In **Table 1**, we offered example practices associated with each paradigm: these are by no means exhaustive, and future researchers should consider how these paradigms can inform other such practices.

5.2. Paradigm-Switching and Cross-Paradigm Connections

While thus far, we have presented paradigms distinctly, most participants in this study enacted multiple paradigms. Yet, the paradigms connect and can even support each other. In our study, individual participants applied a range of paradigms. Accordingly, participants switched between or blended paradigms based on contextual factors such as the course-level, assignment type, learning objective, and perceived risk to the learning experience. Thus, an instructor's policy choices reflect their judgment of the most effective path to achieve learning goals, which this may involving mixing paradigms based on shifting goals or contexts.

Rather than adopting a single, blanket policy, this contextual adaptability demonstrates that GenAI policies and associated instructional practices are contextual. This emphasis on context suggests that the most accurate model for understanding classroom GenAI policy is not a static taxonomy that elevates one paradigm over others. Rather, instructors must assess the situation and select the policy mechanism that best serves the immediate learning goal. Switching between paradigms was often a deliberate, principled choice based on the core objective of each course or specific lesson. Instructors may also strive to blend paradigms. For example, an instructor may employ a Restrictive stance when their goal is to assess learning while simultaneously emphasizing Ethical Use by emphasizing transparency and accountability. The conceptual model in **Figure 1** illustrates this core takeaway: paradigms are not mutually exclusive and can inform other paradigms.

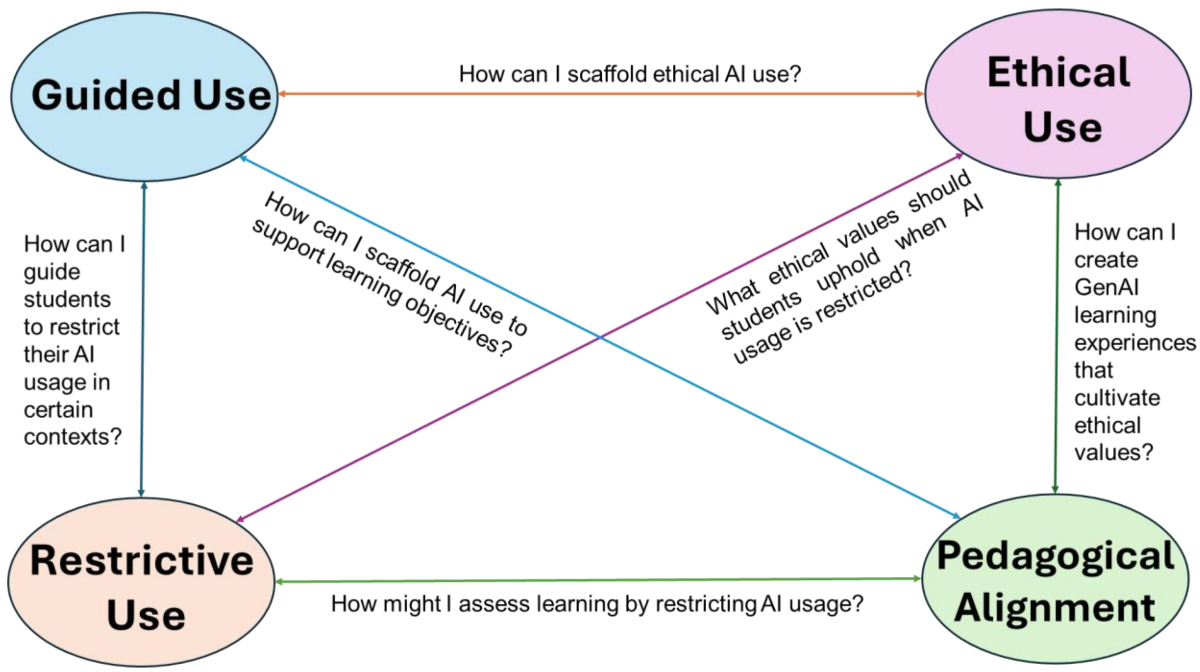

Figure 1. Interconnections between AI Policy Paradigms in Engineering Design Education

Figure 1 reveals the interconnected nature of instructional practices associated with paradigms. The Guided use paradigm is defined by the Instructor in The Loop, Guardrails, and Human Judgment. It represents the foundational framework from which faculty navigate toward more restrictive or more integrative approaches based on context. The Guided Use Paradigm provides the flexible core principles, teachability, oversight, and guidance that can evolve into restriction or be expanded into full pedagogical integration as the learning context demands. The connection between Guided Use and Pedagogical Alignment is achieved by intensifying the "Instructor in the Loop" role from a supervisor to a learning architect. Here, the general practices of providing direct instruction on usage and guidance are not just rules; they are embedded in a deeper Alignment of the Objective with pedagogy. Gen-AI use is no longer merely "allowed with conditions" but is deliberately engineered ("instrumentalized") to achieve specific, high-level learning outcomes, such as overcoming the "learning pit" or enhancing creative exploration.

5.3. Practical Implications for Generative AI Policy in Engineering Education

Here, we consider how study findings can inform future efforts, including guidelines and policies, that institutions of higher education may develop to support instructors' development of their own classroom policies and guidelines.

First, we take the stance that institutions should offer some level of policies and guidance. Our participants expressed a clear desire for infrastructure, shared resources, collaborative time, and supportive frameworks to replace the solitary struggle that many of our participants experienced. Failing to do so places confusion and burden on instructors. The burden is twofold: the Cognitive Load of continuously analyzing where a particular assignment should fall on the spectrum, and the Development Load of creating the specific materials, rubrics, and literacy training needed to operationalize each paradigm shift [41], [42], [43]. Our participants also expressed a clear desire for infrastructure to alleviate this load. Angie pleaded, "I would just love someone [to be] like, I made this. It worked for my students. You should try and see how it goes." Lacking such policy or empirical examples, many faculty may view themselves as working alone. For example, Elizabeth lamented, "I do need some of my colleagues to be thinking about this because I can't be the only one." Elizabeth's quote epitomizes the call for shared repositories of assignment designs, training on learning-design analysis for Gen-AI, and structured time for departmental dialogue to create coherent curricular pathways across the spectrum. [44], [45], [46]

Second, instructors are making value-driven choices regarding if and how GenAI should be used in their courses, and these choices may vary across classes, leading to confusion and uncertainty. As starkly described the consequence of institutional neutrality, the result is that "every man [sic.] for themselves. There's no resources for me as an individual trying to do this. And so then it becomes everyone coming up with randomized, different things." This decentralization leads directly to what Alvin identified as a major problem, a confusing "mess for the students" where policies lack coherence. Hence, there is need for standards so that approaches are "at least somewhat uniform at different levels across classes." [47], [48]

Third, institutions should employ some level of flexibility in their policies while identifying core values and principles to uphold. While our participants expressed a desire for institutional support, they also shared concerns about the inadequacy of rigid, top-down rules. As Angie argued, "I'm actually kind of nervous about the idea of creating policies... Policies are unlikely to keep up. With changes in the models, changes in the way people use them, and changes in our understanding." Universities can use our conceptual model (i.e., **Figure 1**) to this end in three ways. First, institutions may acknowledge that all paradigms are valid in distinct use contexts. Second, to align with participants' desire to anchor guidance in enduring values, institutions may set negotiable institutional principles that support the entire spectrum, for example, transparency, fairness, and pedagogical justification. Finally, institutions can develop resources and developmental opportunities to learn, practice, and iterate on implement these principles. This includes the "training and guidance" in GenAI literacy that Chel advocated for, to be integrated into the curriculum so students learn "really how to use it." It also means offering practical, adaptable resources, as exemplified by Stevie, who adopted a workable framework by taking "an AI policy from one of my colleagues."

5.4. Limitations and Future Work

In this study, we generated paradigms through an interpretative analysis of 17 design instructors' experiences and perceptions in early 2025. This approach leads to several limitations. First, the state of Generative AI in higher education is shifting rapidly: views shared by our participants may have changed since our interviews. Second, our purposive sampling prioritized instructors with moderate to high familiarity with GenAI. This was a deliberate choice; we sought to study policy paradigms among faculty who had developed coherent stances. However, this limits transferability to the broader faculty population. Specifically, we did not synthesize perspectives of faculty who have *not* adopted GenAI. Third, our participant demographics are also limited: participants were from US universities and all were teaching engineering, thus limiting transferability to non-US and non-engineering contexts. Future research should intentionally sample these groups. Fourth, we inductively generated the four paradigms, thus inferring these from participant responses. Moreover, while we presented paradigms discretely, paradigms are not mutually exclusive in practice, and instructors may draw on different paradigms across assignments. Finally, we did not adopt an a priori framework nor did we originally set-out to study paradigms in instructors' practices and beliefs. Future work should focus on the paradigms, such as by seeking to discern the extent to which paradigms resonate with participants and how participants enact paradigms discretely or in combination. For example, future work could present and vet paradigms through communication with design instructors, including, but not limited to, participants in the study.

5.5 Conclusion

This paper's contribution is a vocabulary for faculty and institutions to reflect on and cultivate their own GenAI policy choices. Engineering design faculty are constructing a wide range of responses to GenAI usage in their curricula through a spectrum of interconnected paradigms. Each principle can help faculty and institutions strategically integrate GenAI into courses, programs, and institutions based on learning contexts, including learning goals and learners' needs. The current state places a significant burden on instructors, who act as isolated policy entrepreneurs navigating what one of our participants referred to as a confusing "mess" of disparate approaches. The future lies not in imposing a single, rigid rule but in moving from entrepreneurial burden to supported expertise. Institutions need to implement a model of principled flexibility that amplifies faculty and learners' autonomy while providing the shared resources and literacy training called for by instructors. By offering frameworks and tools, institutions can empower faculty to fulfill their core mission: designing learning experiences that prepare ethical, competent, and adaptive engineers for a world transformed by GenAI.

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Appendix I: Participant Overview

Pseudonym	Years Teaching Design	Years Introducing GenAI in Teaching	Gender Identity	Racial and/or Ethnic Identity
Alvin	16-20 years	2-3 Years	Male	White

Angie	16-20 years	2-3 Years	Female	White European
Casey	3-5 years	2-3 Years	GNC Female	Biracial Asian American
Chel	11-15 years	1 Year or less	Female	White, Middle Eastern
Don	11-15 years	1 Year or less	Male	White
Elizabeth	6-10 years	1 Year or less	Female	White
Humata	46	1 Year or less	Unwilling to disclose.	Unwilling to disclose.
James	6-10 years	1 Year or less	Man and Genderfluid	White
Leia	6-10 years	1 Year or less	Female	White (Cajun)
Maya	3-5 years	1 Year or less	Female	White, Caucasian
Met	6-10 years	1 Year or less	Male	White
Morgan	1-2 years	1 Year or less	Woman	White
Rehaan	3-5 years	1 Year or less	Male	Asian
Stevie	3-5 years	1 Year or less	Nonbinary Woman	White
Sven	6-10 years	2-3 Years	Male	White
Titus	16-20 years	1 Year or less	Male	White
Zeina	1-2 years	2-3 Years	Woman	White, Middle Eastern