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When Can AI be Used Anyway? An Analysis of Engineering Faculty's Generative AI Policies

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Abstract:

Despite being three years from the public release of ChatGPT, higher education engineering course policies are largely determined by instructors, shaping students' understanding of appropriate Generative Artificial Intelligence (GAI) use and their GAI practices beyond the classroom. Differences in GAI policies between classes and sections also make it difficult for students to know when and why GAI use is, or is not, permitted. This decentralized approach to governing appropriate GAI use through engineering course policies raises the questions: What GAI policies do engineering instructors adopt in their classrooms? How do they vary? In this study, 169 higher education engineering faculty members and instructors at 18 universities shared their current, active GAI policies and discussed how they were created. Policies were analyzed using content analysis, which identified three themes based on GAI restriction: no restriction, semi-restricted, and fully restricted. "No restriction" policies are those in which GAI use is fully allowed on all class assignments and activities. "Semi-restricted" policies are those in which GAI use is allowed for some class assignments and activities, but GAI usage is prohibited for other assignments or activities. "Fully restricted" policies are those in which GAI use is not allowed for any class assignment or activity. Content analysis was also used to evaluate the motivations for faculty and instructors to create a GAI policy, such as who created the policy and if a similar policy was previously in use. This analysis compared engineering instructors' GAI course policies, beginning to map the GAI policy landscape in higher education and promoting dialog about navigation strategies for student GAI use in the classroom. Future work includes mapping higher education GAI usage policies against policy decisions being made at the United States Federal level, and comparing the policies of instructors in this study to those of GAI syllabus policy statements publically available in the United States.

Introduction:

Generative Artificial Intelligence (GAI) has disrupted education, providing both challenges and opportunities in the education landscape [1]. GAI has a range of uses from conversational agents [2] to quickly finding information for a user [3]. However, GAI perceptions are not all positive [4]. Educators and students in higher education have noted concerns with accuracy of GAI outputs [5], ethical issues surrounding the use of GAI [6], and concerns on job prospects [7]. Despite these challenges, GAI has quickly found applications in Science, Technology, Engineering, and Mathematics (STEM) higher education.

Many universities initially struggled with what to do about GAI usage in the classroom [8-9]. Some high-level policies were created, largely informing students and educators about the existence of GAI tools and some of the limitations. An example of one of these policies is:

> Generative AI tools such as OpenAI's ChatGPT, Google's Gemini, NotebookLM, and others, have captured the public's imagination as these tools become widely available for everyday use…these novel tools have notable limitations and present new risks that must be taken into consideration when using these technologies [10].

Risks that should be taken into consideration mentioned by Columbia include violation of the privacy rights of individuals, loss or unknown disclosure of intellectual property, and providing biased or unfactual information to users [10]. While these types of policies helped to bring awareness to GAI [11-12], institutional GAI policies often stop short of discussing when GAI can and cannot be used in the classroom [13].

Over three years since the release of ChatGPT, GAI usage policies within the classroom are up to the discretion of the instructors [14-15]. Some instructors choose to use these policies to attempt to ban the use of GAI in the classroom [16]. Other instructors have a different position, either fully allowing the use of GAI or specifying use cases and/or assignments when GAI can be used by the students [17]. This paper aims to show some of these different policies, the various ways GAI usage policies can be classified, and help begin a conversation about ways to develop, adopt, implement, and enforce GAI usage policies in STEM higher education.

This paper answers the following research questions:

RQ1: What GAI policies do engineering instructors adopt in their classrooms?

RQ2: How do GAI policies for engineering instructors' classrooms vary?

Literature Review:

Higher Education Policies

Within higher education, policies seen at the university level include acceptable computing usage policies [18], policies regarding the way a course is conducted, graded, and setup [19], such as course syllabi, and policies regarding plagiarism [20], intellectual property [21], and academic integrity/honesty [22]. Beyond these university level policies, higher education policy research has focused on issues of accountability, affordability, and access [23], equity [24], public policy [25], and academic integrity [26]. Academic integrity specifically remains a focus when it comes to GAI in higher education [27-28].

Academic Integrity

Academic integrity is designed to ensure that students are the ones completing their own work, they are acting ethically during the learning process, and that students graduate from a program with the requisite knowledge to be able to apply specialized skills in industry [29-30]. GAI is often seen as a concern for academic integrity[27-28] as it has been shown to be able to pass engineering classes [31], bypassing the conventional learning process that students are expected to undergo. Beyond being able to complete class assignments, GAI has also led to concerns about the role of learning outside of a traditional in person classroom [32] such as homework assignments [33-34], take home examinations [35], and e-learning [36-37]. While faculty and instructors can have a statement to ask students not to use GAI on these activities, enforcing the policy while students are not in the classroom is increasingly difficult due to a lack of reliable GAI checkers [38].

Previous Generative AI Policy Studies

Previous scholars have explored the role of AI policies when it comes to the use of GAI in the classroom. Eichen explored the relationship between course AI policies, the type of policy, and the impacts on student grade point average [39]. In this paper, the author found that while having a GAI policy positively impacted student grade point average, adding additional components for accountability including AI detection software or disclosure requirements negatively impacted student grade point average.

Similarly, the work performed by McDonald et al. found that many university policies encourage the use of GAI with some providing sample syllabi for instructors to use [40]. The authors of this study found that these policies focused heavily on writing activities, with STEM activities being vague or rarely mentioned throughout. Further, the work by Cahill and McCabe found that undergraduate students were likely to use GAI, specifically ChatGPT, but felt they lacked guidance on ways that GAI could be used appropriately [41]. From these previous studies, it is clear that GAI policies need to be further explored to determine how they can best be implemented in the higher education landscape to support students in understanding the proper usage of GAI, while simultaneously enabling enough trust between students, faculty, and instructors to not negatively impact either party when GAI is used as part of the learning process.

Theoretical Framing:

The Policy Diffusion Theory [42-43] evaluates how policies and practices spread across different groups or regions. Policy Diffusion Theory evaluates how organizations apply *learning*, observing the policy in other settings, *emulation*, conforming to norms and standards, *coercion*, being pressured to adopt a policy, *competition*, adopting a policy driven by competitor choices, and *interdependence*, making policy choices based on other choices already made.

Braun and Gilardi's study explored beyond these initial mechanisms for how policy actors make decisions [44]. Braun and Gilardi broke the policy change process down into the steps of policy change, diffusion, and aggregate pattern of diffusion and convergence. During diffusion, they add the mechanism of *taken-for-grantedness*, policies are considered to be natural choices. Marsh and Sharman's work focuses on the similarities and differences between policy *diffusion* and *transfer* [45]. Marsh and Sharman identified that the focus on the interactions between *mechanisms*, how the policy came about, in *diffusion*, creating a new policy based on best practices and existing policy elements, and *transfer*, adapting an existing policy as is in a new situation, should be increased.

Through a combination of the mechanisms introduced by Rogers, Walker, Braun, and Gilardi, and the focus on diffusion and transfer as suggested by Marsh and Sharman, faculty and instructor GAI use policies will be analyzed with the codebook found below in Table 1.

Table 1

Deductive Codebook Used for Qualitatively Analyzing Student GAI Policies

Code	Definition	Source
Learning	Faculty/instructors adopt a policy based on policies seen in other settings	Rogers, 1962; Walker, 1969
Emulation	Faculty/instructors adopt a policy commonly accepted as the standard	Rogers, 1962; Walker, 1969
Coercion	Faculty/instructors create a policy due to being required to have one	Rogers, 1962; Walker, 1969
Competition	Faculty/instructors create a policy based on choices made by other faculty/instructors	Rogers, 1962; Walker, 1969
Interdependence	Faculty/instructors create a policy due to pre-existing GAI decisions	Rogers, 1962; Walker, 1969
Taken-for-Grantedness	Faculty/instructors create a policy due to choices they see as naturally made	Braun and Gilardi, 2006
Policy Diffusion	Policy created is a combination of existing and new knowledge	Marsh and Sharman, 2010
Policy Transfer	Policy adopted is pre-existing in another similar situation	Marsh and Sharman, 2010

Methodology:

Participants

169 engineering faculty members and instructors were recruited from 18 different engineering universities, selected by size of undergraduate degrees conferred, as reported in the American Society for Engineering Education By the Numbers report [46]. Faculty members and instructors were recruited through an open email invitation to sign up for a 45-60 minute

semi-structured interview on their mental models of GAI and assessment in STEM higher education from January 2025 to December 2025. Of the 169 participants, 118 were teaching at the undergraduate level and 51 were teaching at the graduate level. Demographics collected through an optional survey following the conclusion of the semi-structured interview for the faculty members and instructors included in this interview are listed below in Table 2.

Table 2

Participant Demographics for FMMGAI Interviews

Category	No. of Participants	% of Population
Gender		
Man	86	71.7%
Woman	30	25%
Non-Binary/Non-Conforming	1	0.8%
Prefer not to Answer	4	3.3%
Ethnicity		
Hispanic, Latino/a, or Spanish origin	8	6.7%
Not Hispanic, Latino/a, or Spanish origin	100	83.3%
Prefer not to Answer	12	10%
Race		
East Asian	24	20%
South Asian	15	12.5%
Southeast Asian	1	0.8%
Black or African American	4	3.3%
Middle Eastern or North African	5	4.2%
Indigenous American or Alaska Native	1	0.8%
White	59	49.2%
Prefer not to Answer	12	10%
University Affiliation		
Southeast-LandGrant-A	35	20.3%

Midwest-LandGrant-A	16	9.3%
Midwest-LandGrant-B	5	2.9%
Southeast-Metro-Large	4	2.33%
Southwest-LandGrant-A	14	8.14%
Midwest-LandGrant-C	8	4.65%
Northeast-LandGrant-A	17	9.88%
Southeast-LandGrant-B	16	9.3%
Southwest-Metro-Large	7	4.07%
Midwest-Flagship-A	4	2.33%
Midwest-Flagship-B	10	5.81%
Southwest-Flagship	5	2.9%
Midwest-Flagship-C	2	1.16%
Southeast-Flagship-A	5	2.9%
Southeast-Flagship-B	3	1.74%
Northeast-Private	5	2.9%
Northeast-Flagship	2	1.16%
Southeast-Flagship-C	14	8.14%
Engineering Discipline		
Aerospace and Ocean Engineering	9	5.49%
Architectural Design and Engineering	1	0.61%
Biomedical Engineering	11	6.71%
Civil Engineering	17	10.4%
Chemical Engineering	16	9.76%
Electrical and Computer Engineering	23	14.0%
Computer Science	29	17.7%

Engineering Education	1	0.61%
Engineering Design	1	0.61%
Engineering Science and Materials	3	1.83%
Engineering Technology	2	1.22%
Industrial and Systems Engineering	22	13.4%
Mechanical Engineering	17	10.4%
Materials Science and Engineering	9	5.49%
Mining and Metallurgical Engineering	1	0.61%
Multidisciplinary Engineering	2	1.22%
Class Level Taught		
100/1000 - Undergrad	12	7.02%
200/2000 - Undergrad	18	10.5%
300/3000 - Undergrad	27	15.8%
400/4000 - Undergrad	61	36.8%
500/5000 - Graduate	27	15.8%
600/6000 - Graduate	18	10.5%
700/7000 - Graduate	3	1.75%
800/8000 - Graduate	3	1.75%

Data Collection

During participation in an hour-long semi-structured interview, participants were prompted to discuss their class AI policy, how they developed their AI policy, and the goal(s) they had in developing this policy for their class(es). The following questions were asked to participants:

“What is your current AI policy in your class?”

“How did you develop/come up with your AI policy?”

“What is/are the goals of your AI use policy?”

Interviews were conducted with Zoom with audio transcription running.

Analysis Method

Each question was analyzed using content analysis [47], with each one being analyzed independently of the others. Questions were analyzed independently to analyze faculty/instructor decisions made for each question and at each level, rather than the cumulative decision making process. For question 1, policies were analyzed into themes based on the level of control attempted within the class AI policy, that is how much AI use was permitted, using predefined categories for restricted, semi-restricted, or unrestricted use of GAI within the classroom. Table 3 below defines these categories.

Table 3

Definitions of the GAI Usage Policy Themes

GAI Usage Policy Theme	Definition
Unrestricted GAI Usage	GAI can be used on any and all class activities
Semi-Restricted GAI Usage	GAI can be used on some class activities but is prohibited on others
Fully Restricted GAI Usage	GAI cannot be used on any class activities

For policies which fell in the Semi-Restricted GAI Usage category, a second content analysis round followed based on the activities that were permitted in the policy. The themes defined in Table 4 below were used for this stage:

Table 4

Permitted Usage Themes for GAI as Defined by Faculty and Instructors in the Interviews

GAI Permitted Usage Themes	Definition
Feedback	Using GAI to get feedback on classwork, homework, or other activities from class
Syntax/Debugging	Using GAI to check bugs in code or verify correct spelling/syntax in code
Understanding/Clarity	Using GAI to provide additional info/examples on a topic
Idea Generation/Brainstorming	Using GAI to think of solutions/ideas/next steps on a project
Grammar Correction	Using GAI as “advanced Grammarly", checking for spelling/grammar issues
Search Engine	Using GAI “like Google”, finding quick answers to common questions
Draft Writing	Using GAI to create outlines, first drafts, early drafts

Sketching/Visualization	Using GAI to create mock ups, early diagrams
Practice/Studying	Using GAI to review topics/concepts
Editing	Using GAI to change/add/remove content in a document

The second interview question was organized around the motivators/drivers for faculty and instructors to create their university policy. Through the interviews, analysis suggested that faculty members and instructors were some combination of internally motivated to make their own policy (*self*), adopted a policy following recommendation of or with a colleague (*colleague*), adopted their university's policy (*university*), or adopted the AI usage policy from another university (*other university*). It was also possible that an instructor did not have a policy, in which case they were tagged as such (*no policy*). These policy decisions were also mapped back to the qualitative codebook developed from the Policy Diffusion Theory shown in Table 1.

The third question was for the faculty and instructors who had an AI policy, why they chose to have one for their classes. Themes here were identified for policies aiming to specify or limit what GAI tools can be used (*control*), explain what acceptable and unacceptable use cases of GAI for class are (*guide*), provide a place where the limits of GAI usage for class could be seen by the students (*direct*), enable the instructors to proceed with academic integrity cases (*enforce*), and to have a basis to work from with class examples and future use cases (*specify*). Policy Diffusion Theory helps to provide a theoretical lens through which these themes can be understood if the faculty/instructors were adapting existing policies to inform students, to prevent GAI usage, or to use policies that have shown successful implementation in other settings.

Results:

Prior to exploring the policy themes, the faculty/instructors were split into groups of those who had a GAI policy for their class(es) and those who did not. The results of this grouping can be found in Table 5 below.

Table 5

Presence of GAI Policies for Faculty/Instructors Interviewed

GAI Policy Presence	Frequency
GAI Policy Developed	155
No GAI Policy	17

Question 1:

For exploring the first question asked to participants, “What is your current AI policy in your class?” responses were first analyzed into the restriction level relative to the amount of GAI usage permitted in class. The findings of this are found below in Table 6.

Table 6

GAI Policy Themes for Faculty/Instructor Class Policies on GAI Usage

GAI Usage Policy Theme	Frequency
Unrestricted GAI Usage	5
Semi-Restricted GAI Usage	120
Fully Restricted GAI Usage	30

GAI policies in the semi-restricted usage category then were further grouped using the pre-defined categories from Table 4. The results are found below in Table 7.

Table 7

Use Cases Permitted in Semi-Restricted GAI Policies from Faculty/Instructors Interviewed

GAI Permitted Usage Theme	Frequency
Feedback	55
Syntax/Debugging	98
Understanding/Clarity	76
Idea Generation/Brainstorming	76
Grammar Correction	43
Search Engine	11
Draft Writing	22
Sketching/Visualization	11
Practice/Studying	33
Editing	11

Question 2:

The second question in this part of the interview was “How did you develop/come up with your AI policy?” Responses to this question were analyzed for participants who had a GAI policy, with the findings included in Table 8 for the overlap in policy development with Policy Diffusion Theory and Table 9 for the motivations behind creating their policy.

Table 8

Frequency of Policy Diffusion Codes Assigned to Faculty/Instructor Generated GAI Policies

Code	Frequency
Emulation	91
Interdependence	52
Taken-for-Grantedness	85
Policy Diffusion	59
Policy Transfer	91

Table 9

Faculty/Instructor Motivation to Develop a GAI Policy for Their Class(es)

Policy Motivator	Frequency
Self	78
Colleague	52
University	15
Other University	10

<u>*Question 3:*</u>

The third question asked to participants, "What is/are the goals of your AI use policy?" was analyzed next. This question was analyzed using the pre-defined objectives of *control*, *guide*, *direct*, *enforce*, and *specify* with the results shown below in Table 10.

Table 10

Objectives of Faculty/Instructor Class GAI Policies

Policy Objective	Frequency
Control	31
Guide	39
Direct	50
Enforce	100
Specify	80

Analysis/Discussion:

Prior to question content analysis, it was observed that 17 faculty/instructors did not have a GAI policy for their class. While no single reason was provided by all faculty/instructors who did not have a GAI policy, commonly cited reasons include a lack of understanding what to include in a policy, not feeling they would be able to enforce a policy, and not believing students would follow a policy. Despite some of the perceived challenges and barriers to creating a GAI policy for class, Eichen showed in their work the importance of including these statements (Eichen, 2025). Beyond academic integrity, it is important for students to have clear guidelines from their instructors with how GAI can or cannot be used within classes and for the level of trust to be high enough that the policies do not negatively impact student learning or performance.

Question 1:

Within the results of the first question, it was observed that 30 faculty/instructors had a policy which fully restricted GAI usage, 5 faculty/instructors had a policy which completely allowed GAI usage, and 120 faculty/instructors had a policy when GAI was sometimes allowed to be used, and other times prohibited. While total prohibition of GAI has not been seen as a realistic path forward [48], and uncontrolled GAI usage can be damaging to the learning process [16, 49], these middle ground policies can provide a pathway forward, yet are often highly tailored to the class it applies to.

From the second content analysis round for the semi-restricted policies, it was observed that faculty/instructors largely agreed that debugging, understanding, and brainstorming were acceptable uses of GAI. While the sample size included in this study is limited only to engineering faculty and instructors, this does begin to show promise at creating more consistent discipline specific GAI usage policies.

Question 2:

Following the content analysis of the results in the second question, it was observed that faculty/instructors generally created their own GAI policy, sometimes seeking the guidance of an existing policy at another university (emulation/policy transfer). Despite calls for training [50-51], support [52-53], and guidance on GAI [54-55] for faculty members and instructors when it comes to GAI, actions taken and information gained still largely is siloed and comes from faculty members/instructors experiences and expertise from their discipline and teaching abilities.

Question 3:

When observing the results of the content analysis for the third question, faculty/instructors were seen to commonly observe that GAI policies are designed to accomplish enforcement in their classes. While academic integrity is a commonly mentioned concern when it comes to GAI usage in education [56-58], faculty and instructors do not see this as the primary goal of their GAI class policies, seeing these more aligned with standard expectations that students should be seeking to understand and learn the content for future employment applications and not simply for content or grade mastery.

Research Question 1:

In answering the first research question, “What GAI policies do engineering instructors adopt in their classrooms?”, it was observed that policies generally focus on enforcement of GAI controls (65%) and specifying the use cases and tools of GAI that are considered acceptable use in the classroom (52%). Policies also tended to take a middle ground stance on GAI, with most falling in the semi-restricted usage theme (77%).

Research Question 2:

For the second research question, “How do GAI policies for engineering instructors' classrooms vary?”, it was observed that within these 120 semi restricted GAI usage policies, faculty/instructors did not agree on all the same acceptable use cases. Faculty and instructors were teaching classes at all levels, from entry level introductory and survey classes, up through graduate level advanced and specialized topics within an engineering discipline. While many faculty/instructors agreed that GAI can be used to assist with code debugging (82%), getting more clarity on a topic (63%), and some initial brainstorming (63%), others suggested even looser guidelines, enabling students to use GAI for draft writing (18%), editing (9%) and creating mockups of sketches and diagrams (9%).

Limitations:

This study has a few limitations associated with it. First, this study was conducted only with STEM higher education instructors in the United States. While participants came from a variety of backgrounds, all were actively teaching in the United States in higher education during this study. Similarly, all participants were from engineering disciplines within higher education. While engineering is part of the larger STEM grouping, scientists, technicians, and mathematicians were not included in this participant group. Both of these limitations impact the transferability of the findings of this study beyond engineering faculty and instructors in higher education in the United States.

Additionally, this study focused exclusively on faculty and instructors in higher education. As such, the findings of this study may not be as transferable to the K-12 system, even for engineering classes being taught at this level. Despite these limitations of this study, it is anticipated that the findings of this study can still help to inform GAI policy discussions for STEM higher education faculty/instructors outside of the United States and beyond engineering, and can help to promote dialogue at the K12 level for STEM education, but we anticipate findings of those groups to vary from the findings of this study.

Conclusion:

Following the analysis of 169 interviews completed with engineering faculty and instructors, it was observed that GAI usage policies in the classroom are limited to only specific class instances. Policies, when present, seek to inform students of what proper usage of GAI constitutes, help students stay on track for the learning process, and provide a reference point for students to refer back to with questions of when GAI can be used.

Despite current siloing, faculty and instructors largely agreed on acceptable uses for GAI for debugging, brainstorming, and understanding. While department level or college level buy-in would still be needed, a possible route forward for standardizing GAI usage policies for students could look to explore this semi-restricted route, with decisions on the specific acceptable and unacceptable use cases of GAI being decided at a department or college level for their respective students. Not all faculty/instructors yet have, or feel the need to include, GAI policies, and a first step towards standardizing policies should be to ensure that GAI usage or prohibition is clearly being communicated to the students in these programs. Standardization of GAI policies will enable students to have clear, set expectations for them across disciplinary classes, can be aligned with the desires and needs of industry members who will be hiring engineering graduates, and can promote greater dynamic adaptability in the rapidly changing higher education landscape as GAI continues to be developed and evolve. Faculty and instructors should continue to explore how they can emulate or transfer existing policies into their syllabi for student GAI use, and continue to engage in both regular updates and conversations with how GAI policies came about, if they are working, and what purpose these policies serve in a course to course basis.

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