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# Starting with AI: First Year Engineering Students Perceptions of Generative Artificial Intelligence

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# Starting with AI: First Year Engineering Students Perceptions of Generative AI


## Abstract

This complete paper discusses how Generative AI (Gen AI) is poised as a disruptive tool for industry and a challenge for education. Academic institutions are issuing policies concerning student use of GenAI, yet student perspectives on use, value, and risk remain unprobed. If GenAI is to effectively join the ranks of routine engineering tools like Finite Element Analysis, Computer Aided Design, and Computational Fluid Dynamics, its adoption will require a more active pedagogical role than mere permission or prohibition through policy.

Using Rogers' diffusion of innovations, we track first-year engineering students as they move along the five perceived attributes that shape adoption: relative advantage, compatibility, complexity, trialability, and observability. Early results from a survey administered in the third week of a Introduction to engineering course in a large, southeastern R1 university show that students claim relative advantage (speed, convenience) and basic operational know-how with respect to GenAI tools but report ambiguous compatibility with academic ethical norms and uneven institutional support that makes competent use feel uncertain. In most prior courses, sanctioned opportunities to try GenAI and to see its use in practice have likely been scarce, leaving gaps in trialability and observability and, in turn, dampening diffusion.

We examine how these perceptions evolve across a first-year general engineering course in which GenAI use is structured, scaffolded, and required. By situating classroom activities as institutional supports that explicitly increase trialability and observability, we explore how students' reported understanding develops with respect competence and ethical practice. The contribution of this work is to provide a baseline of student views at the point of where institutional policy is under development, and to provide evidence on how targeted scaffolding and organizational support shift the perceived attributes about GenAI's diffusion in early engineering education.


## Introduction

Generative artificial intelligence (GenAI) is a disruptive technology with unprecedented capabilities to both enhance [1] and undermine student learning [2], especially in higher education [3]. While many institutions are in the process of developing policies on GenAI usage [4], student perspectives on its use, value, and risk have been less systematically examined. If GenAI is to mature into a normalized engineering tool like finite element analysis (FEA), computer aided design (CAD), and computation fluid dynamics (CFD), higher education will need to play a more active pedagogical role than simple permission or prohibition through policy.

We use Rogers' theory of Diffusion of Innovations (DOI) [5] to track first-year engineering student perceptions as students move through the five attributes that shape adoptions – relative advantage, compatibility, complexity, trialability, and observability. Many students' prior K-12 experiences likely offered few sanctioned opportunities to experiment with GenAI or observe legitimate uses in practice, limiting trialability and observability in a way that slows diffusion.

Unlike many other disruptive technologies, GenAI adoption is complicated by questions of academic integrity [6], authorship [7], transparency [8], fairness [9], and sustainability [10]. Recent work on GenAI in higher education has emphasized integrity risks [6], unevenness of institutional guidance [11], and the need for structured supports that promote ethical, learning-centric use rather than blanket prohibition [12].

Early undergraduate students arrive at university with varied prior experience. Many report familiarity with popular AI tools, yet tend to associate GenAI primarily with unethical assignment completion and a short-circuit around learning [13]. As such, GenAI may be viewed as socially or professionally unacceptable even when students recognize potential learning benefits [14].

We explore how these perceptions evolve across a first-year general engineering course at a large mid-Atlantic research university in which GenAI use is structured, scaffolded, and in several instances mandated. By situating classroom activities and out of class assignments as institutional supports that increase trialability and observability, we explore how students' understanding develops with respect to both competence and ethical norming. This work contributes a snapshot of student viewpoints during a period where institutional policy is still under development. Further, we offer evidence on how targeted scaffolding and organizational support can shift perceptions about GenAI in early engineering education.

In this study, generative AI is seen by students in a context of inconsistent guidance and rapidly changing social and ethical views, creating a context in which compatibility and legitimacy are contested. Here, DOI provides a framework to explore our research question:

**How do first-year engineering students' perceptions of GenAI change over a semester when GenAI use is explicitly structured, scaffolded, and in some cases required?**

## Background

Roger's Diffusion of Innovations (DOI) theory [5] is a widely used framework for explaining how new technologies or ideas are propagated through a population or an organization. Rogers defines diffusion as "the process by which (1) an innovation (2) is communicated through certain channels (3) over time (4) among the members of a social system" [15]. The emphasis on communication channels and the social context of the diffusion is especially relevant in educational settings. Here, adoption rarely depends on individual preference alone, but rather is a social process shaped by peers' behaviors and beliefs, instructor modeling, and institutional policy [15]. Within DOI, adoption rates are explained through a set of perceived attributes of the innovations, operationalized as relative advantage, compatibility, complexity, trialability, and observability [16]. In educational studies applying DOI constructs, compatibility is often defined as congruence of the technology with users' beliefs, values, prior experience and needs [17]. Both observability and trialability attempt to capture whether prospective users can experience the innovation and experiment with its practice on a limited basis before committing [17].

In educational contexts, DOI can also describe the staged decision process through which users move from awareness and opinion formation to sustained use. This process is often summarized as knowledge, persuasion, decision, implementation, and confirmation [3]. Throughout this process, those leading the transition are positioned to decrease uncertainty through support, assistance, and feedback provision to early adopters.

Rogers' Diffusion of Innovations has been applied in several education technology adoption contexts, including implementation of learning management systems, e-learning, and virtual laboratories, among others [16], [18], [19], [20].

Boland et.al performed a synthesis of a learning management system (LMS) at Texas A&M and Monash, focusing on the implementation of Blackboard [19]. The students emphasized that diffusion is shaped not only by Rogers' constructs (relative advantage, compatibility, etc.) but also by social pressure and organizational readiness. In this synthesis, Blackboard's compatibility with traditional learning values is highlighted as pivotal in the diffusion process, reinforcing the idea that coherence with existing social systems and culture is a driver of technology adoption. Bond points to the engagement of innovators and early adopters acting as champions to support diffusion through provision of formative feedback during implementation.

Pinho paints a similar picture when exploring the implementation of Moodle as a LMS across several Portuguese universities [18]. Pinho situates compatibility as being explicitly tied to beliefs and values, whereas complexity is treated as inversely related to diffusion, as more readily understood innovations tend to spread more rapidly. Here, observability is directly linked to opportunities to observe the technology and to communicate about it, claiming a positive link between observability of the LMS and actual use of LMS in the academic domain.

A study integrating the Technology Acceptance Model (TAM) and DOI in explaining students' intention to use e-learning systems explores DOI characteristics alongside TAM constructs (usefulness, ease of use, enjoyment) to explain the intention to use the technology [20]. Al-Rahmi here reports that DOI characteristics are tied to perceived ease of use and usefulness. They further frame the teacher role as consequential, arguing that instructors have a responsibility to help students to enhance the learning system and support diffusion while simultaneously emphasizing institutional posture as a lever for diving effective use of technologies.

The prior DOI implementations generally explore technologies whose compatibility challenges center around alignment with institutional culture, pedagogy, and user practice, rather than technology that bring moral concerns about academic work itself. In these studies, compatibility is treated as a fit with values and practices, but the innovations are not seen as tools that can directly substitute for the intellectual work required of learning tasks. As a result, many DOI applications in education implicitly assume that instructor and institutional support can be developed without needing to resolve disputes of what constitutes acceptable learning. In these instances, trialability and observability are assumed, as legitimacy is not questioned.

**Context, Participants and Data Collection**

This study was conducted in two sections of an introductory, first-semester course in a General Engineering sequence at a larger, R1 institution in the southeastern United States. Students in the program must complete the first-year general engineering sequence (along with other STEM coursework) prior to matriculation into a discipline-specific major. Both sections of the course were taught by a single faculty instructor (one of the authors of this work). The total end of semester enrollment across the two sections was 135 students.

At the time of this study, institution- and college-level guidance on GenAI use in coursework was limited and left course-level GenAI policy largely to instructor discretion. Within the course itself, GenAI use was restricted by default. With a syllabus statement "Generative AI is prohibited until explicitly required: and students are instructed to assume it is not allowed unless an assignment explicitly indicates otherwise". When GenAI was not explicitly required, the syllabus frames unauthorized use as an academic integrity violation subject to Honor Code reporting.

GenAI use was intentionally integrated at several points in the semester as a learning support tool, primarily to support reflection and self-assessment relative to the course Student Learning Outcomes (SLOs). Midsemester, students complete an assignment designed to use GenAI as a formative feedback tool. Students created or refined an instructor-generated prompt, used a GenAI tool to work through the SLOs, and then reflected on the AI-generated assessment of their learning progress. At the end of the semester, students completed a summative assignment using a mandatory instructor-drafted GenAI prompt to guide a semi-structured interview in which students showcased their performance with individual evidence. At the end of the activity, students wrote a short reflection on how their views of GenAI had changed over the source of the semester.

Prior to beginning data collection, the institution's Institutional Review Board determined that this study does not meet the federal definition of research involving human subjects. Although the activity was determined not to be human subjects research, students were provided with a clear opt-out notice indicating that course artifacts could be used for course evaluation and scholarly dissemination. Students were informed that opting out would not affect their grades, and that analysis and reporting would use de-identified, aggregated data.

## Methods

We used mixed methods to examine changes in students' GenAI usage and perceptions over the course of a single semester. Quantitative data came from a pair of surveys administered at the beginning of the semester (n = 135) and then again at the end (n=115). As the surveys were de-identified, analyses were conducted at the cohort level. The survey included categorical classification of typical GenAI use frequency (never to daily) and multiple Likert-style items assessing GenAI literacy and the perceived support for GenAI usage. We report usage frequency results as counts and percentages and pre/post comparison using chi-square tests. Likert items are summarized using means and standard deviations using a five point Likert scale with 1 being strongly disagree and 5 being strongly agree.

Qualitative data consisted of student reflections at two separate points – midsemester formative reflections and end-of-semester summative reflections. Analyses were made at the transcript level. The midsemester formative reflections followed a structured template, and excerpts were pulled directly from submitted assignments. End of semester summative reflections did not follow a standard template and were therefore manually extracted from submissions and cleaned. Where reflections were not present or corrupted entries existed, excerpts were retained but were not coded.

Coding was primarily deductive and used an a priori codebook developed on Rogers' Diffusion of Innovation framework. An initial set of excerpts (n ~ 75) were manually coded using our a priori codebook, and several emergent codes were established. The full codebook with definitions is provided in Appendix A. A large language model (LLM) was then used as an independent alternate coder constrained to the same codebook and allowing for multilabel coding. The LLM was restricted to applying the existing codebook rather than generating new themes or data. AI-coded outputs were stored separately from manual coding to preserve an audit train and support direct comparisons. We used multi-label overlap metrics, including micro-precision, micro-recall, micro F1, and mean row-wise Jaccard similarity to assess interrater reliability between human and LLM code application. These checks were used to identify code families most prone to disagreement between human and AI code application, with notable disagreement in the STANCE/DEPTH/ROLE families.

## Limitations

The data in this study were collected in two sections of a first-semester general engineering course taught by one instructor at a single institution. As such, our findings should be interpreted as highly context-specific rather than as broadly generalizable. Evidence is drawn primarily from surveys and course assignments framed as reflection artifacts (including AI-mediated portfolio prompts), which capture student perceptions and sensemaking but do not collect independent observation of GenAI behavior outside the assignments. Because several activities explicitly required and framed GenAI use, responses may reflect assignment design constraints as well as underlying attitudes. Finally, pre/post survey results are cohort-level, and qualitative analysis applies an a priori DOI lens with only limited emergent code development and may under-emphasize themes outside the framework.

## Results

### *Quantitative Results*

Reported GenAI use frequency shifted upward from the beginning of the semester to the end of the semester (see Table 1). In the pre survey (n=135), 17.0% of respondents (23/135) reported never having used GenAI in a typical week, compared to 0.8% (9/115) in the post survey (n=115). At the high-use end, daily use increased from 14.1% (19/135) at the start of the semester to 20.9% (24/115) at the end of the semester.

**Table 1. Changes in GenAI usage from beginning of semester to end of semester**

| Frequency | Pre (n=135) | Post (n=115) |
|---|---|---|
| 0-1x/week | 35.6% (48/135) | 15.7% (18/115) |
| 2-3x/week | 28.9% (39/135) | 33.0% (38/115) |
| >4x/week | 35.6% (48/135) | 51.3% (59/115) |

Five Likert items show statistically significant gains from pre- to -post assessment (Welch's t-test, $p<0.001$) (see Table 2). The largest reported impacts were in knowledge of environmental impacts of GenAI usage and the ability to name multiple GenAI tools (ChatGPT, Claude, Copilot, etc.). Students also reported increased ability to list the advantages and disadvantages of GenAI tools and noted an increased perception of support to use GenAI tools. Here we see a cohort-level shift in more frequent usage and improved awareness of the capabilities and limitations of the tools.

**Table 2. Changes in students' knowledge and perception of GenAI tools**

| Likert Item | Pre (n=135) | Post (n=115) |
|---|---|---|
| Environmental Impacts | 3.20 ± 1.18 | 3.80 ± 1.02 |
| Familiarity with Specific Tools | 3.69 ± 0.90 | 4.21 ± 0.71 |
| List Advantages | 3.94 ± 0.75 | 4.32 ± 0.59 |
| List Disadvantages | 4.08 ± 0.77 | 4.47 ± 0.60 |
| Perceived Support | 3.57 ± 0.75 | 3.94 ± 0.76 |

### *Qualitative Results*

Across both midsemester (n=100 coded excerpts) and end of semester reflections (n = 74 coded excerpts), students commonly described GenAI as beneficial for improving the quality of their work or thinking (RA.QualityInsight). Students often noted the limitations in what GenAI could reliably do in the context of the assignments (OBS.CapabilityLimits). RA.QualityInsights was present in 76% of the midsemester excerpts (76/100) and 97% of summative excerpts (72/74). OBS/CapabilityLimits increased from 50% (50/100) in the midsemester to 76% (56/74) in the end of semester reflections. Students noted both soft limits in capabilities (i.e. generic or misaligned feedback) and hard limits (tool breakdown) which ware both coded as observed capability limitations in the DOI codebook scheme.

Changes in student attitudes in positivity towards GenAI were not observed, but more details and intent on how students planned on using GenAI moving forward were. In midsemester reflections, students frequently concluded the reflections with statements displaying broad aspirational intentions (ACTION.VagueGeneric 47%, 47/100) and limited explicit discussion of future use of the tools (TRIAL.FutureIntent 10%, 10/100). Summative reflections more often included concrete targeted next steps (ACTION.ConcreteTargeted 49%, 36/74) and students explicitly stated intent to continue using GenAI in the future (TRAIL.FutureIntent 51%, 38/74). The increase in concrete intent statements correlated with a decrease in language about vague aspirational use (ACTION.VagueGeneric 11%, 8/74).

A notable subset of end of semester summative excerpts included direct statements that students' views of GenAI had shifted over the course of the semester (SHIFT.ExplicitChange 27%, 20/74), though others reported explicitly that their views had not changed (SHIFT.ExplicitUnChanged 18%, 13/74). A small fraction of students also referenced prior educational contexts where GenAI use was discouraged or prohibited (COMP.PriorNormsRestriction 2.7%, 2/74). In summative reflections, most students expressing future intent to use GenAI also referenced at least one limitation (30/38), suggesting that future use often co-occurred with recognition of tool limitations.

**Discussion**

Our research question asked how student perceptions of GenAI change over a semester when use is explicitly structured, scaffolded and sometimes required. Here we characterize students' change in perceptions as a shift from general, abstract claims of awareness of the capabilities and limitations of GenAI to more bounded and specific future use intentions. Students reported increased support, increases use, and more explicit discussion of capabilities and limitations. At the beginning of the semester, students self-reported a relatively high degree of AI literacy, including the ability to articulate advantages and disadvantages of the technology. Across the semester, however, students' written reflections indicate that there was significant change in how students discussed or conceptualized appropriate use. In midsemester reflections, students commonly concluded with broad, aspirational statements about using AI without any clear boundaries. By the end of semester, student reflections more frequently used explicit, concrete, targeted and bounded plans for future use.

This pattern aligns with DOI's claim of uncertainty reduction through trialability and observability, encouraged through organizational support. In this course, trialability was mandated through scaffolded GenAI interventions that forced experimentations and observation in tool capabilities in a legitimate context. Quantitative results are consistent here – students reported increased perceived support and increased knowledge of capabilities and limitations, along with a reported increased in use frequency.

Importantly, students' end of semester reflections often paired future use intentions against explicit acknowledgement of tool limitations, suggesting that the adoption of GenAI tools was a mature, bounded posture as opposed to a simple observation of efficiency or usefulness. Summative excerpts note GenAI as useful and ethically compatible for reflection, organization, checking work, or generating feedback. Simultaneously, students frequently emphasize the need for verification, the limits of the capabilities, and the need to maintain agency when using the tool. This suggests that the inventions increased observability not only of productive and ethical uses of the technology, but also of failure modes of the technology in practical use, enabling students to align their ethical viewpoints with the technology.

Ethical compatibility did remain contested across the cohort. Even when students acknowledge the learning value of the tool, several excepts describe GenAI as feeling like "cheating" or as "morally wrong". Others continue to note the environmental impacts as ethically untenable, indicating that social and ethical stigma persist even after success trial observations of the tool. Here we see that students may be able to name the pros or cons of tools usage abstractly but may not be able to arrive at a legitimate model of how to use GenAI without short cutting learning or compromising ethical norms. The mandated interventions in the course appear to have partially relieved some of the tension by providing students with legitimate exemplars of learning-supportive use cases.

Finally prior prohibition (mostly in in K-12 contexts) was present but quite rare in the data sets. Only a small fraction of summative excerpt referred to earlier prohibition of GenAI usage. However, these instances do exist where policy precludes legitimate trialability and observability and students therefore are not provided adequate opportunities to develop or see modeled legitimate academic uses. As such, in these instances, students are more likely to position GenAI usages as cheating rather than as a bounded learning tool.

When GenAI use is structured and scaffolded and unambiguous, students' perceptions shifted in three ways: 1) intent moved from vague, generalized aspirations to concrete plans for future use, 2) student more frequently articulated specific limitations and capabilities, and 3) perceived support and reported use increased. Across the semester, the clearest shifts in student sensemaking were in trialability/observability and in compatibility rather than in simple positivity towards GenAI. Students had more direct experience and a first-hand view of limitations and arrived at more explicit ethical framing of GenAI use.

**Conclusions and Implications**

GenAI has diffused rapidly into the workforce, making it unrealistic or even irresponsible for higher education to ignore GenAI. Reviews of GenAI in professional settings characterize accepting adoption across technical sectors [21]. In software engineering, specifically, recent research documents active and growing use of tools such as ChatGPT and Copilot for day-to-day tasking, along with ongoing attention to reliability and verification [22]. In engineering design, early research on generative AI-augmented design has expanded rapidly since 2016, pointing toward continuing diffusion of AI into workplace practice and tools across multiple STEM sectors [23].

Against the context of rapidly increasing use of GenAI in the workplace, prohibition-only approaches to GenAI policy risk the exact conditions under which DOI predicts slow or non-existent adoption. Such policies result in low trialability, low observability, and a high perceived social risk of use. In contrast, our study presents evidence that explicit policy clarity coupled with structured, learning-centric and modeled use can increase student's reported support and authentic understanding of the capabilities and limitations of the technology. Direct observation and ethical norming can move students toward concrete, ethically bounded intentions for future use. Our results suggest that institutions and instructors in higher education should explicitly develop and communicate GenAI expectations, create scaffolded assignments that enable students to observe failure and practice verification of outputs, and promote acceptable use of GenAI to support learning. As such the most responsible stance on educational use of GenAI is likely not prohibition, neutrality, nor blanket permission, but structured and condoned use. Creating scaffolded opportunities for students to practice GenAI in ways that preserve their agency and support the development of the judgment required to ethically use the technology is the strongest policy to support our students.

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**Appendix A: Codebook**

| Theme | Code | Definition |
|---|---|---|
| Relative Advantage (RA) | RA.Efficiency | Student notes that using GenAI for this reflection saved time, felt faster, or was more convenient than other ways of reflecting. |
| | RA.QualityInsight | Student indicates that GenAI improved the quality of insight by surfacing blind spots, organizing ideas, or providing clearer structure for reflection. |
| | RA.LowValue | Student judges that GenAI added little or no value to their reflection (e.g., describes the feedback as generic, redundant, or obvious). |
| Compatibility with Values and Norms (COMP) | COMP.EthicalAlignment | Student describes this use of GenAI as legitimate, responsible, or aligned with ethical and academic integrity norms. |
| | COMP.EthicalTension | Student expresses concern or discomfort about the ethics of using GenAI in this context, such as worrying about cheating, over-reliance, or fairness. |
| | COMP.CourseNormFit | Student comments on how this GenAI use fits or conflicts with perceived course or instructor expectations and rules. |
| Perceived Complexity (COMPL) | COMPL.PromptDifficulty | Student reports difficulty figuring out how to prompt GenAI effectively, including uncertainty about what information to provide or how to phrase the request. |
| | COMPL.InterpretingFeedback | Student reports difficulty understanding or interpreting GenAI's ratings, categories, or suggestions. |
| | COMPL.LowComplexity | Student explicitly describes the GenAI interaction as easy, straightforward, or simple to use for this reflection. |
| Trialability (TRIAL) | TRIAL.LowStakesExperimentation | Student frames the assignment as a safe, low-stakes opportunity to try GenAI or to experiment with its capabilities. |
| | TRIAL.FutureIntent | Student states an intention to try similar GenAI-supported reflection or feedback activities in other courses or future contexts. |

| | | |
|---|---|---|
| Observability (OBS) | OBS.CapabilitiesLimits | Student comments on what GenAI appears able or unable to do well, noting strengths and limitations of its feedback or assessment. |
| | OBS.Comparisons | Student explicitly compares GenAI's assessment to their own self-view, prior feedback from others, or other evaluation methods. |
| Stance Toward GenAI as Assessor (STANCE) | STANCE.Trusting | Student largely accepts GenAI's assessment without challenge, describing it as accurate or correct across most or all points. |
| | STANCE.CalibratedCritical | Student both agrees and disagrees with different parts of GenAI's assessment and provides reasons to justify their own judgments. |
| | STANCE.SkepticalDismissive | Student minimizes or rejects GenAI's authority as an assessor, questioning its relevance, accuracy, or appropriateness. |
| Action Planning Based on Feedback (ACTION) | ACTION.ConcreteTargeted | Student articulates specific, actionable next steps linked to particular skills or outcomes (e.g., defined study behaviors, help-seeking, schedule changes). |
| | ACTION.VagueGeneric | Student offers only broad or nonspecific improvement plans (e.g., "work harder," "manage time better") without concrete strategies. |
| | ACTION.NoActionResistance | Student does not identify meaningful next steps or explicitly resists changing behavior in response to GenAI's feedback. |
| Depth of Reflection (DEPTH) | DEPTH.Descriptive | Student primarily restates or paraphrases GenAI's feedback with little additional interpretation or personal connection. |
| | DEPTH.Interpretive | Student connects GenAI's feedback to personal experiences, course work, or specific incidents, explaining why the feedback does or does not fit. |
| | DEPTH.Integrative | Student links GenAI's feedback to broader identity, long-term goals, ethics, or career trajectories, integrating it into a larger narrative about themselves. |

| | | |
|---|---|---|
| Perceived Role of GenAI (ROLE) | ROLE.CoachPartner | Student frames GenAI as a supportive coach, tutor, or thinking partner that helps them reflect, plan, or understand themselves. |
| | ROLE.Authority | Student frames GenAI as an authority or grader that evaluates or judges their performance or abilities. |
| | ROLE.ToolInstrument | Student frames GenAI as a neutral tool or instrument (e.g., checklist or diagnostic) used pragmatically without much social or relational language. |

**Theme definitions**

**Relative Advantage (RA)** – How students perceive the benefits of using GenAI for reflection compared to their usual ways of monitoring their learning (e.g., faster, more insightful, more organized).

**Compatibility with Values and Norms (COMP)** – How well GenAI-supported reflection fits with students' ethical standards, sense of academic integrity, and perceptions of course or institutional expectations.

**Perceived Complexity (COMPL)** – How easy or difficult students find it to use GenAI effectively for this task, including both prompting and interpreting the feedback.

**Trialability (TRIAL)** – The extent to which students experience this assignment as a low-stakes experiment with GenAI and whether it encourages future experimentation in other contexts.

**Observability (OBS)** – How students describe what they can see about GenAI's capabilities and limits by using it, especially when comparing its assessment to their own or others' evaluations.

**Stance Toward GenAI as Assessor (STANCE)** – How students position themselves in relation to GenAI's judgments—trusting, critically engaged, or skeptical/dismissive of its authority.

**Action Planning Based on Feedback (ACTION)** – The extent to which students translate GenAI feedback into concrete or vague plans for changing their behavior, or resist acting on it.

**Depth of Reflection (DEPTH)** – How far students go beyond restating GenAI's feedback—whether they simply describe it, interpret it in light of experience, or integrate it into broader goals and identity.

**Perceived Role of GenAI (ROLE)** – How students characterize what GenAI is in this context (coach, authority, or neutral tool) and the relationship they imagine between themselves and the system.