Visions of Disciplinary and Education Futures with Generative AI

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Abstract

Generative AI (GenAI) is permeating higher education, with varying implications across disciplinary contexts. Some impacts of GenAI may advance scholars' disciplinary visions, while others may challenge them. This qualitative interview study examined how 17 scholars across 15 distinct academic disciplines understand GenAI's potential and existing impacts on teaching, research, and disciplinary practices, and what values and priorities might lead to variation in their disciplinary responses. We found that participants held several distinct stances about GenAI, sometimes many at once. There was a spectrum of stances, from resistance to skepticism, to neutrality stemming from inaction, to pragmatic stances of GenAI as a tool, or as a positively or negatively transformative disruptor. While there was no clear mapping from stance to discipline, we found that scholars within a discipline held particular commitments to knowledge and ways of knowing that varied in alignment or tension with pragmatic concerns of disciplinary progress and learning. The weighing between these two considerations often explained the valence of their stance. Throughout, scholars also noted the lack of capacity to develop their stances by learning and experimenting, as their time was increasingly consumed by increased workload, some from increased challenges in teaching caused by GenAI. These findings suggest that whether and how disciplines might be transformed by GenAI depend greatly on society's willingness to invest in capacity to create new, transdisciplinary cultures of knowledge that reconsider or recommit to what knowledge should be protected, taught, and sought.

Introduction

The advent of widespread and capable Artificial Intelligence (AI), and Generative AI (GenAI) in particular, is fostering massive excitement by policymakers, industry leaders, academic scholars, artists, engineers, students, doctors, and many others. Some industry titans have speculated that it will trigger economic growth and social transformation on par with the industrial revolution. With these aspirations and risks in mind, the United States, India, China, and other governments have begun mandating universal AI education; research funding agencies such as the U.S. National Science Foundation have rapidly shifted research investments away from longstanding commitments in favor of basic and applied research on AI.

Others are more cautious, with researchers, executives, and activists expressing skepticism and concern about risks of environmental destruction, increased unemployment, amplified harm to already marginalized people, and even risks of human extinction (Bender and Hanna 2025; Vermeer, Lathrop, and Moon 2025). Some have argued for more complete refusal (Slater et al. 2025; Zong and Matias 2024). In response, government bodies such as the European Union are increasingly mandating structures for regulating AI systems and the data used to create them, while other government leaders such as those in the UK have spurned regulations, including enforcement of copyright protections, that they fear would reduce their nation's capacity for technical and economic AI leadership (Ward and Sherrington 2026).

Amidst these opportunities and risks, higher education is at a crossroads. Researchers have enumerated the many challenges and opportunities of AI in research, teaching, expertise, personalized learning, collaboration, communication, and resource constraints (Michel-Villarreal et al. 2023; Peres et al. 2023; Chiu et al. 2023). Others have noted the profound shift in attention by researchers towards applications of AI across academia (Zeivots et al. 2025; O'Dea 2024). And others still have wondered if the ubiquity and disruption of AI demands an entire re-imagining of research, teaching, and our institutions (Dianova and Schultz 2023).

Underlying this upheaval in academia is a fundamental question: How should AI change what it means to be an artist, an engineer, a writer, a lawyer, a scientist, or one of the many other human endeavors in society? These are fundamentally questions about *disciplines* (Baron 2005; Krishnan 2009), and how they could or should change and evolve in response to AI. Experts in higher education set the frame by which new generations imagine the world through disciplinary lenses. Academia often catalyzes paradigm shifts in education, which transform the culture and the economy. Many of AI's impacts are likely to be greatest in the working world, where most professional work is disciplinary in nature. And AI tools themselves are likely to be designed to support specific forms of disciplinary work, e.g., helping radiologists to interpret images of the body and write analyses of them.

While prior work has grappled with the many practical implications of AI in higher education research and teaching in general, it has not systematically examined its potential implications on disciplines themselves. We therefore asked: *What are scholars perspectives on how their disciplines will or should change (if at all), and what implications does that have for higher education research and teaching?* To answer this question, we conducted a set of 17 interviews with scholars at a large public research university who were significantly engaged in reflecting on the implications of GenAI in their disciplines' research, teaching, administration, or public communication. Spanning 15 different disciplines across humanities, the arts, design, science, engineering, social sciences, computing, and information, our interviews revealed numerous potential futures of academic disciplines, and the research, education, and professions that they shape. Our findings represent not only a snapshot of sentiment but a more foundational analysis of the ways that scholars respond to technological change through disciplinary lenses (Blin and Munro 2008).

Related Work

Research on AI in higher education, and GenAI in particular, has increased in volume considerably since the release of ChatGPT in 2022, spanning broad examinations of higher education as a whole, to disciplinary reflections on research and teaching, to quite focused inquiry into the specific effect of large language models (LLMs) on numerous aspects of research, teaching, and learning. We will not survey every article here, but rather provide a sampling of this growing literature, demonstrating what it teaches us, while also demonstrating its lack of engagement with disciplinary variation.

Academic Disciplines are Multifaceted

Many scholars have theorized about the nature of academic disciplines. Some conceptualize them as an intersection of multiple parallel social and organization systems, spanning higher education departmental structures, cultural values and norms, and intellectual frames for learning and sensemaking about the world (Abbott 2002). Others consider the socioeconomic features of professionalization and division of labor, and its shifts over time in response to culture and technological change (Krishnan 2009). Others still examine disciplinarity through inter- and trans-disciplinary lenses, finding that disciplines often serve to define an audience for knowledge, with interdisciplinarity seeking to speak across audiences (Turner 2000), and transdisciplinarity fostering new constellations of theories, methods, and people that ask new questions of the world (Finch, Moreno, and Shapiro 2021). These and other works show that responses to technological change vary by discipline (Orji 2010) because disciplines are different cultures, with different goals, different ways of representing information (Hall, Stevens, and Torralba 2014), different uses of technology, and different audiences. This is true partly because all technologies are cultural artifacts (Benjamin 2019), especially in cultures that elevate technology as deity (Postman 2011).

Adoption and Sentiment has been Rapid

Within this disciplinary backdrop, numerous studies have explored the rapid adoption of GenAI in higher education research and teaching. For example, a 20-country survey found that faculty across higher education globally have highly adopted GenAI across fields, countries, genders, and cultures, using it for writing, content creation, learning support, and teaching (Mohammadi et al. 2026). Other studies have found significant adoption in science in particular (Ding, Lawson, and Shapira 2025). Studies of research publications find that both the use of GenAI and research about GenAI are both on the rise globally (Khan et al. 2024). Some studies show that as adoption has increased, collective faculty sentiment has become more optimistic (Întorsureanu et al. 2025), whereas others show faculty viewing GenAI as both a boon and burden (Gonsalves and Acar 2025). Some studies reveal that sentiments are deeply culturally situated, with countries that value research and learning efficiency being more optimistic about its impacts (Jogezai et al. 2025).

Numerous works either argue for or demonstrate the risks of bias and harm. Some acknowledge the efficiency gains but highlight the way that GenAI can exacerbate inequities (Francis, Jones, and Smith 2025). Others write about the risks of exacerbating "industrialized" forms of higher education that dehumanize learners and knowledge (Aad and Hardey 2025). Some observe foundational questions about GenAI spanning digital divide, sustainability, and well-being (Allison et al. 2025; Ooi et al. 2025).

Disciplines Vary in Response

Numerous works have found that the impacts, perceptions, opportunities, and risks of GenAI in higher education vary by discipline (Eddine, Gide, and Al-Sabbagh 2025). Some show differences in faculty and student attitudes cross STEM and non-STEM disciplines (Kim et al. 2025). Some works explain this difference by noting the epistemic norms and deeper insights about ethics and culture as barriers to adoption (Yang et al. 2026a). But research varies considerably in what it finds, with some studies demonstrating broadly optimistic views of GenAI in STEM (Dewan et al. 2025; de Silva et al. 2026), and others showing broadly unfavorable attitudes across academic disciplines from impacts on teaching (Guillén-Yparrea and Hernández-Rodríguez 2024).

Looking more closely at specific disciplines, some nuances emerge. Research with art education faculty has found a perception of GenAI as a mere tool and not a very good one (Sáez-Velasco et al. 2024). Library and information scientists hold mixed feelings, with a desire to foster literacy, but also a hesitation about threats to academic freedom, intellectual property, and the preservation of knowledge (Morris and Malady 2025; Slater et al. 2025). Some social scientists expect that GenAI will greatly increase the need to understand social forces on humanity because humanity's social interactions will be mediated by GenAI (Bail 2024). Business and marketing scholars note the profound impacts on curricula and tools (Peres et al. 2023). This variation in disciplinary viewpoints suggest that the impacts of GenAI are far from uniform and far from settled but also distinctly disciplinary.

Teaching and Learning is Disrupted

Much of the research on GenAI in higher education specifically focuses on practical questions about teaching and learning, enumerating risks regarding academic integrity, quality control, personalized learning, expertise, curricula, communication, and collaboration (Michel-Villarreal et al. 2023; Chiu et al. 2023; O'Dea 2024).

Some of these works examine potential impacts on pedagogy and curricula. For example, some research advocates for a shift to interdisciplinarity and transdisciplinarity over disciplinary skills (Chiu 2024; Dianova and Schultz 2023). Others examine the need for AI literacy as a new foundation of disciplinary curricula (Farrelly and Baker 2023). Some argue that GenAI is more fundamentally unsettling, challenging assumptions that disciplines make about collaboration, knowledge, and agency, positioning learners as primarily imagining and shaping futures rather than mastering basic knowledge and skills (Zeivots et al. 2025).

Prior work shows that most educators do not feel supported in this transformation. Many have adopted GenAI in their teaching, but in isolation, with no community, guidance, or standards (Lee et al. 2024; Soleimani et al. 2025). Educators are worried about assessment, dependency, privacy, inequity, and bias (Al-Jaghoub et al. 2025). Despite all of this adoption and reflection, studies show that faculty literacy is low (Yang et al. 2026b).

Many of the disruptions particularly concern assessments and academic integrity. Faculty are reacting, e.g., by redesigning assessments (Adnin et al. 2025; Khlaif et al. 2024). Research has enumerated many possible new forms of assessment to support these efforts (Chan and Colloton 2024). Many of the assessments faculty are designing aim to center critical thinking and creativity, out of a fear of loss of these foundational skills (Smolansky et al. 2023). But rather than eliminating or reducing academic integrity concerns, many of these new forms of assessment just shift integrity concerns to other media and contexts (An, Yu, and James 2025).

Amidst all of these faculty efforts to respond, students have their own sentiments. Some studies show that students are quite optimistic about personalized learning support, as well as writing and research assistance. However, they are deeply concerned about accuracy, privacy, their careers, and their ability to be creative and think critically (Chan and Hu 2023; Schei, Møgelvang, and Ludvigsen 2024).

A Shifting Picture

Despite the substantial research in the past four years on the impacts of GenAI on higher education, such as knowledge of how higher education is changing and how it should change, remains hazy. Faculty and students have shifting perspectives; the capabilities of GenAI are changing; and while there is much experimentation, it is also clear that there is little support for faculty to reflect deeply about what GenAI means for higher education, their disciplines, the research and teaching, and the holistic experience of being faculty. While prior work shows *that* sentiments vary across discipline, it does not richly reveal *why*. The goal of this interview study was to examine that why, giving scholars the space to share their visions for their disciplines' futures in research and education, revealing the particular disciplinary ideas, values, and norms that lead to that variation.

Methods

We conducted this qualitative interview study with research-active faculty at a large public university in the United States to understand how scholars across disciplines are making sense of GenAI in relation to their discipline in the university. We aimed to get a stratified set of perspectives across academic traditions and disciplines. In the following sections, we will describe participants and recruitment, study design, and analyses. We note that our epistemic frame in this work is explicitly interpretative, not positivist, and so our goal in describing our methods is recoverability, not generalizability (Scheurich 2014; Small and Cook 2023); i.e., the reader should be able to trace where claims about our data came from, even though their interpretations of data may have led to different claims. Our study methods were reviewed and approved by our university's institutional review board.

Participants

We aimed to recruit research-active scholars who were seen by both the authors and the broader intellectual community around them to be actively engaged in discussions about the futures of their disciplines, whether in their research, teaching, and/or administrative roles, and especially those doing work to question or develop futures for GenAI within these aspects of their disciplinary engagement. To identify potential scholars, the research team created a recruitment list of scholars and academic leaders whose engagement with AI was visible through public communications, teaching innovation, research activity, and academic leadership at our large public research university. We chose our own institution because we had detailed awareness of conversations about GenAI, including mailing lists, interdisciplinary initiatives, and local professional networks. From those local knowledge, we identified a broad pool of potential scholars across the university in different departments. Additional initial inclusion criteria were that potential scholars had at least two years of experience in their current academic or professional context.

After making an initial list of potential scholars, we recruited across disciplinary areas and institutional roles. We did not sample randomly because the initial list overrepresented some disciplines, e.g., computing-adjacent disciplines given our team's own home disciplines. We therefore intentionally sought variation across disciplines and forms of AI engagement. We advanced our goal to capture a range of perspectives across the university by asking colleagues to suggest others to participate in our study and invited their nominees as well. In total, we invited 26 scholars and ran 17 interviews. Recruitment continued until we had coverage across all Colleges/Schools at our institution, and we began

Table 1: Scholars disciplines, by departmental affiliation

ID	Discipline (department)
P1	Economics
P2	Drama
P3	Law
P4	Linguistics
P5	Computer Science
P6	Art and Design
P7	Classics
P8	Information
P9	Information
P10	Computer Science
P11	Film Studies
P12	Human-Computer Interaction (HCI)
P13	Human-Computer Interaction (HCI)
P14	Psychology
P15	Philosophy
P16	Music
P17	Chemistry

to hear recurring perspectives across interviews, reaching some level of saturation. In similar studies (e.g., in human-computer interaction), 12 participants has been a common accepted number of participants for interview studies (Caine 2016). Table 1 shows the final set of disciplines that scholars represented, as indicated by their departmental affiliation (or if they explicitly identified a research community, the name of that community).

Interview Protocol and Data Capture

We developed a semi-structured interview protocol to elicit scholars' perspectives on their disciplines futures, GenAI in relation to their disciplinary expertise, their broader perspectives about the future of higher education, and their research and teaching practices, both *with* and *without* GenAI. The authors collaboratively designed the protocol and refined it across multiple rounds of pilots. In our pilots, each of us conducted an initial interview, then met to debrief the interview experience and identify areas for revision. These pilots led to minimal changes to the interview protocol (e.g., rewording, reordering, and cutting a few questions). Since the pilot interviews were substantively aligned with the final protocol, they were included in the final dataset of 17 scholars. Table 2 shows the final resulting semi-structured protocol, which began with the scholar's disciplinary conception, examined disciplinary change in response to GenAI generally, and in research and teaching in particular.

We conducted all interviews via Zoom video chat or in-person on campus (whichever the participant preferred). Each interview lasted approximately one hour and followed the semi-structured protocol. This format enabled us to ask the same questions across scholars with flexibility to explore discipline-specific concerns, examples, and tensions that came up during the interviews.

We audio-recorded all interviews with scholars' consent. With AI assistance (Whisper or Parakeet automated speech

Table 2: Interview protocol.

Understanding the Discipline Currently (15 min)

- On a high level, please describe your discipline, including the kinds of questions it contends with and the methods it uses.

Where the Discipline's Research Is Going (15 min)

- Where do you envision your discipline going in the future?
- What new questions will people be asking? What methods will they be using?
- What is going to be different about what people will need to know and be able to do?
- What would you like to be able to do with generative AI? And what should be avoided?

Teaching in Your Discipline (15 min)

- What are the learning goals or outcomes for students in your program or classes?
- What are common teaching practices (e.g., in class periods or assignments) in the program, from yourself and other faculty?
- What concepts should people in your field stop teaching versus start teaching, given limited credit hours? And how?
- Are there any changes you want to see in pedagogy, that is, how people teach in your field?
- What role do you want (or not want) generative AI to play in teaching and learning in your field?
- What do you think students should be able to do with AI? Why?

Closing Open-ended Question (5 min)

- Is there anything else you want to share about the future of education?

recognition), we transcribed recordings and manually corrected transcripts for accuracy. The final dataset consisted of 17 interview transcripts, annotated with speakers. We also had notes from during the interviews, including interviewer reflections, emerging questions, and preliminary observations about recurring themes across scholars.

Data Analysis

Initial Scoping Pass We regularly met during the interviews. Our analysis followed a reflexive thematic analysis process (Clarke and Braun 2017). We began with a team-level scoping pass in which each researcher reviewed and discussed the interviews they had conducted. This initial pass allowed us to identify broad areas of analytic interest, discuss emerging patterns across the dataset, and refine the kinds of phenomena we wanted to examine more closely. Rather than beginning with a fixed coding scheme, we used this scoping stage to orient and align the team on the thematic space we would code for and to surface early candidate themes.

Thematic Analysis Next, two researchers independently conducted a close analytic pass across all 17 transcripts. The transcripts were randomly divided between the two researchers, who independently developed open-ended codes based on close readings of the data. Example codes included: "*It might scale teaching*," "*AI is irrelevant to the* *human skill we're developing*, " and "*critiquing AI and critical thinking as part of using AI*." Because our analysis was inductive, we did not treat the coding process as a formal grounded theory procedure, nor did we seek to produce an exhaustive codebook for statistical comparison. Instead, codes served as analytic tools for identifying patterns, tensions, and recurring forms of reasoning across scholars' accounts.

The two researchers then met to compare codes, discuss similarities and differences across their interpretations, and develop broader analytic themes. Through iterative discussion, we refined these themes into a set of analytic claims about how scholars understood and negotiated GenAI in relation to their disciplinary, pedagogical, research, and institutional contexts. Following Hammer and Berland's framing of qualitative claims (Hammer and Berland 2014), we treat our findings as evidence-supported interpretations of consequential patterns in the data (not as frequency-based generalizations). Accordingly, we present claims that we formed from scholars' accounts and illustrate them with representative excerpts rather than using counts as the primary basis for significance. This approach to qualitative analyses is used across the social sciences (Leavy 2014), including broadly in human-computer interaction research (McDonald, Schoenebeck, and Forte 2019), and specifically in research on interaction with GenAI (Kapania et al. 2025; Solyst, Wilcox, and Madaio 2025).

Member Checking After completing the thematic analyses, we created a summary and outline of the results to send out to scholars for member checking, a qualitative analysis approach where researchers show outcomes from analyses and scholars can assess and provide feedback (Elo et al. 2014). We did not expect a large number of responses, given how busy the scholars were and that engaging in member checking was voluntary. We received responses from 6 of our 17 scholars. While part of member checking is to support validation of analyses, we also used their responses to inform a final audit of our analyses. When scholars offered concerns or emphases on their perspectives, we returned to the original transcripts to look for additional nuance, counter- or supporting evidence that could deepen the findings. For example, one scholar's response suggested that our initial phrasing did not capture a distinction they made between dismissing AI outright and refusing particular uses of AI under certain conditions, so we revisited the interview transcript and refined our interpretation and language we used to address this distinction. Some scholars also pointed out literature we could connect to in our framing of this research, which we took into account.

Positionality and Reflexivity Because this study used an interpretivist frame, our identities and lived experiences in relation to disciplines and GenAI were an essential factor on our design, conduct, and interpretation of interview data. We therefore share our positionality here and our reflexive practices for accounting for it in our analyses.

The first author is a postdoctoral researcher with a PhD in Human-Computer Interaction. Her experiences as an Asian American interracial adoptee from a single-parent household raised in the Midwest of the United States inform her views on technology's role in society; she often reflects on intersectionality, ponders how things are not always as they seem, and has a strong desire to contribute to efforts of social equity. Our second author is a queer, transgender, Danish and Chinese gen Xer and parent, raised in the Pacific Northwest. She is a professor of information and computer science who views her work as inherently transdisciplinary, drawing upon computer science, design, sociology, education, and learning sciences to invent new programming languages, theorize about computing, learning, and society, and to build political coalitions around educational justice and trans rights with youth and teachers, including in relation to the disruptions of GenAI. The third author is a married, cisgender, childless man of Ashkenazi Jewish descent; he is in his mid-40s and wrestles daily with a painful chronic illness. He is a full-time professor of computer science and has had experience leading a research group at a large technology company. He has a PhD in Learning Sciences, an interdisciplinary field rooted in education, cognitive science, anthropology, and design, and his design-oriented research deeply examines learning about AI and computer science, typically in relation to other disciplines.

As a team, we leveraged our diversity in identity, interests, and viewpoints on GenAI as an asset, using it to challenge each other with re-framings, create productive disciplinary tension in interviews, and make sense of the disparate viewpoints in our data.

Results

Across the interviews, one notable form of individual variation among scholars was clear: Some had exceptionally firm and rigorously reasoned stances about GenAI in relation to their discipline; some held multiple even conflicting stances, and even debated themselves mid-interview; and some refused to hold stances, instead calling for more time, observation, and experimentation. Given this variation, our results do not represent the specific perspectives held by individual scholars, but rather, the multiplicity of collective stances that scholars held, and how they were connected to their disciplines from an interpretive (vs. generalizable) standpoint. As we present the results thematically, we substantiate claims with quotes from participating scholars, and individual scholars may therefore appear in multiple sections.

Resistance: This is Not Meaning

One stance, often visible in critical perspectives on AI more generally (Bender et al. 2021), was that GenAI was simply not worth their discipline's time and attention, or even the world's. The linguistics scholar we spoke to, for example, described her discipline as particularly concerned with the meaning of language, which is inherently tied to both the speaker and recipients of language. In contrast, she noted:

> *And the thing that's super frustrating about the large language models and the way they're used is that they are still just models of the distribution of word forms and text, but everyone's pretending they're something else... So I think, yeah, I don't know too many linguists*

who are super excited about large language models. (P4, linguistics)

This stance stemmed from a foundation of her discipline's intellectual framework, that the word forms in language are not meaning. Similarly, the design scholar we spoke to felt that the way LLM's collapse history and time was fundamentally antithetical to transparency and meaning. He shared:

> *...with a large language model you have a completely distorted time perspective on things, right, you have hundreds or thousands of years of material you have like one snapshot in like 2022 where all of this stuff was aggregated, right, it actually violates so many pillars that we have in in good scholarship right like being transparent about who you are, where you come from, what you did, what you know, what you don't know, what position you have, what bias you have. (P6, design).*

This stance held, independent of the pragmatics of social and technological change, that because LLMs collapse and decontexutalize meaning, they are not worth our attention, or at least worth being highly skeptical of.

Over-hyped: This is Something But Not Everything Claimed

Another more skeptical stance some held was that while GenAI was clearly demonstrating some capabilities of value, it is far from a complete replacement for human knowledge and skill.

One version of this sentiment was that the particular skills in disciplines were fundamental and not within reach of GenAI. For example, the music scholar noted that GenAI could not support embodied, relational, or affective forms of practice, noting that musical experience involves feelings that GenAI continues to miss and simply could never replace:

> *This experience... compared to algorithmic composition, there's a felt response — a psychic vibration, and you feel someone look at you — there's another sense, to feel something. (P16, music)*

Others noted that technology was fundamentally irrelevant to learning and researching some phenomena. For example, P7 (classics) explained that students do not need a computer to learn about *"gladiators and ancient athletics and Archimedes and how to measure the circumference of the Earth. You don't need that here. And you don't need your phone."* Rather, some scholars argued that intentionally removing technology from both learning and scholarship, GenAI included, was part of focusing on disciplinary content.

Other scholars emphasized judgment and tacit expertise. P3 (law) suggested that AI could not replace skills such as *"developing a rapport with the client," "arguing persuasively,"* or *"exercising judgment with messy facts,"* which were key aspects of legal education. P4 (linguistics) further described *"critical thinking [as] not something that can be outsourced."* P9 (information) similarly noted that human experts better understand *"social stigma, distrust, and domain-specific [concerns that a machine may not] really understand."* These positions pointed to disciplinary skills and values that were fundamentally humanist, positioning their discipline as for and about human and social relationships.

Even scholars who were enthusiastic and optimistic about the possibilities of GenAI argued that disciplinary knowledge remained necessary. P10 (computer science) suggested that GenAI may reduce emphasis on *"coding mechanics,"* but students still need *"high-level concepts for understanding and designing software systems."* P8 (information) described GenAI as a *"Mario Kart accelerator pad,"* in that it was useful if students know where they are going, but harmful if they lack direction. In these cases, GenAI was useful only when students already had enough expertise to guide, interpret, and critique it, and that such expertise was exactly what their discipline was trying to foster.

Whereas the stances above spoke of basic and foundational disciplinary skills, others spoke of disciplinary excellence. For example, the economist (P1) observed:

> *I don't think AI can write a so-called 'top five paper' yet. So it's like, you know, I mean, I've occasionally heard people say in other fields, like, oh, you know, so-and-so has 100 papers, you know. (P1, economics)*

Similarly, P7, the classics scholar, said:

> *It's very, very, very easy to spot LLM learners, right? It's always mediocre, I'm always like, "you literally can do better," and so when we have our first meeting of 101 in the Fall, we all meet together as one big group, and it's a course about 120 people. And then we split it into three sections. But actually, the main thing is you all can write better. (P7, classics)*

Whether basic skills or advanced skills, scholars across disciplines felt firm that GenAI was neither replacing the foundations or the pinnacles of disciplines but rather the mean, mediocre center.

No Capacity to Know

Perhaps the most neutral stance we observed was scholars that had no stance out of principle: Because they had not had capacity to experiment with GenAI, they could not form an opinion about its impacts on their discipline.

Some noted that the simple lack of time in increasingly overburdened higher education workloads:

> *I think I'd probably do more with AI, but I don't have the bandwidth (P1, economics)*

> *It again feels so early that I feel like we're at a stage now where this is where I just feel like the best place, the best thing you could do with Gen AI is to like get the most experimental artists you can together and fund them. (P2, drama)*

> *Am I supporting the existing system of capitalism? Or am I also here to help challenge students to push them*

beyond and imagine a better future beyond the conditions of the capitalist rules of the game? I think a lot of computer scientists aren't necessarily thinking about the question because we're just too overloaded with students. (P5, computer science)

Whereas the stances above concerned time to use and understand GenAI's capabilities, others with deep technical knowledge of what LLMs are and are not lamented the great imbalance of investments toward GenAI and away from other possible futures that explicitly resisted GenAI:

One of my ongoing frustrations is that the resources, the sort of federal, state, and then university resources end up following corporate interests all the time. So, like, computer science gets the most money. Why? Because computer science gets the most money out in the corporate world. (P4, linguistics)

These scholars observed that even when disciplines provide unique stances from which to realize futures with and without GenAI, there was bias in who is given the freedom to imagine those futures (usually toward computer science and computing-centric for-profit industries).

Just a Tool, Let's Adjust

Another stance was fundamentally pragmatic, viewing GenAI as a new tool that was capable of streamlining some tasks, like any other form of automation, but also requiring shifts in how disciplinary skills, research, and teaching unfold.

One version of this stance was that GenAI could do some of the unimportant things in disciplinary work. The law scholar (P3) hoped it could help them to generate flow charts that students found helpful in reasoning about arguments discussed in class and synopses of book chapters that publishers wanted for marketing materials. The human-computer interaction scholar (P8) noted that it was helping his novice design students ideate in greater quantity, getting them outside of their fixed views on interaction design. The economist (P1) hoped it might free them from tedious and time-consuming administrative paperwork. And the music scholar (P16) viewed it as similar to a metronome, offering some basic scaffolding, but only to "*broaden and deepen our human-making – not an equal partner.*"

As a tool, scholars across disciplines argued that faculty and students needed to engage GenAI critically and intentionally in their research and teaching. P9 (information) described showing students hallucination examples early in a course to support early critical thinking and awareness of AI limitations. P11 (film) argued that students need critical thinking and AI literacy (especially focusing on evaluation) so they do not simply accept or reject AI without reflection:

The first step is definitely critical thinking because if you know how to look at something and not just either accept it or reject it without thinking about it, then that will help lead you in a lot of different directions. ... I think that as long as educators and students are thinking about ways to be responsible and intentional about learning and teaching, we'll be fine. (P11, film)

Similarly, P17 (chemistry) emphasized that students need to understand when AI is *"guessing based on probabilities,"* especially when different phrasings produce different answers. In other words, aspects of AI literacy like understanding of probability and non-determinism in AI could be essential to effective GenAI tool use.

Some scholars framed GenAI as a subject of learning itself, when their discipline was concerned with developing expertise *about* tools, given its increasing ubiquity and permeance in daily life. For example, P3 (law) used AI hypotheticals to teach legal reasoning:

I like to use AI and robot hypotheticals because that's what I study, and they're kind of fascinating. So, you know, can you sue when blank or should this AI related activity be subject to strict liability or negligence? (P3, law)

P12 (HCI) emphasized in courses *"to have students be sort of critical consumers of the tech, you know, critical consumers, users of these technologies, and critical designers of these technologies"* by asking where systems come from, who benefits, and how they affect equity and human flourishing. P2 (drama) argued that it was important to *"bring students into very creatively critical engagement with AI in the same way that, say, one would be thinking about site-specific work or community-engaged work."*

Throughout, scholars who took this pragmatic stance of GenAI as a tool emphasized a need for experimentation to understand the strength and weaknesses of the tool. Yet scholars also described barriers to experimentation. P13 noted that scholars may be experimenting privately but not sharing because of fear and judgment in academia:

I see a lot of fear. It's like if I do that, then the students are going to say that's inappropriate. Or if I do that, my colleagues are going to think I'm not doing my job. Or like, what if I give students misinformation? So I feel like when I talk to people, I seem to notice that there is a lot of experimentation going on, but it's not being shared very much because there's a lot of shame or concern about what other people would think. (P13, HCI)

P14 (psychology) observed that students often have limited ideas about AI use beyond basic prompting, describing students as:

...basically zero shot prompting of like front end LLMs and not much more than that and not particularly sophisticated prompting and not really not going much beyond just asking a question to an LLM, so that's something we know we have to work on. (P14, psychology)

Experimentation was seen as critical to support students in learning how to really harness the affordances of GenAI.

Some scholars also described changing their own views over time as tools improved and as their use of them improved. P17 (chemistry) mentioned, *"I think if I would have answered this question like a year ago, I'd have been like, it's garbage. We can't use like this. There's no place for it.*

But I have totally changed my mind about that ... Just things have accelerated and gotten better and better."

Some scholars also connected experimentation with broader forms of *transdisciplinary convergence*. Rather than viewing experimentation as a way to understand the role of GenAI disciplines as they exist currently, some scholars described it as a way to test how disciplinary boundaries may become more flexible. For example, P2 (drama) brought up how theater skills already *"traverse a lot of different things ... lighting, architecture ... installation art,"* and more. He was especially interested in how GenAI could play a part in building new connections between domains and sub-domains and how creative processes may change when cycles of iteration become faster. He argued that the way to figure out GenAI's possible meaning for students, and for the academy more broadly, should be through collective, situated experimentation:

> *But the thing that I do know right now within the educational context is that the best thing we can do right now is to bring students into very creatively critical engagement with AI in the same way that, say, one would be thinking about site-specific work or community-engaged work, or in cross-cultural kinds of collaboration. And the critical skills, and the conceptual skills, and the technical skills required to develop questions, ways of interrogating, ways of partnering with, ways of exploiting, ways of fucking with, you know like I think those critical creative skills will be the things that will be very durable.*

P17 described an enthusiasm for GenAI's potential to help researchers with *"finding connections between very different ideas and concepts,"* that were all connected to chemistry, including biology and physics. Further, they argued that doing so was critical to the future of GenAI:

> *We are ... building models for chemistry, like for chemistry research. And I think the danger there is that that model will only know that information. And so having something that's broad enough or smart enough that it can say, 'Hey, you're working on this, but you know people over here in physics have been thinking about this concept, and it seems like there's maybe a connection here. What do you think?' I think that helping people see that there are bridges and similar ideas in very different spaces could be immensely helpful and could be a really useful thing for a very big AI model. (P17, chemistry)*

Across these accounts, experimentation was about innovating how to leverage a new tool and about further probing where disciplinary concepts and practices may converge.

It's Transformative in Good and Bad Ways

The final stance we observed through interviews was that GenAI was disruptive, transformative, and unignorable, and that disciplines needed to urgently evolve.

Some of these stances came from places of optimism and curiosity. For example, P2 (drama) suggested that GenAI is a *"completely new ... technology ... process and hardware and interactive, you know, form, literally, it's actually totally fascinating."* Additional sentiments that characterized GenAI as emerging pointed out how, while academia may be skeptical, it's certainly not all bad, and more important, there's opportunity to explore use cases. For example, P11 (film) suggested there needed to be more nuanced thinking about using GenAI: *"I would love for it to be something that more people are thinking and talking and writing about, because right now, most of what exists that I've read, at least in the field, is ChatGPT is bad, and here's why."* The design scholar (P6), while holding skeptical stances, also imagined its possibilities:

> *It's a new archive overall system that pulls things together, right? It's a new file organization ... An interesting queryable connective system that makes you find things you're not looking for, right? Because it uses pattern detection, and it's powerful. It's great. And it might be greater and better than anything else. And sure, it could control everything, but it could exactly do the opposite, right? You think about the decentralization that the internet created, right? And the idea that, you know, you cannot control it because it's networked and everything has binds, right? AI has a promise. (P6, design)*

Some of this optimism was specifically in the context of disciplinary teaching and learning. Some saw GenAI as useful for scaling feedback, supporting self-directed learning, and helping students practice. P14 (psychology), who also held a professional development leadership position for bachelor's students, regularly thought how students might *"use AI to learn on their own ... before engaging more deeply with faculty."* P15 (philosophy) suggested that AI could *"help students practice responding to objections in a lower-stakes setting."* P13 (human-computer interaction) imagined GenAI helping students with *"ideation so instructors could focus [more] on ... guidance,"* like helping students choose among ideas and understand design implications.

Several believed that because GenAI had reached a particular level of capability in their discipline, it was necessary to restructure curricula. The economist (P1) suggested, "*I think that that would be kind of a cool, a great kind of move for the field to make things more expansive at the kind of introductory level.*" The film scholar (P11) noted, "*Is this something that we want to teach? And if so, to what extent and in what ways? ... I think that it would be good for us to make a decision in some direction about how we want to be invested in it and engaged with it.*" Similarly, P5 imagined:

> *Because you're going to be using GenAI in the future, because it's going to be relatively easier to implement the things you want to do ... can I actually picture a world that is different from what, you know, now that I have all this extra time, can I actually spend that in creative and productive ways? (P5, computer science)*

While these stances indicated an eagerness to re-examine their discipline's foundations, they also pointed to unignorable disruptions in teaching. Scholars were especially concerned about overreliance. P5 (computer science) warned that GenAI could increase students' overconfidence, such that *"it can contribute to that overconfidence too, in terms of thinking about like, well, there are already all these complicated rules, and you can very easily convince yourself that you know the rules."* P12 described students relying on AI so much that they became difficult to redirect midway through a course:

> *Maybe 50 to 75% of students show up for class. And the course evaluations are just as good. And I think the class is just as good, if not better. But there's like a different engagement. And I don't know. I don't quite know what's causing that. And then there's a couple of students that are, again, I think they're relying on AI so much. Every once in a while, I'll catch it early enough to fix the problem. and say this is not going to go off. But sometimes I just don't catch it until about halfway through. And ... the students already kind of lost it for the class. (P12, HCI)*

Relatedly, P15 (philosophy) described cheating as *"demoralizing"* for scholars and harmful for students' *"self-respect."* P16 (music) worried that if students outsource the *"creative kernel,"* the loss could be significant: *"At the end of the day, they're the ones losing out, of finding the idea within themselves and their own questions about finding meaning in the world."* Across these examples, overreliance was an academic integrity problem, and furthermore, it was a threat to learning to develop a disciplinary identity.

This shift in student behavior also required scholars to urgently reconsider what assignments are meant to assess. P9 (information) told students that AI-generated output is now *"the minimum bar."* From this view, students need to demonstrate insight beyond what GenAI can produce. In particular, several scholars suggested that introductory courses had some of the largest changes. P5 (CS) argued that intro programming may shift because students will use GenAI to implement code, *but* students will still need fundamentals to understand what programs do and evaluate AI-generated output, but this further opened opportunities to focus on bigger questions:

> *Programming is like a central part of computer science and academia, whether we like it or not ... that's going to change with generative AI I think the things that you will want to teach in an intro programming course ... I'm thinking it may not change as much as vibe coding ... it's going to be relatively easier to implement the things you want to do, [so] it becomes a bigger question [of], why are we doing this? And what feature do we actually want? And is this actually helpful? And can I actually picture a world that is different from what, you know, now that I have all this extra time, can I actually spend that in creative and productive ways? (P5, CS)*

Assessment was a major concern across a number of disciplines. P12 (HCI) mentioned how their course was *"starting to feel like it's breaking"* due to students using GenAI to do the *"selection of tough readings"* that were a key part of the coursework. P17 (chemistry) further argued that standard problem sets may become *"almost impossible"* to use as evidence of learning because students can use AI tools to generate answers. P15 (philosophy) also noted that AI use could complicate how scholars evaluate writing, especially when stylistic fluency is not the main learning goal. P13 (HCI) suggested shifting assessment toward students' ability to explain and defend their work in person, rather than grading only reports that GenAI could help produce:

> *So I feel like then if they leverage generative AI to try to imagine, and then they have a better understanding of design implications, but maybe they cut corners, and they do it, then we should change our grading practices. Then we should say, now I want you to present them. I'm not going to grade you on the report. I'm not going to grade you on the part generative AI could give you. I'm going to grade you on your capacity to stand in front of me right now and explain them as design implications. (P13, HCI)*

Together, these comments suggest that GenAI is forcing scholars to clarify what they actually want students to learn: producing an artifact, understanding it, critiquing it, or defending it. And more generally, it was leading some scholars to reconsider the foundational skills of their discipline.

Discussion

We return to our research question: *What are scholars' perspectives on how their disciplines will or should change (if at all), and what implications does that have for higher education research and teaching?*

Across our interviews, we found five distinct stances held by scholars across academia, which we might broadly summarize as resistance, skepticism, uncertainty, incrementalism, and transformation. Some held multiple of these stances and even shifted between them in our conversations, sometimes based on topic or context and sometimes because of an openness in their perspectives. There was no emergent mapping between disciplines and these stances; rather, our interpretation is that which stances a scholar held was intricately connected to the substance of their discipline, whether their attention was on the disciplinary edge of knowledge or its foundations, and to what extent they examined GenAI through a pragmatic lens. Finally, while all scholars spoke about research and teaching in distinct terms, they also spoke about them as deeply interconnected, with changes in teaching provoking changes in disciplinary conception and changes in disciplinary possibilities provoking changes in learning goals. Some even positioned learning contexts as places for disciplinary experimentation with GenAI.

Across these findings, there was also a strong thread of humanist values (Davies 2008) in every conversation but in different ways. Some centered the particular responsibilities of this moment, in this world, and viewed GenAI skeptically through their disciplinary lens, seeing little for it to offer the world's broader challenges (e.g., P7, classics: "*Because it's not thinking, right? . . . Why would I use something that's worse than me? I'm a really good thinker, and I'm a professional thinker and a professional writer*"). Others, particularly designers and artists, viewed it through the lens of reason and free inquiry, wondering about the possibilities GenAI might offer for new forms of human experience and discovery (e.g., P6, design: "*Generative AI is like a moped. And you are a teenager . . . And now that you can go into the other village, you can meet people there, and you can see how things are going.*" And others still saw GenAI through a lens of care wondering how GenAI might help or hurt students' growth and transformation, and their role in supporting it; e.g., P17, chemistry: *"I hope it doesn't replace me, the educator, because that's everything. I really hope it doesn't replace TAs . . . as budgets get squeezed, the temptation to replace human labor with AI is obvious."*

While our findings reveal the intricacy with which disciplinary viewpoints interact with GenAI as a technology, they also reveal quite clearly that all of academia is wrestling with its meaning. Every scholar noted the disruptions to teaching and assessment caused by GenAI, as well as how their stances shaped their response. And most scholars noted just how little time they had to invest in responding, given their ever increasing responsibilities. This calls back to Berg and Seeber's critiques of higher education's neoliberal focus on scholarly "productivity" and "efficiency" and their call for more "slow professoring" that centers reflection and dialogue (Berg and Seeber 2025). Such calls are, of course, in stark tension with the often stated efficiency goals of adopting GenAI in higher education. And ironically so, as many of the scholars in our interviews wanted that time for reflection and dialog to make better sense of how and whether to use GenAI in their work.

Comparing these findings relative to prior work on GenAI in higher education, we find that, indeed, disciplines vary on multiple dimensions, from response to technological change, sentiment, adoption, and values. This is itself not surprising, as prior work has clearly demonstrated that disciplines are multifaceted in their response to technological change and GenAI. However, our particular findings begin to demonstrate *why* they vary: Because individuals within a discipline hold particular commitments to knowledge and ways of knowing that are sometimes in tension with pragmatic concerns of disciplinary skills. Consider the most skeptical scholars in our interviews: Their resistance was not due to the particular facts of what GenAI can or cannot do, or how that might change the world, but rather, *whether* it should, given what we know, and given our broader moral commitments to society. In the same way, scholars who approached GenAI from a utilitarian lens did not embrace GenAI because of hype, but because they saw it offering specific benefits and specific costs. Across the set of interviews, variation stemmed from how different individuals weighed moral and pragmatic concerns, and that weighing was influenced by the disciplinary knowledge, values, and norms that informed their viewpoints.

Ultimately, this small interview study is only a sample of stances held by expert scholars at one institution, with findings that may be interpreted as interpretive versus generalizable. We do not claim that they represent all stances held or even that the stances are persistent. Our findings suggest that future work, if it were to address these limitations, might look to substantially different cultures of higher education, or disciplinary and transdisciplinary iconoclasts, to understand what *new* disciplinary cultures are emerging from the tensions imposed by the volume of attention on GenAI. Such work might reveal how and why disciplines are changing, and whether these changes are driven by disciplinary values, or the broader incentives of efficiency and productivity.

Our findings raise several questions about how current disciplines, as well as industry and governments, might invest to better understand the possibilities of GenAI within and across disciplines. This might involve collaborative, value-aligned partnerships across institutions to understand both possible innovations, but also creative forms of resistance. Governments might also consider that the range of regulatory guardrails for GenAI might be best explored across academic disciplines, rather than just in computing or policy, recognizing that artists and other creatives have at least as much to contribute to discovering this landscape as scientists and engineers do.

Finally, we end by observing the very clear and unequal distribution of time and resources for all of this work across disciplines. Higher education institutions are faced with the challenge of providing time and funding for faculty to experiment with possibilities for reshaping their disciplines with GenAI technologies, but both are increasingly scarce. Across the interviews, we were struck by how most curious, optimistic, and expansive visions of what disciplinary and educational changes GenAI could support came not from faculty in science, technology, engineering, or mathematics (STEM), but from faculty in the arts in this study. This is inverted from most governmental efforts, which attempt to spur innovation in AI through computer science and STEM more broadly, through a workforce preparation lens. While growing the economy and its workforce are worthy goals, our interviews suggest that it would also be worthwhile for governments to support the arts and cross-disciplinary communities that engage in artistic thinking.

In the absence of federal support, the institution we studied invested in some transformation. After the interviews concluded, a new Vice Provost of AI was appointed, and some external funding was structured as internal grants to support experimentation and transformation. Additionally, some academic units made one-time investments in faculty summer salary to build frameworks to support faculty experimentation in teaching, while also reckoning with the underlying weaknesses in current pedagogy and assessment that GenAI had exposed. Our results suggest that these kinds of investments, and others, might be essential to re-imagining both research and teaching, including standpoints of both radical embrace and resistance. But history would also suggest that they are not likely to be ample enough or equitably distributed across disciplines.

We hope that we can collectively find ways, in the U.S. and globally, to invest in thoughtful futures with — and without — GenAI, to support human flourishing. We hope this study of disciplinary diversity helps us imagine how we might do that together.

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