

“It’s Not Just a Technology, but a Team Member”:
Generative AI Use Among Students in CPED Doctor of Education Programs

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ABSTRACT

The rapid adoption of generative artificial intelligence (genAI) in higher education has created both opportunities and challenges for Doctor of Education (EdD) students and their institutions. While EdD students increasingly integrate genAI tools like ChatGPT into their academic work, their usage patterns, ethical decision-making processes, and critical evaluation strategies remain poorly understood. This study explored how EdD students in Carnegie Project on the Education Doctorate (CPED) institutions use genAI and how those practices relate to institutional guidance and faculty-student relationships.

Guided by a conceptual framework of metaliteracy and generative AI literacy, this study explored genAI use across cognitive, behavioral, affective, and metacognitive domains. Survey data were collected from 190 EdD students across North American CPED institutions, followed by four focus groups with 20 participants. The survey measured usage patterns, ethical awareness, and evaluation strategies, while focus groups provided deeper insight into decision-making and help-seeking behaviors.

Findings revealed that expectations for generative AI use and acknowledgment were often unclear across institutions and programs. In the absence of specific and consistent guidance, students developed their own personal guidelines for use, grounded in scholarly values such as originality, expertise, and voice. Participants described using generative AI not only as a tool for specific tasks, but as 24/7 academic support. Many reported turning to it first for feedback, clarification, and idea development before reaching out to faculty or peers, though they described varied approaches to transparency, often shaped by concern about how their use might be perceived. Although students

expressed confidence in their ability to evaluate AI-generated output, their descriptions revealed uneven technical understanding.

These findings informed the *Shifting Pedagogical Interactions and Relational Instructional Ties (SPIRIT) Model* that illustrates how institutional ambiguity and identity-driven decision-making contribute to the integration of genAI as frontline academic support. As students increasingly use genAI for tasks traditionally associated with faculty mentoring and guidance, the sequencing of faculty-student interaction shifts. Rather than replacing faculty mentorship, these patterns suggest a reorganization of academic support pathways within CPED-aligned doctoral programs. The study concludes with implications for doctoral program design and future research in AI-mediated higher education.

DEDICATION

To my son, Kellan:

You can achieve the goals you set for yourself.

To my husband, Mike:

Thank you for being the supportive partner I always dreamed of.

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CHAPTER 1

INTRODUCTION AND PURPOSE OF THE STUDY

Introduction

The sudden launch of *ChatGPT* in November 2022 was an incredible technological disruption. Over one million people experimented with it over its first five days, and 100 million tried it out within two months (Lambert & Stevens, 2023; Marr, 2023). Unlike previous technologies which took more time to gain traction, such as the slow increase in internet use or adoption of mobile phones, generative AI use exploded, and it has transformed how professionals and students approach their work (Black & Betts, 2025; Scott-Branch et al., 2023). In higher education, generative AI has sparked both concern over academic integrity, as students may complete entire assignments with a single prompt, as well as excitement about its potential to speed up routine tasks (Werse & Smith, 2025). Educational leaders, faculty, and students are grappling with how best to use (or not use) this new tool that emerged seemingly overnight (Buss et al., 2025). This study will investigate how Doctor of Education students utilize generative AI in their academic work in order to inform more effective policies as well as training approaches and implications for doctoral education.

Larger Context

When OpenAI released *ChatGPT* to the public in late November 2022, it quickly went viral (Marr, 2023). *ChatGPT* enthusiasts posted what they produced on social media, prompting others to try it for themselves. The high visibility of *ChatGPT*'s potential led to over one million users signing up to use the tool in just five days. As *ChatGPT* exploded in popularity, an AI arms race began. Competitors scrambled to

release their own LLM chatbots, like Google's *Bard* (now *Gemini*), Microsoft's *Copilot*, *Claude*, and others (Rudolph et al., 2023). The technology that underpins these chatbots is evolving at a breakneck pace. Since its initial release in November 2022, eighteen more versions of *ChatGPT* alone have been released (*ChatGPT*, 2025).

ChatGPT and other popular generative AI tools including *Claude*, *Copilot*, and *Gemini* are examples of large language models (LLM), a type of artificial intelligence system trained on vast amounts of digital text. By processing text, an LLM model “learns” the statistical patterns of language use, including how words, sentences, and concepts typically appear together. This learning enables an LLM to generate largely coherent and contextually appropriate text in response to user prompts, though what it produces isn't always factual (“Large Language Model,” 2024). Additionally, the default for many of these generative AI tools is to further train the underlying LLM on the information and documents that users feed into the tools (Crompton & Burke, 2024; Sabzalieva & Valentini, 2023). This means that personally identifiable information such as names, employers, Social Security numbers, and home addresses become part of the training corpus, making it risky to enter personally identifying information.

Whereas a search engine like Google presents a list of discrete websites in response to a user's search terms, an LLM like *ChatGPT* functions as if it is a person responding to the user's queries (Lee et al., 2024). Rather than just search for a set of keywords, users can ask questions in natural language and receive detailed replies. With Google, users had to scan a long list of results, including sponsored results and advertisements, evaluating each resource for what they needed. With *ChatGPT*, rather than a list of sources, users are presented with a generated “answer” as if it is

unimpeachable fact, with no obvious advertisements or clutter. However, *ChatGPT* and other LLMs often hallucinate these “facts.” These *hallucinations*, unique to this technology, refer to those times when a LLM’s output is false or misleading (Crompton & Burke, 2024). An example of hallucinations is LLMs’ tendency to create citations for scholarly articles that don’t exist (Chen & Wang, 2025). As LLM outputs are based on statistical modeling stemming from their training corpus, there is no true thought behind these answers, and outputs can be entirely nonsense.

And yet, hallucinations have not dimmed Americans’ enthusiasm for generative AI. Generative AI chatbots are being used as religious advisors (Jackson, 2025) and therapists (Chapin, 2025). They serve as the perfect romantic partner (Hill, 2025a) and are also used to write online dating profiles and communicate with prospective real-life dates (Sussman, 2025). They write abstracts of scholarly publications, entire scholarly articles, and even letters to editors of scholarly journals (Kolata, 2025). They are being used to write books, creating entire catalogs for invented publishing houses (Dankowski, 2025). Furthermore, they offer up detailed guides to performing criminal acts (Burgess, 2025), give instructions for devil worship (Shroff, 2025), foment conspiracy thinking and encourage paranoid delusions (Hill, 2025b), and they also, most tragically, instruct children to kill themselves (Payne, 2024).

It’s clear that generative AI chatbots are easily anthropomorphized, with entire platforms such as Character.AI dedicated to offering chatbots that serve as conversation partners, friends, and confidantes. Indeed, there is evidence that generative AI companies purposefully create anthropomorphized chatbots (Ji, 2024; van Es & Nguyen, 2025). For students, chatbots can both provide emotional support, as if it were a friendly instructor,

and help with many aspects of academic work (Jin, 2025). Students use LLMs for all stages of the writing process, including brainstorming, outlining, drafting, and revising (Buss et al., 2025; Crompton & Burke, 2024). Additionally, hallucinations can be a feature, not a bug, when brainstorming (Chen & Wang, 2025). In particular, these generative AI tools excel at helping writers overcome writer's block (Ramaul et al., 2024). Younger adults have generally been quick to adopt new technologies that will increase their productivity, particularly in regard to research and writing assignments (Kennedy & Funk, 2016). They are using generative AI alongside Google for their information needs and don't differentiate between the two (Gruenhagen et al., 2024). As of 2025, 85% of undergraduate students reported having used generative AI to assist with coursework in the last year (Flaherty, 2025). Doctor of Education students are regular users of generative AI as well (Buss et al., 2025; Harris et al., 2025; Minimo & Bueno, 2024). Yet, students are unclear where the line is drawn between generative AI use and academic integrity violations (Buss et al., 2025; Chen et al., 2024; Harris et al., 2025). Additionally, students are overly trusting of generative AI technology and are poor judges of output accuracy (*Listening to Learners*, 2024).

The Need for Generative AI literacy in Higher Education

As *ChatGPT*'s popularity soared, *ChatGPT* gained an early notoriety among faculty as a shortcut for students to write discussion posts and other writing-based assessments (Gruenhagen et al., 2024). Faculty and student affairs officers at colleges and universities worldwide scrambled to catch up and understand how students were using these tools (Nzenwata et al., 2024). Now, generative AI guidance for syllabi is still being drafted and debated, and many faculty are still unsure what policies to set and even more

unsure of how to enforce them (Kumar & McGray, 2024). Yet, a ban on using generative AI tools is impractical. Even if generative AI is banned by faculty, 51% of students stated that they would use these tools anyway (Bharadwaj et al., 2023, p. 19). In response to these concerns, companies like Turnitin began developing “AI Detectors” to assist faculty in preventing academic integrity violations among their students. Turnitin widely states that their AI detector has an error rate of 1-2% (*Why you should use caution with AI detectors*, n.d.). However, Turnitin’s own publications show that the error rate is closer to +/- 15% (Turnitin, 2023). This indicates that a percentage of students are being falsely accused of academic integrity violations. AI detectors are unable to reliably detect AI-produced content, and worse, frequently flag original content as being produced by AI (Al-Shabandar et al., 2024; Batista et al., 2024; Weber-Wulff et al., 2023). Meanwhile, more students than ever are using generative AI. Student use of generative AI has grown steadily since 2023, following the release of *ChatGPT* and the wider adoption of similar tools. In 2023, only 14% of students reported using generative AI frequently (defined as daily or weekly), but that number more than doubled to 36% in 2024 and rose further to 42% in 2025 (Shaw et al., 2025).

It is clear that students would benefit from guidance in ethical and critical usage of generative AI. However, generative AI technology is moving faster than the pace of scholarly research and published studies to assist faculty in guiding students are scarce. It’s only relatively recently that articles on generative AI are being written with an educational focus due to the pressure of students’ *ChatGPT* usage on educational contexts. From 2021-2023, following the launch of *ChatGPT*, there was a spike in articles written by academics in educational disciplines. In this timeframe, 28% of articles

on artificial intelligence had a first author with an education affiliation, which was more than any other subject (Crompton & Burke, 2023).

This shows that scholarship is developing on the use of generative AI in educational contexts, and more recently, generative AI literacy. AI literacy is defined “a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace” (Long & Magerko, 2020, p. 2). AI literacy is one key to guiding students in using generative AI responsibly in their academic studies, though it may be best combined with metacognitive skills (Gruenhagen et al., 2024). With the lag in scholarly publishing and the impact of generative AI on higher education, surely more articles focused on these topics in educational contexts are in the pipeline, including entire issues devoted to the topic. The CPED journal *Impacting Education* devoted an entire issue to generative AI in early 2025 (CPED, 2025a). But as generative AI technology only seems to accelerate, it’s likely the scholarly publishing cycle will trail behind. Meanwhile, there is a clear need to explore how students are using generative AI in order to better guide them in ethical and critical usage.

Local Context

The setting for this action research study is the member programs of the Carnegie Project on the Education Doctorate. The Doctor of Education (EdD) degree is intended to be a degree for practitioners that will apply what they learn in their professional contexts, in contrast to typical PhD programs in education which prepare students for positions as tenured faculty in colleges and universities. More than 150 Doctor of Education programs are members of the Carnegie Project on the Education Doctorate (CPED). CPED was

conceived as a grassroots effort in 2007 to better define the EdD degree, particularly in relation to the education PhD (Perry, 2015). Faculty in EdD programs participate in CPED's design work. "The goal of the consortium has been for shared learning to take place at the national level but for the design process to evolve at the local level" (Perry, 2015).

CPED members share the goal of creating high-quality EdD programs that develop practitioners and leaders who will address challenges in educational settings (2022). CPED members believe that "the professional doctorate in education prepares educators for the application of appropriate and specific practices, the generation of new knowledge, and for the stewardship of the profession" (2022a). CPED member programs develop their EdD programs according to the CPED Framework, which is a set of guiding design-concepts which overall focus on practical application (CPED, 2022a). Students in CPED programs develop identities as *scholarly practitioners*, "individuals who have the knowledge, skills, and dispositions they need to solve the problems of practice they routinely encounter" (Zambo et al., 2015). Students in these programs ultimately create a *dissertation-in-practice*, which focuses on addressing real-world problems of practice ("The CPED Framework", 2022). While CPED programs adhere to common principles and design features, they remain distinct in how they implement these concepts (Zambo et al., 2015). For example, Arizona State University's program, housed in the Mary Lou Fulton College for Teaching and Learning Innovation, focuses on action research, with the goal of developing students to identify as not just scholarly, but scholarly and *influential* practitioners: "individuals who have the abilities they need to lead change and improve local situations" (Zambo et al., 2015, p. 233).

EdD students are unique compared to students in other doctoral programs. Students in EdD programs tend to skew older than those in doctoral programs in other disciplines (Choi et al., 2021). Fifty nine percent of students in CPED EdD programs are between 30 and 50 (Carnegie Project on the Education Doctorate, 2020). In other programs and disciplines, students tend to seek a doctorate more quickly after completing lower degrees (Choi et al., 2021). EdD students, upon entering an EdD program, generally already have over a decade of professional work experience in the education field (Butin, 2010). Because they are already employed in a professional role, EdD students often choose this degree in order to develop as scholar-practitioners (Buss, 2019; Nyunt et al., 2023). Though, “doctoral students enter their advanced studies with diverse intentions and motivations, ranging from deepening one’s engagement with a particular research interest area to career change or advancement” (Choi et al., 2021, p. 92). EdD students typically study while working full-time, balancing schoolwork with professional responsibilities and, often, raising a family, as 45.4% of students have a dependent under 18 at home (Geesa et al., 2022; National Center for Science and Engineering Statistics, 2024). Because they do have responsibilities in addition to studying, EdD students enrolled at least one institution use generative AI as a time saver, as well as to help them get unstuck (Buss et al., 2025).

Role of the Researcher

I have a dual role: I am both the researcher for this study as well as a student in a CPED member program. I fit the profile of the average EdD student. I’ve worked in education for over 10 years, I returned to school to pursue an EdD nine years after completing my last degree, I’m in my 40s, and I’m raising a young child. I have a

professional, though atypical, role in education as a freelancer and part-time graduate instructor. Professionally, I train educators (mostly librarians) in online pedagogy and in generative AI use in educational contexts, and I freelance as an instructional designer for libraries and higher education. I also teach part-time in a learning design and technology graduate program, and previously taught full-time for six years in a similar program. Many of my own graduate students use generative AI in their work, yet do not acknowledge its use, and I am unsure of how to teach my students how to use generative AI, especially when my courses offer little time to do so.

I matriculated as a student in Arizona State University's (ASU) EdD program in January 2023, only two months after *ChatGPT*'s original release. In my experience in the program, I have received little guidance on use of generative AI in my courses or from my faculty directly. Upon reviewing the syllabi for my courses, about one third of the syllabi had statements on the use of generative AI by students. The statements that were included were brief, about a paragraph, and stated that I should cite any use of generative AI tools. This limited guidance left me uncertain of the ethics of using generative AI, and I was unclear whether the statements meant that any use, even brainstorming, was required to be cited. As a student, I would have liked more guidance on when and how to use generative AI tools. This uncertainty, combined with the rapid development of generative AI tools and my own professional experience, ignited my curiosity in exploring how students use generative AI as part of their academic studies in order to better understand what kind of training or guidance would be most helpful.

Problem of Practice

In the relatively short time since *ChatGPT* was released, generative AI tools have exploded in variety and availability. College students in particular have emerged as enthusiastic users of generative AI (Bharadwaj et al., 2024), as have Doctor of Education students (Buss et al., 2025; Harris et al., 2025) but students often lack understanding about how to use it ethically (Gruenhagen et al., 2024). Research conducted in the local context corroborated these findings, confirming that EdD students at ASU have concerns about ethical usage. A recent study was performed by ASU's Doctor of Education faculty to explore how students in the program were using generative AI. Buss et al. (2025) surveyed students and conducted several interviews to learn more about what generative AI tools they were using, how they were using them, and what their concerns were related to generative AI. They found that students were using generative AI as a time saver: using it to check their grammar or get their secondary research started. They also found students were using it for "getting over the activation barrier," to help them get started with a task, for instance, by brainstorming or outlining, or to help them better understand a particular reading (p. 44).

Yet, while the student participants were adopters of generative AI for their academic studies, they expressed concern about limited confidence in their ethical use. Participants stated that they wished faculty would "guide students on how to use [generative AI] ethically" (Buss et al., 2025, p. 45). The faculty-authors expressed that "providing guidelines about ethical use of AI is of the utmost importance to ensure students do not hesitate in using AI and that they do not use it inappropriately" (p. 47). One strategy to meet this need is for individual faculty to provide guidelines and specific

instructions for generative AI use in their courses. Another way is for the faculty, or more likely, the program or larger institution, to offer students formal training on critical and ethical usage of generative AI.

The findings from Buss et al. (2025) had similarities with my own findings from a preliminary study in which I interviewed higher education professionals at ASU about students' use of generative AI. The six ASU educators that I interviewed, which included faculty, a librarian, and instructional designers, expressed an array of concerns about students' use of generative AI. Participants expressed concerns about academic integrity and students' ability to evaluate output as novices in a subject. One of the interviewees stated that students have a less-developed "bullshit meter" than their faculty and thus have greater difficulty judging the accuracy and relevancy of generative AI output. Several of the participants agreed that there is a need for both faculty and students to be trained on the design and functionality of generative AI, and how to use these tools critically and ethically.

The problem of practice is that EdD students are increasingly using generative AI in their academic work. Yet, students struggle to use these tools ethically and critically. Doctor of Education students' usage of generative AI tools is not well understood, necessitating exploratory research in order to better inform how to guide student use.

Purpose of Study

The purpose of this study is to explore how doctoral students at CPED institutions use generative AI as part of their academic studies. Findings will inform generative AI policy as well as best practices in guiding student use.

Research Questions

To that end, this study will answer the following research questions:

1. What generative AI tools do doctoral students in CPED institutions use in their academic work, and how do they make decisions about when, how, and to what extent to use these tools?
2. What concerns do doctoral students in CPED institutions have regarding academic integrity, ethics, and the responsible use of generative AI in academic work?
3. What factors influence doctoral students' ability to critically evaluate generative AI output as part of their work in CPED EdD programs?

Summary

As generative AI was released in late 2022 and continues to evolve quickly, there is limited scholarly literature on doctoral students' use of generative AI. Through this study, I will contribute to the scholarly body of literature on how doctoral students are using generative AI in their academic studies. This study will offer implications for how CPED member programs' leadership and faculty might more formally guide and support their students in use of generative AI.

CHAPTER 2
LITERATURE REVIEW AND CONCEPTUAL PERSPECTIVES
GUIDING THIS PROJECT

Introduction

The advent of generative AI technology in late 2022 was a major technological upheaval in higher education. Three years later, both educators and students are still learning the best ways to use (or avoid) generative AI technology, including how it complements or differs from other technologies. Because generative AI can be used for a variety of academic purposes, including research, learning, and writing, the goal of this study is to offer some insight into how Doctor of Education (EdD) students are using it in order for educators to set policy and plan training (Note: Throughout this chapter, the word “students” refers to EdD students in particular unless otherwise indicated).

I have played a variety of roles in higher education and have a stake in better understanding generative AI usage. I have years of experience as an instructional designer, as graduate faculty, as an academic librarian, and now as a doctoral student. As an instructional designer and faculty, I’ve had to adjust course designs to account for graduate students’ generative AI use. As an academic librarian, I was an information literacy instructor that taught students how to find, evaluate, and use information sources. As a student, I’ve used generative AI to help me learn, to assist in secondary research, to advise on research study design, and to help me with writing. The lens of my professional and student experience leads me to be especially interested in *information behavior* as relates to generative AI, because this new information technology is both an elaboration on as well as a departure from the information retrieval systems that precede it.

Information behavior is defined as the “many ways in which human beings interact with information, in particular, the ways in which people seek and utilize information” (Bates, 2017, p. 2074). This study focuses on doctoral student information behavior as relates to their academic goals or coursework.

Academic use of generative AI is an *information behavior* (Huvila & Gorichanaz, 2025; Sebastian, 2025). Generative AI is a different and more flexible tool than the more rigid information retrieval systems like library databases and search engines. Generative AI can perform tasks, play roles, and facilitate a variety of information uses including evaluating, summarizing, analyzing, editing, and writing, whereas traditional information sources like library databases merely offer information retrieval. While generative AI has an unfortunate tradeoff of hallucinations (among other major flaws), its flexibility and ability to be queried using natural language is enticing enough to learners to choose to add this tool to their academic toolkit, and often, to use it in place of more credible sources (Zhai et al., 2024).

Because doctoral students use a variety of information sources and tools including generative AI to accomplish their academic goals, I will argue that the framework of metaliteracy offers a robust set of concepts to understand and describe doctoral students’ information behavior because it takes a high-level perspective of information behavior (Mackey & Jacobson, 2014). Metaliteracy describes the behaviors, dispositions, and roles necessary for a learner to be an ethical and critical consumer and producer of information taking a high-level perspective of information behavior (Mackey & Jacobson, 2014). When seeking information, learners regularly switch between a variety of information sources, including library databases, web-based resources, and now generative AI

(Mackey & Jacobson, 2014). generative AI literacy defines the skills and knowledge necessary to use generative AI technology effectively, such as understanding how generative AI produces information and how the information produced is biased and prone to hallucinations (Jin et al., 2024). These literacies suggest that effective information behavior may involve both metacognitive awareness and a working understanding of generative AI tools. These topics will be further explored in the following sections.

Literature Review

The use of the term *literacy* springs from The New London Group's (1996) coining of "multiliteracies," which broadened the concept of literacy from written language to an epistemological stance that visuals and other non-written forms of communication are just as valuable in specific cultures and contexts as the written word, and just as necessary to be able to decode and understand. In this literature review, I will describe metaliteracy's roots in information literacy, as it is helpful to understand how student information behavior has evolved with technology, and then I will describe how generative AI literacy can add to an understanding of doctoral student information behavior. Later, I will describe a framework comprised of both literacies.

Information Literacy

Prior to widespread availability of high-speed internet and web-based communication, print resources were, by definition, physical, and needed to be stored, organized, and consulted at their place of storage. At institutions of higher education, library resources and other university services like writing centers could only be used in-person. Secondary research was often conducted in-person at a library, with librarians on

standby to help students find and use what they needed. Information was only available in physical formats (including print and audio). One of the major effects of computing technologies was to transform the way that information is transmitted, accessed, stored, and understood. As computers became more widespread, and high-speed internet widely available, electronic information retrieval became the norm. Card catalogs were replaced by online public access catalogs, and print indices became outdated as electronic information retrieval systems went online.

Information literacy was coined in 1974 by Paul Zurkowski, president of the Information Industries Association (IIA) (Kapitzke, 2003). The IIA was formed to advocate for businesses that produced and sold information, and Zurkowski conceptualized information literacy as describing the skills and knowledge that would be needed for employees to be successful in the fledgling information services sector. Interest in information literacy exploded in the 1970s and 1980s as computing's ability to transform information access and communications became clear (Webber & Johnston, 2000). Librarians, well-established as gatekeepers of print information, also saw the potential of electronic information retrieval technologies and embraced the concept of information literacy. The Association of College and Research Libraries (ACRL) described information literacy in a landmark report as the ability to “recognize when information is needed and have the ability to locate, evaluate, and use effectively the needed information” (Association of College and Research Libraries, 1989, para. 4).

Soon after the ACRL's information literacy report, the World Wide Web became publicly available in 1993 (Hoffman & Blake, 2003). Immediately, new web-based resources began to compete with traditional published resources. Anyone could post

messages to the web and create public websites. These new resources stood side-by-side with traditionally published and vetted library resources, and college students frequently treated them equally and used them interchangeably (Larsen, 1996). But while traditional resources like published encyclopedias went through strict editing processes, the web had both experts and non-experts “creating non-refereed webpages on a vast array of topics at a vast range of quality and depth” (Larsen, 1996, p. 89). The freeing of information from its physical container was (and continues to be) a point of confusion for students. While print journals and books offer obvious visual clues about what they are and the experts that wrote and edited them, electronic resources divorce these print materials’ content from their format, adding an additional challenge to students conducting secondary research. With the availability of electronic information, the divorce of information from its format, and web resources competing with traditional published resources, the ability to *evaluate* information becomes very important. In the face of these challenges, librarians took on a new role as information literacy instructors: information guides rather than gatekeepers.

Information literacy standards were codified by ACRL (2000) as the information literacy Competency Standards for Higher Education. These new standards offered librarians a series of learning outcomes and performance indicators that they could adopt as instructors of information literacy. These standards included:

1. The information literate student determines the nature and extent of the information needed.
2. The information literate student accesses needed information effectively and efficiently.

3. The information literate student evaluates information and its sources critically and incorporates selected information into his or her knowledge base and value system.
4. The information literate student, individually or as a member of a group, uses information effectively to accomplish a specific purpose.
5. The information literate student understands many of the economic, legal, and social issues surrounding the use of information and accesses and uses information ethically and legally.

These standards were a good start for teaching information literacy to college students, yet further technological development caused them to quickly become outdated. The early 2000s saw internet access become commonplace. Information behavior continued to evolve with the development of Web 2.0, which referred to the ability to easily create web-based content without having to code, rather than passively consume. This period also saw the rise of social media. From 2000-2010, new social media platforms were growing in popularity and offering new sources of information. In 2010, users of Facebook (launched to the public in 2006) posted 700 updates per second, while Twitter users (also launched in 2006) created 600 tweets per second (Hall, 2025; Martin, 2011). While early web-based content was static and relatively unchanging, soon social media content, search engine results, and shopping recommendations became driven by artificial intelligence algorithms in order to increase user engagement and manipulate online behavior (Botes, 2023). Sensational and emotional content is often used by algorithms to drive user behavior, yet the opacity of algorithms obscures this manipulation from internet users and allows users' emotions to be exploited.

With the increase in types and availability of information sources, increasing ability for anyone to post information online, and affective nature of web-based content, once again, it was becoming more difficult in the 2010s to understand the evolving information ecosystem and which sources could be trusted (Martin, 2011). ACRL's information literacy Standards did not account for such complexity in the information landscape. Criticism of the Standards grew because they positioned students as simply consumers of information and failed to account for the political and social aspects of information literacy, as well as the bias and misinformation that was more likely to occur in online sources (Foasberg, 2015; Mackey & Jacobson, 2011). In the face of evolving information technologies like social media, Mackey and Jacobson (2011) wrote their seminal piece reframing and expanding information literacy as a *metaliteracy*.

Metaliteracy

Mackey and Jacobson (2011) proposed expanding the concept of information literacy to incorporate finding and using information from a variety of platforms and technologies. Whereas information literacy describes consumerist behaviors used more often with text-based and traditional research resources, metaliteracy expands information literacy to encompass all of information behavior including information production across a variety of digital platforms, such as social media. Metaliteracy recognizes that responsible and ethical consumption and production of information is important in an increasingly participatory and algorithm-driven information ecosystem (Mackey & Jacobson, 2011).

Metaliteracy is a pedagogical framework that describes four interconnected domains that are essential for an individual to master in order to be considered

metaliterate (Mackey & Jacobson, 2022). Similar to ACRL's information literacy standards and competencies, metaliteracy describes what an individual should be able to do (behavioral domain), but also describes what they should know (cognitive domain), how they should feel or be oriented in attitude (affective domain), and their capacity for self-awareness, particularly in self-reflection and strategizing (metacognitive domain). These domains are described in greater detail in Guiding Concepts.

The inclusion of metacognition is one of the main factors that sets metaliteracy apart from information literacy, as metaliteracy emphasizes the role of metacognition in driving responsible and ethical behavior.

“To be metaliterate requires individuals to understand their existing literacy strengths and areas for improvement and make decisions about their learning. The ability to critically self-assess different competencies and to recognize one's need for integrated literacies in today's information environment is a *metaliteracy*” (Mackey & Jacobson, 2014).

Metacognition is “generally understood as the process of thinking about one's knowledge and consciously making decisions or taking actions to enact or pursue further knowledge” (Mackey & Jacobson, 2014, p. 10). Responsible and ethical use and distribution of information is only possible with metacognitive skills that allow a person to be mindful of one's emotional state and goals as relates to information.

Mackey and Jacobson argued that the addition of metacognition was an essential update to information literacy. By employing metacognitive skills, information seekers would be able to critically evaluate the many formats and platforms available to them, adjusting their evaluation, analysis, and use based on the source and format of the

information. For purposes of this study, the science of metacognition is worth exploring in greater depth. This study explores how doctoral students reflect on and regulate their use of generative AI in academic contexts, with particular attention to how metacognitive awareness shapes ethical decision-making.

Metacognition

Metacognition offers additional insight into students' information behavior, including how they choose and use information tools to achieve their academic goals. Metacognition stems from the seminal work of Flavell (1979), which described children's ability to think about their own thinking, particularly in relation to learning. Flavell described two components of metacognition: *metacognitive knowledge* and *metacognitive experiences*. *Metacognitive knowledge* refers to a person's beliefs or knowledge as relates to a particular cognitive task. *Metacognitive experience* is a moment of self-consciousness, or sudden "sense of puzzlement" where an individual pauses to think about what is being experienced (Flavell, 1979, p. 908).

These concepts may be illustrated with a real-world example. Rhodes (2019) describes a student expressing disappointment to her professor after her poor performance on an exam. She had believed that the exam's format played into her strengths and selected study strategies based on that belief, only to be surprised by a low exam score. In this case, the student's *metacognitive knowledge* was her personal beliefs on the types of exam formats at which she believed herself to excel. Her affective experience of surprise and disappointment is an example of a *metacognitive experience*. These two phenomena, metacognitive knowledge and metacognitive experience, both

play into a person's goal setting for a particular cognitive enterprise and shape the way they act to achieve those goals (Flavell, 1979).

Nelson and Narens (1990) built on Flavell's research by describing a framework of metacognition related specifically to learning. Through the lens of metacognition, they describe learning as being comprised of two processes: *monitoring* and *control*. When a learner thinks about their learning, evaluating and assessing what they know and what they don't know, this is *monitoring*. When a learner adjusts their learning strategies or goals based on their monitoring, this is *control*. In relation to information behavior, students set goals for their learning and coursework. Figuring out what they know and don't know is an act of *monitoring*. Setting specific strategies to act on that information and find what they need is *control*.

Nelson and Narens' concepts of monitoring and control have been found to apply to a wide variety of situations outside of learning, such as social processes and health (Rhodes, 2019). In social situations, individuals may monitor their interactions with a partner, and implement control by adjusting their voice, words, or body language accordingly. Same with health: a person might monitor their physical feelings, and choose to exercise or eat in response, thus implementing control. These are both situations that also illustrate information behavior. Social situations may be utilized to share gossip or get a recommendation for a new hair stylist; being mindful of how one feels is also a source of information about one's body. Similarly, as a learner is choosing specific sources and tools to use for information research, they will monitor the process and gauge its success. Monitoring and control are both competencies that students may practice in order to be more effective at information-seeking.

While Nelson and Narens describe monitoring and control as behavior processes, Kuhn (2022) argues that metacognition should be recognized as a disposition in addition to a competency. This argument echoes Mackey and Jacobson's (2022) argument that attitudes and affective states play an important role in information behavior, as these orientations shape how an individual strategizes to find information and then uses the information found. Kuhn (2022) states, "one may have the competence to exercise metacognition but it will count for little if one lacks the disposition to do so" (p. 1). In order to exercise effective metacognitive skills, an individual must have the goal to act metacognitively. They must value their metacognitive abilities in order to use them regularly and regularly self-evaluate how well they use them. A metacognitively-oriented individual must also be aware of their pre-existing beliefs and be open to revising those beliefs depending on what they learn. Kuhn states that metacognition is most possible in environments that facilitate mental self-management, and that allow for and encourage an individual to continually self-monitor and maintain vigilance. While metacognition can be taught, it is a difficult process to monitor and study, as metacognitive processes happen inside the mind.

Any situation in which the mind is both the instrument and object of study, when the individual is both the observed and observer, is defined as *Comte's paradox* (Nelson & Narens, 1990). A person is an imperfect measuring device of their own thoughts and metacognitive processes (Nelson & Narens, 1996). What a person reports might be distorted or reported in error. But rather than giving up on studying metacognitive processes, Nelson and Narens (1990) argue that Comte's paradox can be overcome by conceptualizing behavior and metacognition as happening at different levels. Real-time

thoughts and thinking, as they happen in real-time, are located at the *object-level*. An individual's awareness of their thinking happens at the *meta-level*, which is higher and influences the object-level. When studying a person's metacognitive processes, it should not be assumed that the person's reports are entirely truthful, because an individual will be an imperfect reporter. But a person's reporting of their mental processes are data as well, at the meta-level, and offer insight into the object-level. Furthermore, "a system that monitors itself (even imperfectly) may use its own introspections as input to alter the system's behavior" (Nelson & Narens, 1990, p. 128). The very act of studying metacognitive processes affects those same metacognitive processes, and the model used to study those metacognitive processes directly affects the judgments made as a result of that study.

While studying metacognitive processes may provide an imperfect look into how students think and strategize, such study may yet provide insight into student information behavior when using generative AI. Just as strong metacognitive skills are useful for effective learning and information seeking, these skills are important to help students successfully use generative AI for learning and academic coursework. A solid foundation in the technology that underpins generative AI and knowledge of how generative AI prompting works are also important in order to leverage these higher order skills when using generative AI. Research on the skills and competencies to use generative AI effectively are still developing, but Jin et al. (2024) have described a new generative AI literacy that is helpful for better understanding student information behavior in this area.

Generative AI Literacy

ChatGPT's release in November 2022 forced a breakthrough of artificial intelligence (AI) awareness into public and cultural consciousness, but AI technology has existed for many years. AI is everywhere, including in commonly used platforms and applications. AI technology powers Amazon's Alexa and Apple's Siri. AI technology powers navigation apps, weather forecasting, streaming apps like Netflix, and recommendations on shopping platforms (Maese, 2025). A clear and specific definition of AI is hard to come by because of the complexity of this technology. It was first defined in 1956 as the production of intelligent machines and has since been broadened to describe computing systems that can learn and perform cognitive tasks, such as problem-solving (Ng et al., 2021).

The ubiquity of AI technologies coupled with the lack of AI awareness among the public has led to calls for an AI education well before *ChatGPT*'s release in 2022 (Long & Magerko, 2020). An "AI for K-12" working group developed standards for students in K-12 settings that specified what each grade should know about AI (Touretzky et al., 2019). This group came up with five "Big Ideas":

1. Computers perceive the world using sensors.
2. Agents maintain models/representations of the world and use them for reasoning.
3. Computers can learn from data.
4. Making agents interact comfortably with humans is a substantial challenge for AI developers.
5. AI applications can impact society in both positive and negative ways.

While Touretzky et al. did not use the term *AI literacy*, their development of these standards and argument that these concepts are essential for citizens of the 21st century provided a foundation for further research.

Long and Magerko (2020) used Touretzky et al. (2019) as a foundation for their seminal work on AI literacy. Just as prior literacies were developed for specific digital formats and technologies, Long and Magerko argued for the need for an AI-specific literacy. The authors defined AI literacy “a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace” (Long & Magerko, 2020, p. 2). An AI literacy builds on digital literacy, which describes computer usage, but extends beyond use of specific devices to include an understanding of AI-specific concepts, capabilities, and limitations (Long & Magerko, 2020). For instance, it’s important for users to know that the use of AI systems to underpin daily technologies is often obscured, even though private personal data is often collected, stored, and used by AI, leading to concerns about privacy and surveillance. Additionally, AI-powered algorithms on online platforms including social media and search engines have led to a rise in articles written expressly to leverage these algorithms by producing *clickbait*. Clickbait is intended to elicit an emotional response in order to receive more views and distribution. The ability of AI algorithms to personalize content has also led to *filter bubbles*, in which users receive a particular set of information which may differ completely from another user (Long & Magerko, 2020). All of these concepts, which affect the order and type of information presented to users, are essential to understand in order to be AI literate.

Ng et al. (2021) built on Long and Magerko's (2020) work to propose four aspects of AI from which to build a framework for teaching AI Literacy. Through an exploratory review of relevant literature, they identified essential AI literacy concepts and distilled them into four categories: (1) comprehension, (2) application, (3) evaluation, and (4) ethics. The first three categories were explicitly mapped to Bloom's taxonomy to support the development of a pedagogical framework for AI literacy:

- *Know and understand*: Recognizing AI systems and comprehending basic concepts
- *Use and apply*: Implementing AI knowledge in different contexts
- *Evaluate and create*: Analyzing, assessing, and developing AI applications
- *Ethical issues*: Understanding human-centered considerations like fairness and privacy

Ng et al. (2021) argued that the ability to recognize AI systems and understand how they work is essential to being able to use these systems in a way that preserves privacy, respects intellectual property, and facilitates effective information behavior.

When *ChatGPT* was released in November 2022, it became very popular very quickly (Marr, 2023). It was a new form of AI: generative AI. In contrast to the obscured AI technology that powers daily technologies, *ChatGPT* presented as a chatbot that allowed users to interact and experiment directly with AI through natural language, similar to communicating with another person (Lee et al., 2024). "For the first time, people could easily converse directly on almost any topic with an AI chatbot using natural language to discuss and 'look up' information instead of retrieving it from search engines, Wikipedia, academic databases, or primary sources" (Sallai et al., 2024, p. 2). Generative AI systems are different than search engines like Google or Bing. Search

engines were designed to provide relevant results based on the keywords that the user enters. Same with library databases. They tended to be very literal, and entering queries in the form of questions and paragraphs had the effect of less relevant results. In contrast, generative AI systems are very flexible in responding to a variety of user prompts (Tankelevitch et al., 2024). Chatbots produce complete outputs in response to keywords, to questions, and to tentative descriptions. A chatbot's response is not only tailored to the query, but also often contains an invitation to clarify or ask for more information. Instead of a long list of search results, generative AI systems give answers. They respond in full sentences and paragraphs, as well as non-text responses as relevant, such as images or mocked up web pages or apps.

Additionally, unlike Google and Bing, generative AI systems do more than simply provide information or generate content. They also appear to critique and discriminate between sources, summarize and analyze information, and edit and write. Yet a major challenge with using generative AI systems for information retrieval in contrast to more traditional systems like search engines and library databases is the fact that generative AI system outputs are *non-deterministic* (Tankelevitch et al., 2024). With a traditional search engine, or with a library database, the same query will result in the same set of search results, every time. With generative AI, an identical query entered multiple times can produce noticeably different outputs. This non-determinism may complicate learners' ability to form stable mental models, or schemata, of how these systems behave, making it more difficult to predict outcomes or refine strategies over time. As Tankelevitch et al. (2024) note, this uncertainty may require learners to adopt more flexible, adaptive prompting strategies supported by strong metacognitive skills.

Furthermore, chatbots aim to please. Generative AI-based chatbots tend toward sycophancy, which means that chatbot responses will generally agree with users, flatter them, or validate their feelings (Cheng et al., 2025). Sycophancy can be problematic for two reasons. More dangerously, chatbots will encourage users' delusions, or encourage them to self-harm. More innocuously, chatbots will tell users what they want to hear, leading to less accurate responses as they will validate users' existing beliefs or worldviews. As chatbots tend to respond with authority, responses that are skewed due to sycophancy can be difficult for users to detect.

This new type of information retrieval system necessitates a new type of literacy. Thus, Jin et al. (2024) introduced a specialized form of AI literacy, generative AI literacy, focused specifically on generative AI tools that can be used for writing learning objectives and assessing student mastery. Being able to gauge individuals' generative AI literacy is particularly important in educational contexts as a large percentage of generative AI users are students using it for homework help and academic studies (Lee et al., 2024; Merrill & Lerman, 2024). Jin et al.'s framework builds directly on Ng et al.'s (2021) four facets of AI literacy, retaining the three Bloom's-aligned categories (comprehension, application, and evaluation), and focusing the ethics component on generative AI:

- *Know and understand*: how generative AI is defined, how a Large Language Model (LLM) works, how prompts shape output, and what retrieval-augmented generation is
- *Use and apply*: the role of context in shaping generative AI output, ability to retrieve and synthesize information

- *Evaluate and create*: trustworthiness of LLM outputs, evaluating based on LLM knowledge cutoffs, cross-checking information to ensure accuracy
- *Ethical issues*: understanding model biases, recognizing that generative AI algorithms are opaque and poorly understood, privacy concerns

Jin et al.'s generative AI literacy incorporates some focus on ethics and critical evaluation of content creation but largely concentrates on the technical functions of generative AI.

The technology of generative AI is very important to understand, particularly for students using it for academic work, as the technical limitations of generative AI lead directly to flawed outputs that are difficult to detect (Ogunleye et al., 2024). Additionally, generative AI presents privacy concerns as content entered into a chatbot is often added to the training corpus and may be regenerated and presented to another user (Crompton & Burke, 2024; Sabzalieva & Valentini, 2023).

The ethical and critical concepts presented in Jin et al.'s (2024) framework are not well-detailed. Additionally, generative AI literacy is limited by definition and design as it focuses only on generative AI. While this specialized literacy is valuable for its insights into generative AI technology and effect on use, it lacks a developed conception of users' critical thinking or metacognitive skills as related to this technology, which is especially relevant as many students use generative AI as an academic tool alongside Google and library resources (Gruenhagen et al., 2024). Yet, the four concepts that comprise AI Literacy and generative AI literacy, *know and understand*, *use and apply*, *evaluate and create*, and *ethical issues*, are useful for understanding and guiding doctoral student behavior with generative AI. These four concepts echo Mackey and Jacobson's four domains of metaliteracy, which include behavioral, cognitive, affective, and

metacognitive. These concepts will be interwoven and used to define this study's guiding concepts.

Related Studies

Scholarly literature on students' use of generative AI is limited. It's only since the release of *ChatGPT* in late 2022 that AI-focused studies are being published more frequently by scholars in the field of education. Prior to *ChatGPT*'s release, most literature on AI and AI literacy was written by computer scientists and scholars in human-computer interaction (Crompton & Burke, 2023). Since *ChatGPT*'s release, there are several published empirical studies that have focused on undergraduate and graduate student usage of generative AI in higher education (Chen et al., 2024; Kumar & McGray, 2024; Nakatani & Jiang, 2025).

The University of California, Davis, conducted a survey of their undergraduate students to learn how these students used and perceived generative AI (UCD Center for Educational Effectiveness, 2024). Of their 31,000 undergraduate students, 1,361 responded to the survey, which was distributed by email. The researchers did not provide a description of their survey, including authorship or number of items. The survey included Likert-scale items in which respondents reported how frequently they used generative AI for various academic tasks, such as brainstorming, writing support, and research assistance, as shown in the reported results. Other Likert-scale items asked respondents to report agreement with a variety of statements related to ethics, generative AI usage, and generative AI technical knowledge. Respondents were also able to provide open-ended responses to express their views on the technology. The researchers found that 61% of respondents used generative AI at least rarely, while 40% stated that they

used it regularly (several times in a quarter). Respondents used it as a tutor and as a writing aid, including proofreading, editing, brainstorming, and outlining. The majority of students (92%) agreed that they should use other sources to verify any AI-generated information.

Chen et al. (2024) examined university students' behaviors and perspectives on generative AI through the lens of Ng et al.'s (2021) four domains of AI literacy: utilization, interaction, evaluation, and ethics. The researchers wrote an original survey comprised of 26 questions across the four domains, which also included a set of demographic questions. Survey items were multiple-choice with the option for respondents to provide open-ended elaboration. Chen et al. distributed their survey to undergraduate and graduate students at a regional university located in the United States via email. Of 8,493 students, 462 responded, and 218 of those reported having used generative AI tools. Via the survey, researchers found that students used generative AI as a free on-call assistant and tutor that helped them when they felt stuck or unsure how to proceed. Students used generative AI for brainstorming, summarizing, outlining, literature reviews, and data analysis. They also used it for editing, including proofreading and, to a lesser extent, generating writing. Yet, students used generative AI more as a supplemental tool to support their own work, rather than generate it wholesale. Over 40% of respondents stated that AI-generated responses were generally inferior to their own writing. They were overall skeptical of the accuracy and reliability of AI-generated output, and the majority (72.1%) used secondary sources to confirm information generated by chatbots.

Kumar and McGray (2024) conducted an international study of postsecondary students' usage of generative AI. The researchers used the Unified Theory of Acceptance and Use of Technology to study student usage using a survey posted to Prolific, an online research platform. Based on the responses of self-identified students (n=1,021) representing 54 nationalities, researchers found that 73.1% of students used generative AI for their academic work. The study concludes that educational institutions should acknowledge the widespread use of generative AI in academic settings and develop appropriate policies rather than attempting to prohibit these tools. The authors suggest further research to understand students' motivations for using or not using generative AI tools.

Three recently published studies focus exclusively on Doctor of Education students. Minimo and Bueno (2024) explored EdD students' perceptions of generative AI usage in relation to writing and academic integrity at a university in the Philippines. The researchers used a case study design, including interviews, and the lens of the Technology Acceptance Model (TAM) to inform their research design and data analysis. Students (n=10) reported using generative AI tools for proofreading, grammar checking, and generating ideas, and expressed concern about lack of originality when overusing generative AI, as well as academic integrity concerns. The authors recommend developing clear guidelines for generative AI use.

Harris et al. (2025) used a mixed methods approach (survey and interviews) to study generative AI usage for writing among EdD students in a program based in the Pacific Northwest. The respondents (n=19) used generative AI tools primarily to proofread and check grammar, assist with research and literature reviews, and to improve

organization and structure of research papers. They found that while participants generally trusted generative AI for grammar and spell-checking (63% expressed trust), they were more skeptical about AI's ability to facilitate research communication, with 47% indicating generative AI tools were not conducive to effectively communicating research findings. The study also showed that participants had concerns about ethical usage, plagiarism risks, and the reliability of AI-generated content. The researchers conclude with a suggestion for programs to offer guidance and training on generative AI use to students.

Buss et al. (2025) used action research (survey and interviews) to explore how students in the EdD program at Arizona State University use generative AI. The researchers used the Technology Acceptance Model to inform their survey construction and interview protocol. Similarly to Harris et al. (2025), the study found that students (n=45) used generative AI for editing and improving their writing, summarizing information from research studies, locating relevant research articles, and for helping overcome barriers to writing. Students used generative AI to save time and to jump start their work when they felt stuck or unsure. They also found that students had concerns about ethical usage and academic integrity and were unsure about how to balance productive use with limiting development of their own expertise. Additionally, “participants asked that program faculty members and leaders integrate AI usage into coursework and guide students on how to use it ethically,” which echoes Harris et al.’s (2025) suggestion to provide guidance to students (Buss et al., 2025, p. 45).

Guiding Concepts

In this section, I will describe the guiding concepts for this study, all of which stem from metaliteracy and generative AI literacy. First, I will describe the domains of metaliteracy and how they apply to generative AI usage, and then I will describe the concept of ethics as applies to information behavior and generative AI usage. Although metaliteracy domains are analytically distinct, they frequently overlap in practice; for the purposes of this study, domains are separated to clarify analytic alignment between conceptual framework, indicators, and codes.

Metaliteracy Domains

Metaliteracy positions learners as both consumers and producers of information, which is relevant to both Doctor of Education (EdD) student secondary research practices as well as their production of content for assignments and their dissertations (Mackey & Jacobson, 2014). The metaliteracy framework is used in this study to conceptualize EdD students as reflective practitioners with agency, rather than mere consumers of AI-generated content. This agency manifests in their abilities to make informed decisions about generative AI tool use, critically evaluate generative AI outputs, understand ethical implications, and reflect on their academic practices involving these technologies. Metaliteracy is compatible with cognitive constructivism because it does position individuals as having agency and using information according to their own unique lived experiences (Mackey & Jacobson, 2014).

The metaliteracy framework is organized into four interconnected domains that describe the knowledge, skills, and dispositions of a metaliterate learner: behavioral, cognitive, affective, and metacognitive. Each of these domains has application and

relevancy to student usage of generative AI as I will describe below, and each domain was used to guide development of the methodology used in this study. Information practices and dispositions are described by Mackey and Jacobson (2014, 2022). Practices related to generative AI in each domain are described by Jin et al. (2024).

Cognitive domain. Learners should be aware that they are part of an information ecosystem, and are not just consumers, but producers (Mackey & Jacobson, 2014). When using information sources, learners should verify expertise, understand copyright and intellectual property, assess source type, and distinguish between opinion pieces and fact-based content (Mackey & Jacobson, 2022). EdD students are using generative AI as another tool in a suite of information tools for academic purposes (Black & Betts, 2025). In relation to use of generative AI for information consumption and production, the cognitive domain includes recalling fundamental AI concepts such as how Large Language Models (LLMs) work, generative AI's capabilities and limitations such as knowledge-cutoffs, and the bias inherent in generative AI (Jin et al., 2024). This knowledge is essential to be able to use generative AI effectively in way to produce accurate and relevant output.

Observable indicators of the cognitive domain in this study include participants' ability to describe basic generative AI concepts, such as how LLMs generate text, what limitations they have, and how these limitations affect their academic use, and also if they know institutional policy and how to put it into practice. For example, survey items ask students to indicate their level of agreement with statements such as "I understand the technical limitations of generative AI," while open-ended questions prompt them to describe how they evaluate AI-generated content. Survey items ask about participant

knowledge of institutional policies related to generative AI, and if they know when to formally acknowledge their use. The focus group also featured related prompts such as asking how students judge the credibility or usefulness of AI output, especially in light of limitations inherent to the technology. These questions are meant to gain insight into the knowledge and awareness that are emphasized by both metaliteracy and generative AI literacy (Jin et al., 2024; Mackey & Jacobson, 2022).

Behavioral domain. The knowledge described above is essential to effectively navigating the information ecosystem including generative AI, selecting appropriate tools, and using them productively. Learners should be able to apply their knowledge in order to evaluate information sources including generative AI output, create new content, and ethically and responsibly share content (Mackey & Jacobson, 2022). In the context of generative AI usage, the behavioral domain includes skills like crafting effective prompts, selecting appropriate generative AI tools, recognizing AI-generated content, using generative AI tools to solve specific challenges, and identifying when they should acknowledge their use of generative AI (Jin et al., 2024). Additional skills include being able to identify hallucinations and sycophancy and working to minimize their impact. A metaliterate and generative AI-literate learner evaluates AI-generated content for quality, accuracy, and relevancy to their academic goals, and they are able to appropriately and thoroughly cite their use of generative AI in the content they create and share.

Observable indicators of the behavioral domain include students' reported practices when they use generative AI for academic work. Survey items ask about frequency of generative AI use, the tools that respondents use, as well as the purpose of use (such as brainstorming, summarizing, and editing). Open-ended survey items and

focus group prompts further explore how respondents use generative AI tools in practice, such as their prompting strategies, how they decide which tools to use, and how they evaluate AI-generated outputs. These items are intended to capture student engagement with generative AI, in line with the behavioral concepts of metaliteracy and generative AI literacy (Jin et al., 2024; Mackey & Jacobson, 2022).

Affective domain. Metaliteracy asserts that information behavior has an affective dimension (Mackey & Jacobson, 2014). Learners should be aware of their affective response when navigating information ecosystems, including when consuming, using, evaluating, and sharing information. Awareness of affective responses is also a cognitive and metacognitive process (Mackey & Jacobson, 2022). Per this domain, information engagement is not purely intellectual but also involves emotional responses, attitudes, and values. In relation to generative AI, the affective domain includes attitudes toward generative AI technologies, confidence in using generative AI tools, awareness of ethical issues surrounding generative AI, and motivation for using generative AI systems responsibly (Jin et al., 2024; Ng et al., 2021). A metaliterate and generative AI-literate learner feels confident in their use of generative AI as an information tool. They should be able to identify affective responses to AI-generated content and act on them, including being able to identify output designed to flatter or be servile. Learners should also be able to monitor their affective state and how it affects their use, evaluation, and distribution of AI-generated content, including in relation to and compliance with academic integrity.

Observable indicators of the affective domain in this study include students' attitudes, emotions, and values related to generative AI use. Survey items capture levels of confidence in using generative AI, concern about academic integrity, and awareness of

institutional policies. These indicators are captured through survey items like “I am concerned about potential academic integrity issues while using generative AI.” An open-ended survey item asks students to report any concerns that have about use of generative AI related to their EdD coursework and research. Furthermore, focus group prompts ask students to describe emotions and attitudes related to generative AI use, including whether generative AI has affected the development of their own expertise and scholarly identity. Respondents’ affective responses are relevant to understand students’ ethics related to generative AI, which is central to metaliteracy and generative AI literacy (Jin et al., 2024; Mackey & Jacobson, 2022).

Metacognitive domain. This is perhaps the most important domain in relation to generative AI usage because generative AI output is non-deterministic (Tankelevitch et al., 2024). The metacognitive domain describes metacognitive skills such as self-awareness and reflection as important to being a critical and ethical consumer and producer of information. Per this domain, learners continually reflect on their information behavior, including how and when they use technology for information purposes, so that they may improve their strategies and processes (Mackey & Jacobson, 2014). A metaliterate learner has a reflective understanding of how and why they learn, what they do and do not know, their preconceptions and biases, and how to continue learning (Jacobson & Mackey, 2013). This domain promotes self-awareness about one's information practices and learning processes in order to continually improve those practices (Mackey & Jacobson, 2022). In relation to generative AI, metacognition is important for reflecting on one's interactions with generative AI systems, understanding personal biases when interpreting generative AI outputs, and continuously iterating and

revising learning strategies as this technology evolves (Flavell, 1979; Tankelevitch et al., 2024; Zimmerman, 1989). “Users with high metacognitive awareness are better equipped to assess AI-generated outputs, identify potential errors, and adapt their strategies accordingly” (Lee et al., 2024, p. 4). A metaliterate and generative AI-literate learner continually reflects on their decision-making and strategizing when choosing to use generative AI. They think critically about when to use it, and when and how to integrate output ethically into their work. They also balance use with developing their expertise and scholarly identity, and be aware of how they set goals, implement strategies, and revise their approach to use generative AI appropriate for academic purposes. Additionally, metacognition is helpful to explain how students decide when and how to use generative AI as well as develop strategies for ethical and effective generative AI use.

Observable indicators of the metacognitive domain in this study include how student perceptions of goal setting, reflecting on their thinking, and strategizing when using generative AI. Survey items ask students to rate their agreement with statements such as “I regularly reflect on how the use of generative AI influences my thinking” and “I actively monitor how my use of generative AI affects the development of my own expertise.” Focus group prompts ask participants to describe how their approach to AI use has evolved over time and how they decide when to use AI. These responses offer insight into students’ metacognitive awareness, including planning, monitoring, and strategizing, which aligns with the metacognitive dimensions of metaliteracy (Mackey & Jacobson, 2022; Lee et al., 2024; Zimmerman, 1989).

Ethics

Both metaliteracy and generative AI literacy offer insight into ethical information behavior when using generative AI. Mackey and Jacobson (2022) describe ethics as being integral in each of the four domains of a metaliterate learner, as ethical behavior is integral to their definition of a metaliterate learner. However, they do not define “ethics” or “ethical,” except in relation to producing truthful information, and in their 2013 work, relating respect for intellectual property, including copyright law, to ethics. They also emphasize critical thinking as being a skill of an ethical information producer (Mackey & Jacobson, 2022). Jin et al. (2024) describe ethics considerations related to generative AI as awareness of LLM model biases, copyright issues in content generated by AI, and privacy concerns.

For EdD students, ethics includes adhering to institutional academic integrity policies. Academic integrity policies generally stipulate that students produce their own original work for assignments and coursework. For example, Arizona State University’s academic integrity policy states that it is dishonest for students to either attempt or engage in:

- g. Plagiarism, or the use of another’s words, ideas, materials, or work from the Internet or any other source without properly acknowledging and documenting the source. Students are responsible for knowing the rules governing the use of another’s work or materials and for acknowledging and documenting the source appropriately.
- h. Claiming credit for or submitting work done by another or through the unauthorized use of technology (Office of the University Provost, n.d.)

Yet, generative AI may be used by students to produce ghostwritten assignments that are difficult or impossible to detect as such, making policies difficult to enforce (Bittle & El-Gayar, 2025). Per metaliteracy, part of being an ethical information producer includes turning in original work and acknowledging use of outside sources (Jacobson & Mackey, 2013).

Aside from student behavior, artificial intelligence has a long history of bias that makes it a problematic technology. In her landmark work "Algorithms of Oppression: How Search Engines Reinforce Racism," Dr. Safiya Noble (2018) dove deep into the ways that AI-powered algorithms are biased and reinforce systems of oppression. The technology that underpins Google's web search is an artificial intelligence system that uses machine learning algorithms to rank search results (Das et al., 2015). Noble argued that Google's algorithms are both designed by a workforce that lacks diversity, and, additionally, the algorithms are trained on large datasets that contain content that is biased, prejudiced, and full of stereotypes. As a result, Google's algorithms will return search results that perpetuate these same issues. For instance, Dr. Noble showed that a search for the term "black girls" returned pornographic sites, which she discovered when she was searching for gifts her nieces might like. The only way to discover clues as to how these algorithms work is to analyze their output through searches, which Dr. Noble did and documented.

Generative AI has similar problems, as models are trained on vast amounts of data, and the contents of these datasets are not made public. While earlier experimental LLMs were trained on curated datasets to avoid generating problematic (e.g., racist and sexist) content, creating more complex models necessitated datasets that were so large,

filtering and curating were deemed impossible (Hao, 2025). Companies like OpenAI turned to scraping internet resources non-discriminately to feed into their models. Instead of filtering input data, developers turned to output filters instead, which are often ineffective and easily thwarted. Just as Google search results tend toward racism, LLMs and generative AI-based image generators also tend toward creating racist and sexist content. For instance, as produced by image generators, “‘attractive people’ are young and white. ‘Housekeepers’ are Black and brown. ‘Engineers’ are men” (Hao, 2025, p. 114). These problems are a direct result of using an unfiltered dataset to train these models. These datasets are also problematic because of intellectual property violations. It is clear that models were trained on copyrighted content without the permission of copyright holders, such that OpenAI and other companies are facing lawsuits from institutions like The New York Times (Hao, 2025).

In addition to built-in model bias, generative AI is frequently criticized as being an unethical technology because of the massive amounts of electricity and water that data centers use in the service of developing and serving this technology (Zewe, 2025). Data centers use extreme amounts of public resources. One estimate ranks data centers as “the 11th largest electricity consumer in the world, between the nations of Saudi Arabia...and France” (Zewe, 2025, Paragraph 11). Data centers may also cause harm to local communities. Data centers in places like metro Phoenix, Arizona, place a strain on existing electrical grids, which raises prices for residents (Klepp, 2025). Existing and planned data centers also strain already limited water resources, causing concerns about sustainability (L’Heureux, 2025).

Observable indicators related to ethics include respondents' perceptions of academic integrity and behaviors that comply with institutional academic integrity policies, as well as respondent reports that describe their knowledge and behavior when using generative AI. Respondents may also describe concerns about generative AI technology, including issues related to privacy, copyright violation, environmental impact, and harm to vulnerable populations.

Conceptual Framework

These conceptualizations of the cognitive domain, behavioral domain, affective domain, metacognitive domain, and ethics as relates to information behavior and generative AI usage were used to inform this study's design. The guiding concepts for this study informed this study's research questions as follows. The first research question, *What generative AI tools do doctoral students in CPED institutions use in their academic work, and how do they make decisions about when, how, and to what extent to use these tools?*, was used to investigate the cognitive, behavioral domains, as well as inform a conceptualization of students' metacognition and ethics in their decision-making. The second research question, *What concerns do doctoral students in CPED institutions have regarding academic integrity, ethics, and the responsible use of generative AI in academic work?*, explored the affective domain and students' conceptualizations of ethics. The third research question, *What factors influence doctoral students' ability to critically evaluate generative AI output as part of their work in CPED EdD programs?*, investigated the cognitive and behavioral domains as relating to understanding and using generative AI output.

This framework is appropriate for EdD students in Carnegie Project on the Education Doctorate programs because one of the design-concepts of these programs is to develop students as scholarly practitioners (“The CPED Framework”, 2022). “Research is a central part of doctoral students’ training to become scholars,” states Choi et al. (2021, p. 93). “In addition [to] acquiring technical research skills, students must adequately develop their sense of independence as knowledge creators, rather than knowledge consumers.” The inclusion of this design-concept affirms metaliteracy’s positioning of metaliterate learners as both creators and consumers. Additionally, just as metaliteracy positions metacognition as an essential domain, self-reflection is an important part of the process of developing EdD students as scholar-practitioners (Choi et al., 2021). “Reflection allows students to become self-aware and leads to students’ self-assessment of their development of identity as scholars” (Choi et al., 2021, p. 105). Next, I will describe how this framework will be applied in this study’s research design.

CHAPTER 3

METHOD

Introduction

In this chapter, I will lay out my overall research design and plan for this study. Using a theoretical framework of metaliteracy with specific emphasis on metacognitive awareness and concepts from generative AI literacy, I explored how Doctor of Education students use generative AI tools as part of their academic studies. Next, I will share the initial cycle of inquiry, research design including setting, participants, and innovation, as well as the research methods and the role of the researcher.

Initial Cycle of Inquiry

I conducted an initial cycle of inquiry in Fall 2024 to gain further insight into my problem of practice. This qualitative study investigated educator perspectives on graduate student use of generative Artificial Intelligence (AI) at Arizona State University. Through semi-structured interviews with six educators, including three faculty, two instructional designers, and a librarian, the cycle explored educator experiences and observations regarding AI adoption in higher education. Thematic analysis of interview transcripts revealed four key themes:

1. Student uncertainty about boundaries of generative AI use
2. A tension between productivity and process when using generative AI
3. The importance of developing students' critical evaluation skills for AI-generated content
4. The need for generative AI guidance and training for both students and faculty

Educators expressed particular concern about students' limited ability to evaluate AI-generated content while emphasizing a need for guidance and further training on these topics.

Student Uncertainty About Boundaries

Academic integrity was cited as a concern related to student use of generative AI. Many students do not disclose use of generative AI in their coursework but fail to disclose out of fear or uncertainty about faculty expectations. Four educators, including Professor Dawes, instructional designer Holden, Professor Nagata, and librarian Inaros, brought up the reluctance of students to discuss how they used generative AI in their coursework. Professor Dawes stated, “you can tell that language is not the language that somebody would normally use” in student assignments, indicating possible use of generative AI, yet the assignment lacks acknowledgement of the use of generative AI for completion. A reason why students may not disclose is that “they're maybe [using generative AI for assignments], but they can't really talk about that with their professor because the professor may have a different opinion on whether they should or shouldn't use it,” said Professor Nagata. “They're nervous about it,” said instructional designer Holden. However, librarian Inaros pointed out that generative AI tools may be incredibly useful for students who speak English as a second language. “So especially for people who, for whom English might not be their first language, it's a great tool, right? Or even if you're just struggling, it might help you out with some of the writing process and thinking through process.”

While students are reluctant to disclose, educators may be interested in guiding individual students in their use of generative AI. Approaching those conversations can be

difficult. “I can't definitively say it was written by AI. So, I have to give the student kind of the benefit of the doubt,” Professor Nagata said. They continued, “but in some cases, I mean, in this one case that the student says they're using *ChatGPT* and how they're doing it, but I can educate them. It's kind of a different story if they say, ‘I’m not using it at all.’ And it looks appears like they are. And it's kind of a contradictory because I'm really trying to promote AI.”

Librarian Inaros described the importance of generative AI disclosure as a method of taking ownership. Not just to clarify that generative AI was used in completing the assignment, but also to take responsibility for use. “Part of that disclosure is telling how and why you used a tool or what you did using the tool. But also having an additional disclaimer there of, ‘I’ve reviewed all this as the human being. I've reviewed this and I take responsibility,’ right?” said Inaros.

Tension Between Productivity and Process

Participants described a tension between the appeal of increased productivity when using generative AI and skipping over the labor of creation. Instructional designer Holden and librarian Inaros noted that students may be missing out on experiencing the process of production, particularly, the learning process, when they overuse generative AI. Many users value generative AI because it helps increase productivity: it will take on the tedious tasks that they don't want to do. The downside of allowing generative AI to take over the production and those tedious tasks is that the user may be missing out on what Librarian Inaros describes as outsourcing the “productive struggle” of the process that leads to the product. Instructional designer Holden expressed a similar concern: “when does production not become the important part...when is process the important

part?” Instructional designer Johnson elaborated on the dangers of overuse. “I don't know what the effects it has on learning, but, you will definitely see that the quality of assessment students submit with AI is much higher on average than assessments that are done without AI. But you know, you never know how much they're actually learning, which is really tough to gauge.”

Intellectual property is also unclear when a collaboration with generative AI is particularly extensive. Sometimes the user may iterate a prompt many times in order to generate a specific output. But when does that product created in collaboration with generative AI “stop becoming the AI's work and start becoming the person's work?” asked instructional designer Holden. This indicates a lack of clarity on those times when it is unclear which partner in a human-generative AI partnership did more work leading to an output.

The same blurred line exists between productivity and process, and between acceptance use of generative AI and academic integrity violations. Instructor guidance is important when it comes to generative AI use. Instructional designer Johnson said, “to be honest, I think students especially are much more familiar with AI than professors are and what they need is not guidance, but like what they need to know is where their AI use should end.” Professor Nagata stated that they provide guidance on use: “I provide students either prompts or tools or in some cases, I might say on this particular assignment, you know, a review of a qualitative article, ‘I don't want you to use any AI because I want you to think.’”

Developing Students' Critical Evaluation Skills

While students increasingly turn to generative AI for writing and research assistance, their critical evaluation skills can be lacking. This is a problem because generative AI has a tendency to hallucinate, that is, to generate information that is misleading or completely false. In regard to using generative AI for research, Librarian Inaros said that they tell students, “your bullshit meter compared to your professor's bullshit meter, who's been doing this for a long time, right, is going to be a little bit different. They'll be able to see through the BS much more quickly than the AI is producing. It's going to take you longer.”

When conducting secondary research, it's important to evaluate sources for accuracy and relevancy. For instance, peer-reviewed articles often provide all of the information needed to evaluate the quality of a study. “But on the AI side, you know you just type something, you get an answer. And the same need is still there, you know to check with the validity of the AI answer. And I feel students don't do that,” said Johnson. “I would not recommend the use of it for anything that's factual,” said Inaros. “The question always remains, if it's not actually doing anything that's knowledge based, then how can we ever trust that thing?” Yet, Professor Nagata argued that understanding a generative AI tool can help prevent students from misusing it:

For example, if students are using [*ChatGPT*] for research to find articles, it'll just make things up. If they're using a tool like Perplexity, it doesn't make things up. You can actually go back to the actual sources on that. If you're using Research Rabbit, it's looking at a database of actual scholarship. So, without knowing that,

the students can get themselves in trouble without knowing what the strengths and weaknesses of the tool are.

Educating students about specific platforms may assist them in appropriate usage.

Need For Generative AI Training for Students and Faculty

Training may be a means to teach both students and faculty how to use generative AI in accordance with its strengths and limitations. “Everybody needs to be more up to speed on literacy about what these tools can do and what they can't do and how they work. And then you get there by trying them and practicing with it,” said Professor Nagata. Instructional designer Johnson agreed: “[Faculty] need to be open and willing enough to experiment with these tools to see what could happen. And you know, not be discouraged after, you know something goes wrong.” An understanding of the underlying technology may help guide users in appropriate use and better understand output.

For instance, generative AI output is based on statistical modeling, which limits accuracy of output. Inaros stated,

If I put in a prompt and all of a sudden it starts shooting out text, it looks miraculous and it is. And I will say, it is amazing, right? But at the same time, it's like when you keep coming back to, like, there's no real thought behind it. This is not new knowledge. You know, this isn't like reading a journal article where a scholar has put a lot of time and thought, has verified their work, etc. What I'm doing is getting some approximation of something that looks like it is useful.

Professor Dawes stated that practical instruction on mechanics of using generative AI might be important. “It seems to me that we need instruction on writing prompts. We need models. We need to know how to ask it. We need to know how to get it to ask us

questions back. So that it's just not providing us answers, but it's providing us questions so we can think about things differently or in a rational theoretical, researchy way, whatever way we ask it to help us.”

Professor Burton stated a need for practical training in use of generative AI. “There needs to be a little bit of time with experience with general prompts and seeing, you know, how LLMs respond and that's probably maybe about two hours of sort of training and exercises. And then probably tutorials for specific tools and specific things that might be useful.”

Findings of Initial Cycle of Inquiry

The findings suggest that many of the concerns these educators brought up in relation to generative AI may be at least partially addressed through training and greater instructor guidance. Students were described as uncertain about boundaries of generative AI use, leading to possible academic integrity violations. They were also described as overusing generative AI and thus missing out on developing as learners or scholars. Participants also described students’ lack of critical evaluation skills when it came to generative AI output. These concerns may be alleviated with formal training as well as instructor guidance in their courses. Overall, findings indicate that students would benefit from developing metacognitive skills specific to generative AI. This cycle informs the problem of practice as well as the study’s instrument design and data analysis.

How Findings Inform This Study

The findings from the initial cycle directly inform the design of this study in several ways. First, uncertainty about boundaries of generative AI use shaped the focus of my first research question, which explores how doctoral students make decisions about

when and how to use generative AI tools. This uncertainty also influenced the design of survey items that explore students' decision-making processes. Second, educators' concerns about the tension between productivity and process informed my second research question's focus on academic integrity and ethical considerations, with corresponding survey items and focus group questions that explore this tension from the student perspective. Third, the finding that students may lack critical evaluation skills directly shaped my third research question, which examines factors influencing students' confidence in evaluating generative AI output. This led to the inclusion of specific survey items measuring self-efficacy in evaluation and metacognitive awareness. Finally, the expressed need for training and guidance influenced my decision to explore varied institutional approaches through a cross-institutional study rather than focusing solely on ASU. The focus group protocol was also designed to elicit students' perspectives on what guidance would be most beneficial, providing actionable insights for CPED programs. By building on these initial findings, this study moves from identifying educators' concerns to exploring students' actual experiences and needs, creating a more complete picture of generative AI use in doctoral education.

Researcher Positionality

Constructivism is both an epistemology and a broad learning theory. It posits that every learner experiences learning differently. Each learner views a topic or new knowledge through the lens of their own lived experience and prior knowledge. No two learners learn the same because they both have unique experiences (Provenzo & Provenzo, 2009). Cognitive constructivism, a type of constructivism, posits that knowledge is actively constructed by learners through mental processes and interactions

with their environment (Lowenthal & Muth, 2009). Per cognitive constructivism, learners must work to construct their own understanding of a topic or concept and integrate it into their existing knowledge and lived experience, or *schema* (Sullivan, 2009). Schemata are the “mind maps” that help humans make sense of the world.

Schemata work when the world is predictable. Yet, the output of generative AI is not predictable. Generative AI output is non-deterministic: output is freshly generated and different every time, even in response to identical queries (Tankelevitch et al., 2024). The non-determinism prevents an individual from forming an accurate schema of what to expect from generative AI. This may be one reason that the ethics around generative AI usage in higher education are still forming: existing schemata of ethics and academic integrity in relation to technology do not readily apply to generative AI usage, because generative AI is a different type of information retrieval system than what has come before. Generative AI was also introduced relatively recently, in late 2022, and it will take time for mores to develop around ethical and critical use. Tankelevitch et al. (2024) state that one way this challenge can be met is by teaching individuals metacognitive skills, as it will take high self-awareness and ability to be flexible to use generative AI effectively, ethically, and critically. Additionally, learners may develop schemata grounded in metaliteracy and generative AI literacy to help them navigate the ethics of using generative AI for academic purposes.

Cognitive constructivism aligns well with the concepts of metaliteracy and generative AI literacy, because both literacies offer a pathway to developing schemata that assists learners in developing as ethical and critical information consumers and producers. Additionally, cognitive constructivism is especially relevant for Doctor of

Education students, as they generally enter their programs as professionals already working in the field of education. They may be more likely than other students to have deep life and working experiences that shape how they learn. As a theory, cognitive constructivism serves in this study as an overarching guide for exploring and understanding EdD student usage of generative AI. As educators and adults, EdD students have already developed identities as competent users of information, and a greater ability than undergraduate students to create schemata in order to use generative AI effectively and ethically (Choi et al., 2021).

Research Design

The initial cycle of inquiry and my literature review both informed my research design. My findings in my initial cycle echoed those found in the literature: Doctor of Education students are uncertain about boundaries of generative AI usage in their academic work (Minimo & Bueno, 2024), limited student ability to evaluate AI-generated content (Harris et al., 2025), and that students both seek and need guidance and training related to use of generative AI in academic contexts (Buss et al., 2025; Harris et al., 2025; Minimo & Bueno, 2024). The first cycle of inquiry explored educators' perspectives of graduate student generative AI use at Arizona State University. This cycle of inquiry explored Doctor of Education students' use of generative AI usage among Carnegie Project on the Education Doctorate (CPED) programs, which includes Arizona State University. Whereas previous studies used the Technology Acceptance Model (Buss et al., 2025; Minimo & Bueno, 2024), this study instead used a framework grounded in metaliteracy and generative AI literacy to explore doctoral students'

generative AI usage patterns, their concerns and decision-making related to responsible and ethical use, as well as their ability to evaluate generative AI output.

To guide this investigation, the study answered the following research questions:

1. What generative AI tools do doctoral students in CPED institutions use in their academic work, and how do they make decisions about when, how, and to what extent to use these tools?
2. What concerns do doctoral students in CPED institutions have regarding academic integrity, ethics, and the responsible use of generative AI in academic work?
3. What factors influence doctoral students' ability to critically evaluate generative AI output as part of their work in CPED EdD programs?

Setting and Participants

The setting for this action research study was Doctor of Education programs that are members of the Carnegie Project on the Education Doctorate (CPED), which works to improve the Doctor of Education (EdD) degree (CPED, 2022). As of 2025, 153 programs were a member of CPED (CPED, 2025b). As described in Chapter 1, the EdD is intended for practitioners that wish to apply their knowledge and skills in their professional contexts, in contrast to PhD programs which prepare students for academic faculty positions in higher education. CPED offers a set of design concepts for EdD programs, which includes a focus on developing students as scholarly practitioners who will use what they learn to implement change within their contexts (CPED, 2022a). CPED's design principles also feature a problem of practice which is a "persistent, contextualized,

and specific issue embedded in the work of a professional practitioner,” as well as a dissertation in practice, which addresses the problem of practice.

CPED member institutions are classified in one of three phases: *designing and developing*, *implementing*, and *experienced* (CPED, n.d.). Institutions in the *designing and developing* phase are planning a new EdD program and do not have currently enrolled students. Institutions in the *implementing* phase have either revised an existing EdD program or are offering a new program that has admitted students and might have graduated a cohort. Institutions in the *experienced* phase feature an EdD program that has been running for several years and has graduated several cohorts. Only institutions in the *implementing* and *experienced* phases were selected for inclusion in this study, which was a total of 110 institutions. As the researcher’s institution, Arizona State University (ASU), is also a member of CPED (and is in the *experienced* phase), see Appendix A for permission to conduct research in the ASU EdD program. See Appendix B for IRB exemption.

Data collection took place in September to November 2025. Students were recruited to participate in this study via several methods. First, I posted a call for participants to a CPED EdD student group on Facebook. Second, I contacted CPED EdD program directors to request assistance in distributing study information to their students. I emailed the directors of Arizona State University’s program, and I emailed 78 randomly selected directors out of the 110 programs that were in the *implementing* or *experienced* phases. Of those directors contacted, 27 confirmed distribution of the study information to their students. It is unknown if other directors distributed study information. Third, committee member Dr. Dunnigan, as Lead of the Artificial Intelligence CPED

Improvement Group, distributed the study information to the group members, which was a total of 15-20 institutions. These approaches, while not exhaustive of all CPED members, provided sufficient institutional diversity to explore patterns across different program contexts. Participation in this study was voluntary with no consequences for non-participation. The incentive provided for this study was an invitation to a webinar presenting the study's results. A total of 190 students completed the survey. Of those respondents, 20 also participated in one of four focus groups. Next, I will describe the instruments used in this study, data collection procedures, and how the data was analyzed.

Instruments and Data Collection Procedures

In this study, I used a sequential multiple methods design which included surveys and focus groups to comprehensively examine how doctoral students integrate use of generative AI into their academic work. This approach combines quantitative and qualitative data collection strategies, allowing for both breadth and depth of understanding (Plano Clark & Creswell, 2014). The sequential design enables initial quantitative and qualitative tendencies to inform additional qualitative inquiry, providing richer insights into doctoral students' generative AI usage patterns, their metacognitive strategies for achieving their information goals, and their decision-making processes for determining when and how to use these tools responsibly and ethically.

A multiple methods approach is appropriate for studying generative AI literacy among EdD students for several reasons. First, the emerging and rapidly evolving nature of generative AI requires both breadth (capturing usage patterns across institutions) and depth (understanding nuanced metacognitive processes). The survey provided a

comprehensive snapshot of behaviors and attitudes across CPED institutions, while focus groups enabled exploration of the metacognitive processes that are central to my theoretical framework but difficult to capture through structured items alone. This approach is especially appropriate for EdD students who, as scholarly practitioners, regularly engage in reflective practice. The focus groups provided an opportunity for collaborative meaning-making.

Additionally, use of multiple methods addresses key limitations in previously published research, which has primarily consisted of single-institution studies using solely the Technology Acceptance Model. By combining quantitative measures of generative AI usage with qualitative exploration of metacognitive awareness and self-regulated learning, this study created a more complete picture of how doctoral students navigate ethical and critical dimensions of this new technology. This integration of methods allowed for triangulation of findings that will strengthen the credibility and transferability of results across CPED member institutions.

Survey

First, participants completed a survey instrument containing 23 items distributed across the study's guiding concepts related to respondent information behavior, as described by metaliteracy: behavioral domain, cognitive domain, affective domain, and metacognitive domain, as well as ethics as described by metaliteracy and generative AI literacy (Jin et al., 2024; Mackey & Jacobson, 2022). The survey contained items intended to capture generative AI literacy and usage patterns, ethical considerations in academic contexts, and metacognitive awareness when evaluating AI outputs (see Appendix C for pilot and full survey). It also collected information on participation

demographics. A survey was an appropriate choice for this study because it allows efficient collection of data from a large population, allowing for exploration of patterns and themes. I created an original survey for this study rather than one that was prevalidated. The reason for this is that no prevalidated survey was available, likely due to the novelty of this technology. There is a precedent for creating an original survey, as Chen et al. (2024), Kumar and McGray (2024), Minimo and Bueno (2024), and Buss et al. (2025) also created original surveys for their studies. Following best practices (Creswell & Guetterman, 2019), the survey that I created incorporated attitudinal, personal, and behavioral questions with both closed (Likert-scale and multiple choice) and open-ended response formats (e.g., “How do you decide when to use a generative AI tool as part of your academic work?”).

The survey was organized into five sections. The first focused on what generative AI tools respondents use, how often they use them, and the purposes for which they use them. It includes three closed-ended items asking about these patterns of use (tools used, frequency, and purpose), which captures the behavioral domain, then two Likert-items that asked students to rate agreement with statements related to decision-making around generative AI, which capture the metacognitive domain:

- When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI.
- I consider multiple strategies, including whether to use generative AI, when approaching EdD tasks.

This section concluded with an open-ended item asking students to describe their decision-making related to generative AI. Responses included descriptions relating to the behavioral, cognitive, and metacognitive domains.

The second section focuses on student concerns related to generative AI, as well as respondent knowledge of their institutional policies on generative AI as well as respondents' formal acknowledgment practices related to generative AI (cognitive and behavioral domains). Respondents were asked to rate agreement with four Likert-items related to these concepts:

- I understand when it is appropriate to use generative AI as part of my EdD coursework and research.
- I am concerned about potential academic integrity issues when using generative AI.
- I know what my institution's policies are regarding generative AI use.
- I understand when to acknowledge my use of generative AI.

It concluded with an open-ended item asking students to describe their concerns about generative AI (affective domain).

The third section of the survey focuses on student evaluation practices related to generative AI output. Respondents were asked to rate their agreement with three Likert-items related to evaluation practices and knowledge (behavioral and cognitive domains):

- I can effectively evaluate the quality and accuracy of AI-generated content.
- I verify AI-generated information against other sources.

- I understand the technical limitations of generative AI (e.g., hallucinations, knowledge cutoff dates).

This section closed with an open-ended item that asks respondents to describe their evaluation strategies (behavioral and cognitive domains).

The fourth section of the survey is focused on metacognitive practices.

Respondents were asked to rate their agreement with three Likert-items on this concept:

- I regularly reflect on how use of generative AI influences my thinking.
- I actively monitor how my use of generative AI affects the development of my own expertise.
- I use generative AI outputs as starting points rather than finished work.

The section ends with an open-ended item asking respondents to share anything else about their use of generative AI. This section concluded the survey items that relate to the study's indicators.

The fifth section of the survey contained four items that capture student demographics. Respondents were asked to report their gender, age range, race/ethnicity (they could select multiple), and year in their Doctor of Education program. Like all survey items, these items were optional.

Several strategies were employed in order to ensure content validity. First, survey items were aligned with the study's guiding concepts as described by metaliteracy and generative AI literacy (Jin et al., 2024; Mackey & Jacobson, 2022). To test validity, the survey underwent pilot testing with a small sample representing the target population. Pilot participants provided feedback on item clarity, relevance, and interpretation. Based

on this feedback, survey items were eliminated or revised for clarity and alignment with research questions and guiding concepts.

The survey was designed for reliability by using consistent item formatting (e.g., Likert scales), by using common assessment types such as frequency and multiple-choice items, and by including definitions of concepts, such as “generative AI tools.”

Participants were also asked to respond based only on their use of generative AI for their Doctor of Education program work. Demographic items were located at the end of the survey to reduce cognitive load, as these items are less demanding of participants than the survey’s other items. By placing items with the lowest cognitive load at the end of the survey, this reduced fatigue effect on more substantial and cognitive-intensive items (Krosnick & Presser, 2010).

Focus Groups

The second phase of my research consisted of conducting four focus groups over Zoom, with a total of 20 participants among the groups. Focus group participants were selected from survey respondents (Creswell & Guetterman, 2019). Potential participants indicated their interest in participating in a focus group via a questionnaire linked to the survey’s conclusion page. The survey and the questionnaire were not connected in order to ensure anonymity for survey responses, as the questionnaire collected contact information. More respondents were willing to participate in a focus group than were needed, so 32 participants were randomly selected, with 25 of those responding and finalizing focus group scheduling. Ultimately, 20 students participated in one of four focus groups. A focus group size of 5-6 participants is optimal for facilitating in-depth discussion while still capturing diverse perspectives (Krueger & Casey, 2015),

particularly when exploring metacognitive processes related to generative AI decision-making. Focus groups were an appropriate choice for this study because they allowed deeper exploration of themes and data collected via the survey instrument, including more in-depth reflection on participants' experiences with generative AI. See Appendix D for the focus group protocol. To minimize researcher influence, an external moderator facilitated these discussions (Creswell & Guetterman, 2019). Sessions were conducted and transcribed using Zoom. Participants were asked to select a pseudonym to increase anonymity. The focus group facilitator provided only anonymized transcripts, not the recordings, to the researcher.

Following participant self-introduction that included year in their Doctor of Education program and something participants do for fun; the focus group was organized into five sections. All items in the focus group protocol were open-ended. The first section asked participants to describe how they first used generative AI for their doctoral work, and what they believe is appropriate or inappropriate use. This section captured information related to the behavioral and cognitive domains, as well as participants' ethics. The second section asked participants to describe any guidance or training offered by their institutions related to generative AI, which was related to the cognitive domain. The third section asked participants to describe decision-making around generative AI, including when and how they use it for academic purposes, how they formally acknowledge their use, and how they evaluate AI-generated output. That section captured information related to the behavioral, cognitive, and metacognitive domains. The fourth section asked participants to reflect on how generative AI affected or shaped their expertise and doctoral identity, which is relevant to the affective and metacognitive

domains. In a final conclusion section, participants were asked to provide advice to their leadership related to generative AI use by students, and to share anything else they wished.

I scheduled a pilot focus group session in order to test the protocol but did not make any revisions to the protocol as a result. Thus, the pilot focus group became the first of four focus group sessions, and its data was included as part of the larger dataset analyzed for this study.

Data Analysis

In this section I will describe how I analyzed the data. This study employed multiple methods, with results triangulated between the quantitative and qualitative methods. Instruments include a survey and focus groups. My data collection included a survey instrument with a mix of closed- and open-ended items, as well as a series of four focus groups that featured open-ended items.

Quantitative data collected via the survey was analyzed using a combination of descriptive and inferential statistics to examine doctoral students' tool selection and usage patterns, ethical awareness and concerns, and metacognitive decision-making processes related to generative AI. This analysis provided a foundational understanding of how EdD students integrate AI tools into their academic work. Data preparation began with downloading survey responses from QuestionPro and using Microsoft Excel to finalize the data set. Responses from survey participants that did not complete the survey were removed, with survey completion defined as working through the end of the survey and submitting responses. Additionally, survey respondents that were not currently enrolled EdD students, as identified by selecting “Not Applicable” for year in EdD program, were

removed from the data set. SPSS was used to perform descriptive statistical analysis of the quantitative data collected, which included frequency distributions and percentages for demographic variables including gender, age, race/ethnicity, and program year. Measures of central tendency, including means and standard deviations, were calculated for all Likert-scale items. Additionally, when the assumption for chi-square was met, specifically, that no more than 20% of expected cell counts were less than 5, I conducted chi-square tests of independence to examine associations between demographic variables and Likert-scale responses (Salkind & Frey, 2020).

Both inductive and deductive coding approaches were used to analyze qualitative data collected from the survey and focus groups. All qualitative data analysis was conducted using HyperRESEARCH. No generative AI tools or platforms were used for any aspect of data analysis. Inductive coding allowed for the identification of emergent themes not anticipated in the research framework, while deductive coding aligned tendencies and patterns with the study's theoretical underpinnings (Tenny et al., 2022). I coded data from the survey first and used preliminary findings to review and finalize the focus group protocol. Then, the focus groups were conducted, and I coded the data collected.

I conducted two cycles of coding. My first approach to qualitative data analysis was to use Initial Coding. Saldaña (2021) describes Initial Coding as an appropriate approach for a first cycle. Initial Coding is open-ended and not bound by a formula or specific process. Instead, the qualitative researcher is to begin coding using one or more approaches, examine initial codes for similarities and differences, and start thinking about what categories may be emerging as the coding progresses. This coding approach may

incorporate other coding approaches such as In Vivo, Process, or Values Coding. I looked to my research questions for guidance on how I should approach Initial Coding, including what additional approaches to use. I chose to create my own codes to answer my first research question (how students are using generative AI). I used a loose “who, what, where, when, why” framework to begin coding student usage in order to answer this research question. I used Values Coding as an approach under Initial Coding to help answer my second research question (what student concerns are with generative AI). I examined the data for how students expressed their values, attitudes, and beliefs, and coded the data accordingly. This was a useful approach to understand both student concerns and how they conceptualized use of generative AI by themselves and by their peers. I used Process Coding for my third research question (how they are evaluating generative AI output) as Process Coding uses gerund verbs to describe what the participants are doing.

I used Operational Model Diagramming as a transition from the first cycle of coding to the second cycle. This is a method of visually diagramming the concepts that are being uncovered by the coding process in order to understand how they are related (Saldaña, 2021). Using PowerPoint, I visually mapped out my research questions, the concepts they contained, how my coding approaches related to each other, and how the codes could be organized and categorized. This transition method helped focus the data analysis process, specifically in organizing and categorizing the codes.

I used Pattern Coding as my second coding approach. Pattern Coding is used to group your first cycle codes into themes, concepts, or categories (Saldaña, 2021).

Whereas the first cycle was mostly inductive in approach, for my second cycle, I looked

again to my research questions for deductive approaches to organizing my coding. For my first research question seeking to understand what students are using generative AI for, I created categories of *who*, *what*, *when*, and *how* to group codes. I grouped the codes produced using Values Coding related to student concerns about generative AI into one of a handful of categories such as *intellectual property* or *scholarly identity*. I produced relatively few process codes (about 10) to describe student evaluation behavior, so I did not categorize or group these codes further.

These two rounds of coding produced more than 90 codes. I conducted multiple cycles of reviewing my coding work to reduce the number of codes to 16. I also reorganized my codes into categories that roughly corresponded to each research question. Please see Appendix E for a list of codes, their descriptions, and their categories. Finally, I pulled reports for each code from HyperRESEARCH and analyzed for themes using Microsoft Word.

Beyond identifying themes, I engaged in an interpretive synthesis using Braun and Clarke's (2006) reflexive thematic analysis approach, which emphasizes that themes are not merely discovered but actively constructed through analytic engagement with the data. In their framework, the final phases of thematic analysis involve defining, refining, and naming themes in ways that capture patterned meaning across the dataset. As I reviewed and refined the 16 finalized codes and their associated themes, I examined how these themes interacted across research questions and whether they reflected a broader organizing process. This analytic step moved beyond categorization toward abstraction, allowing me to conceptualize the findings as a coherent system rather than discrete results. Through iterative diagramming and memo writing, I identified identity-mediated

ethical self-governance as the central construct linking themes related to institutional ambiguity, scholarly values, transparency practices, and relational learning. The resulting conceptual model represents an interpretive integration of themes grounded in the data and aligned with Braun and Clarke's emphasis on theorizing as part of rigorous thematic analysis.

Conceptual Framework and Research Design

The conceptual framework described in Chapter 2 was used to guide construction of the survey instrument as well as focus group protocol for this study. It also provided a lens through which to analyze the collected data. The survey and focus group protocol offered insight into the four domains of information behavior as framed by metaliteracy (behavioral, cognitive, affective, and metacognitive), as well as student perspectives on generative AI as a technology (knowledge and usage). The survey and focus group measured the key concepts of generative AI literacy (technical knowledge and usage), ethical considerations related to generative AI use in academic contexts, metacognitive awareness when engaging with generative AI tools, and decision-making processes that influence how doctoral students integrate these tools into their academic work.

The framework also informed my understanding of how doctoral students critically evaluate generative AI outputs. Metaliteracy's cognitive domain provides a theoretical basis for understanding how students apply their knowledge to assess the accuracy, relevance, and quality of AI-generated content. The metacognitive domain offers insight into how students reflect on their information behavior and adapt their strategies accordingly. Meanwhile, generative AI literacy contributes technical understanding of AI systems' limitations, such as hallucinations and outdated

information, which are essential considerations when evaluating outputs. Together, these elements create a theoretical lens for examining the factors that influence doctoral students' evaluation abilities.

This framework guided both the structure of the research questions, the research methodology, and interpretation of responses. RQ1 focused on usage of generative AI tools and how they make decisions about using these tools. This question was informed by Generative AI Literacy's conceptualizations of technical knowledge and skills, as well as metaliteracy's metacognitive domain, specifically student self-awareness of information behavior and their strategies for achieving information goals. RQ2 focuses on students' concerns related to academic integrity, ethics, and responsible usage of generative AI. This question was informed by metaliteracy's behavioral, cognitive, and affective domains as they relate to navigating academic integrity. It was also informed by Generative AI Literacy's conceptualization of ethics. RQ3 focuses on the factors that influence students' ability to critically evaluate generative AI output. This question was informed by Generative AI Literacy's conceptualization of technical knowledge, as well as metaliteracy's metacognitive domain, focusing on metacognitive strategies for evaluation. Throughout the analysis, patterns of generative AI usage and metacognitive awareness were identified through both deductive coding based on the framework and inductive coding that allowed for emergent themes.

In previous sections in this chapter, I described how survey and focus group protocol items were organized and aligned with this study's guiding concepts. Please see Table 1 for how this study's guiding concepts were operationalized and aligned to data collection and analysis methods.

Table 1*Alignment of Research Questions, Conceptual Framework, and Methodology*

Research Question	Guiding Concepts	Data Collection Method	Analysis Approach
RQ1: What generative AI tools do doctoral students in CPED institutions use in their academic work, and how do they make decisions about when, how, and to what extent do they use these tools?	<i>Behavioral domain:</i> GAI tool choice, tool usage <i>Cognitive domain:</i> GAI knowledge; prompting strategies <i>Metacognitive domain:</i> self-reflection on strategies and decision-making related to use of generative AI	<i>Survey items Q1-Q3:</i> GAI tools used; frequency; purpose <i>Survey items Q6, Q11, Q15:</i> Open-ended items <i>Survey items Q4-Q5:</i> Likert-items related to setting goals and strategies when using GAI <i>Survey item Q6:</i> Open-ended question on decision-making <i>Survey items Q16-Q18:</i> Likert-items related to self-reflection, self-monitoring	<i>Survey items Q1-Q3:</i> Descriptive statistics <i>Survey items Q6, Q11, Q15:</i> Thematic analysis <i>Survey items Q4-Q5:</i> Descriptive statistics <i>Survey item Q6:</i> Thematic analysis

Research Question	Guiding Concepts	Data Collection Method	Analysis Approach
		<i>Focus group item Q4:</i> Open-ended question about decision-making process	<i>Survey items Q16-Q18:</i> Descriptive statistics
		<i>Focus group item Q8:</i> Open-ended question about how GAI usage has affected development of scholarly identity	<i>Focus group item Q4:</i> Thematic analysis
			<i>Focus group item Q8:</i> Thematic analysis
	<i>Ethics:</i> academic integrity and appropriate usage	<i>Survey item Q6:</i> Open-ended question on decision-making	<i>Survey item Q6:</i> Thematic analysis
		<i>Focus group item Q5:</i> Open-ended question on when you can use GAI output in your work	<i>Focus group item Q5:</i> Thematic analysis
RQ2: What concerns do	<i>Cognitive domain:</i> Understanding institutional	<i>Survey items Q7-Q10:</i> Likert-items related to ethical concerns	<i>Survey items Q7-Q10:</i> Descriptive statistics

Research Question	Guiding Concepts	Data Collection Method	Analysis Approach
doctoral students in CPED institutions have regarding academic integrity, ethics, and the responsible use of generative AI in academic work?	policy on generative AI usage; describing responsible generative AI usage; identifying when to formally acknowledge generative AI usage	<i>Focus group item Q3</i> : Open-ended question on guidance/training from programs	<i>Focus group item Q3</i> : Thematic analysis
	<i>Behavioral domain</i> :	<i>Focus group item Q6</i> : Open-ended	<i>Focus group item Q6</i> :
	Interpreting and adhering to institutional policy; formally acknowledging generative AI use	question on formally acknowledging GAI use in work	Thematic analysis
	<i>Affective domain</i> : Values and attitudes related to generative AI usage	<i>Survey item Q11</i> : Open-ended question on concerns related to GAI	<i>Survey item Q11</i> : Thematic analysis

Research Question	Guiding Concepts	Data Collection Method	Analysis Approach
	<i>Ethics</i> : academic integrity; responsible/appropriate use; data privacy	<i>Survey item Q11</i> : Open-ended question on concerns related to GAI <i>Focus group item Q2</i> : Open-ended question on appropriate/ inappropriate use	<i>Survey item Q11</i> : Thematic analysis <i>Focus group item Q2</i> : Thematic analysis
RQ3: What factors influence doctoral students' ability to critically evaluate generative AI output as part of	<i>Cognitive domain</i> : evaluation strategies; knowledge of aspects of GAI technology that affect evaluation (e.g. hallucinations)	<i>Survey items Q12-Q14</i> : Likert items on evaluation practices <i>Focus group item Q7</i> : Open-ended question on evaluation strategies	<i>Survey items Q12-Q14</i> : Descriptive statistics; Correlational analysis with year in program, age range, and gender <i>Focus group item Q7</i> : Thematic analysis

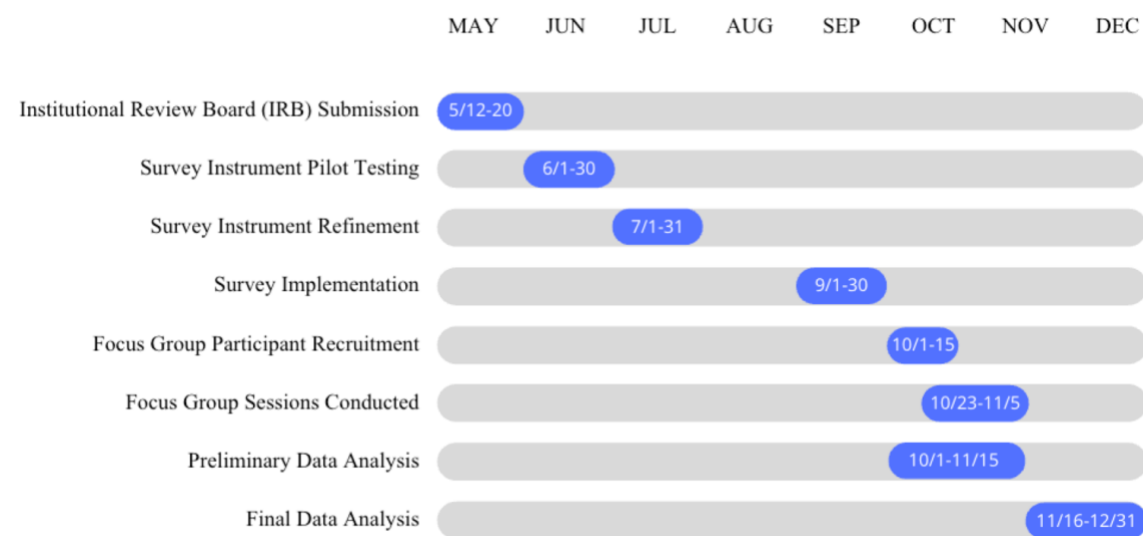
Research Question	Guiding Concepts	Data Collection Method	Analysis Approach
their work in CPED EdD programs?	<i>Behavioral domain:</i> implementing evaluation strategies	<i>Survey item Q15:</i> Open-ended question about evaluation strategies	<i>Survey item Q15:</i> Thematic analysis

Timeline

The timeline of the entire study was eight months, from May through December 2025. The survey instrument was piloted in June and refined in July. The final survey was implemented in September. Focus group participants were recruited in early October, and focus groups were facilitated by an external moderator in late October and early November. Data analysis was conducted starting in October and completed by December 31, 2025. See Figure 1 for details.

Figure 1

Research Timeline



Limitations

This study faced several limitations that can be categorized into researcher positionality, methodological constraints, and contextual factors.

Researcher Positionality

As both researcher and doctoral student in the context under study, my dual role presented potential for bias in data collection and interpretation. My own experiences with generative AI and personal views on its use in academic contexts may have unconsciously influenced how I framed questions, interpreted responses, and drew conclusions. While I implemented reflective journaling and peer debriefing to mitigate these effects, and used a neutral moderator for the focus groups, complete objectivity is not possible in action research where the researcher is embedded in the context (Mertler, 2020).

Methodological Limitations

The self-selected nature of participation means tendencies and patterns may overrepresent the perspectives of students who are already engaged with generative AI and interested in discussing it. The survey instrument was sent to a selection of CPED institutions rather than all member programs, which limits representativeness as well as generalizability of study results. As focus group participants were selected from survey respondents, all qualitative patterns will reflect this same potential bias.

Additionally, students may not have been accurate in self-reporting their generative AI usage due to faulty recollection or concerns about academic integrity. Responses to open-ended items in the survey were generally short, limited to a paragraph or less, and many respondents chose not to respond to the open-ended items. What students did write in response to the survey's open-ended questions may not accurately describe their regular practices in relation to generative AI. Additionally, capturing a full illustration of metacognition was inherently challenging, as these are internal cognitive

processes (Nelson & Narens, 1990). While focus groups provided an opportunity to more deeply explore these topics, time constraints and participant patience were finite, and participants' responses may not have been completely accurate either, meaning the complete reality of student experiences could not be fully captured.

The structure of the survey may also have inadvertently shaped students' responses to the open-ended items. For example, three Likert-scale items that asked respondents to rate agreement with statements related to evaluating AI-generated output were followed by an open-ended item asking respondents to describe their evaluation strategies. Specifically, respondents were asked to rate agreement with the statement, "I verify AI-generated information against other sources," then, in their open-ended statements, many respondents described verifying AI-generated information against other sources. The positioning of the Likert item prior to the open-ended items likely primed respondents to discuss the topic of the preceding items.

Contextual and Temporal Limitations

The rapid evolution of generative AI technology created significant temporal limitations, as usage patterns and ethical considerations may have shifted substantially even during the study period. Survey items may have become outdated and failed to capture behaviors related to the latest iterations of generative AI. Furthermore, though CPED programs share common principles, they vary in implementation, student demographics, and institutional cultures, limiting generalizability to non-CPED doctoral programs or professional contexts outside of education.

Despite these limitations, the study's mixed methods approach and triangulation of data provided valuable insights that can inform policy and practice within the specific context of CPED doctoral education during this critical period of generative AI adoption.

Summary

In this chapter, I described a previous cycle of inquiry and the research design for this cycle. The research design included setting and participants as well as the research plan and the role of the researcher. The goal of this research is to better understand how Doctor of Education students utilize generative AI in their academic studies in order to inform policy, guidance, and training.

CHAPTER 4

RESULTS

Introduction

In this chapter I will present the results of my data analysis. This chapter is organized by my three research questions, preceded by a summary of participant demographics. Results from the survey and focus groups, both quantitative and qualitative, will be interwoven in order to present an account of doctoral students' use of generative AI in CPED Doctor of Education programs. This chapter focuses on patterns, themes, and illustrative evidence.

A total of 190 students participated in this study, which included both a survey and focus groups. All respondents completed the survey, and 20 also participated in a focus group. In addition to closed-ended survey responses, 170 participants provided at least one open-ended response, resulting in a substantial qualitative dataset derived from survey comments and focus group transcripts.

Qualitative tendencies and patterns are presented through themes developed from an initial inductive coding process, followed by deductive categorization aligned to the study's research questions. Within each research question, coded data was analyzed for themes and presented in this chapter. Codes and themes were also considered in relation to the conceptual framework, which are noted where relevant. As discussed in Chapter 2, although the behavioral, cognitive, affective, and metacognitive domains of metaliteracy are conceptually distinct, they often overlap in practice; this overlap was also evident in the tendencies and patterns found in this study.

Tendencies and patterns are presented by research question to maintain analytic alignment. A cross-cutting interpretation of these is presented in Chapter 5. Each research question section begins with a brief overview of the associated code and its related themes, followed by quantitative results and qualitative evidence that illustrate how participants described their experiences and perspectives. A summary table depicting codes and related themes is provided to orient the reader, see Table 2.

Table 2

Research Questions, Codes, and Themes

Research Question	Code	Related Themes
RQ1	Assistant	Editing
		Writing Feedback
		Summarizing
		Manage Literature Reviews
	Lines and Boundaries	Acceptable Support vs. Unacceptable Authorship
		Process vs. Product
		When Uncertainty Leads to Avoidance
		Complete Avoidance of Generative AI
	Neveruser	Never Uses It – Except
		Save Time/Be More Efficient
	Productive	Screening Articles
		Summarizing
		Originality and Ownership
	Scholar*	Expertise
		Voice
		Overcome an Obstacle
	Stuck	

Research Question	Code	Related Themes
		Brainstorming
		Writer's Block
	Thought Partner	24/7 Availability
		Learn Through Talking
		Tutor
RQ2	Acknowledging Use	Unsure How to Acknowledge
		Don't Have to Acknowledge
		"Bad Optics"
		AI Assistance Erodes Ownership
	Concerned About	Where the Line Is
	Overuse	Feel Dependent on AI
	Fear of Being Accused	Policy Violations
		Retroactive Punishment
	GAI Policy	No Clear Policy
		Policy Varies
		Use Even Though It's Banned
	Scholar*	We Will Lead on AI
	Training and Guidance	Not Been Trained
		Wants Training
RQ3	GAI Knowledge and	Questionable Practices
	Prompting Strategies	
	Scholar*	Personal Expertise
	Verification Practices	Verifies Information
		Hallucinations

*Code and related themes appear across multiple research questions.

Participant Demographics

In this section, I will present participants' program status, gender, age range, and race/ethnicity. Study participants were distributed across all program years: 26.8% were first-year students, 27.4% were second-year students, 28.4% were in their third year, and 15.8% were in their fourth year or beyond. See Figure 2.

The gender distribution among participants was comparable to published data on CPED students as well as those that earned education doctorates in leadership and administration. Of participants, 73.4% were female, 22.3% male, and 2.7% non-binary. See Figure 3. This ratio is comparable to 2024 graduates of education doctorate programs in educational leadership and administration, who were 68.3% female and 31.7% male (National Center for Science and Engineering Statistics, 2024). Similarly, CPED

Figure 2

Distribution of Program Status of EdD Students

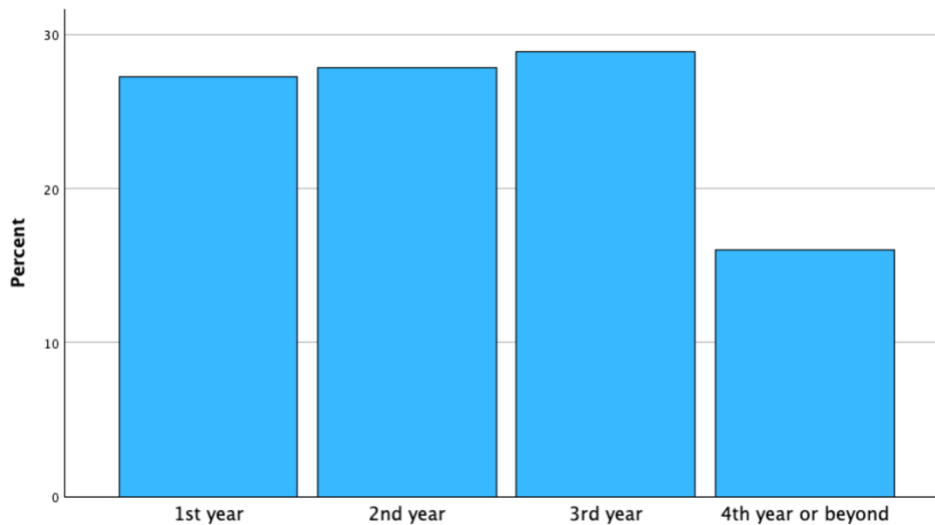
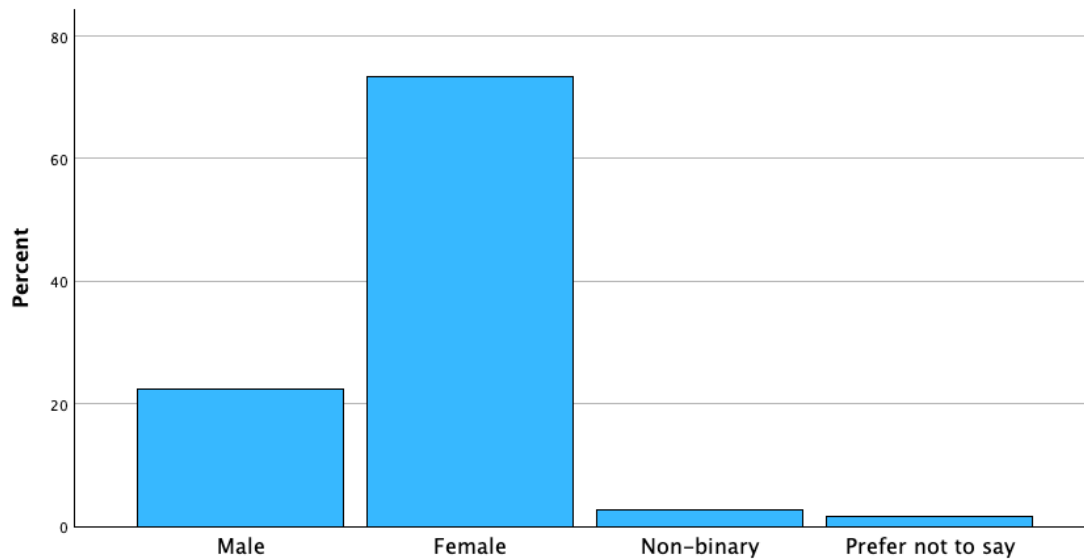


Figure 3

Gender Distribution of EdD Students



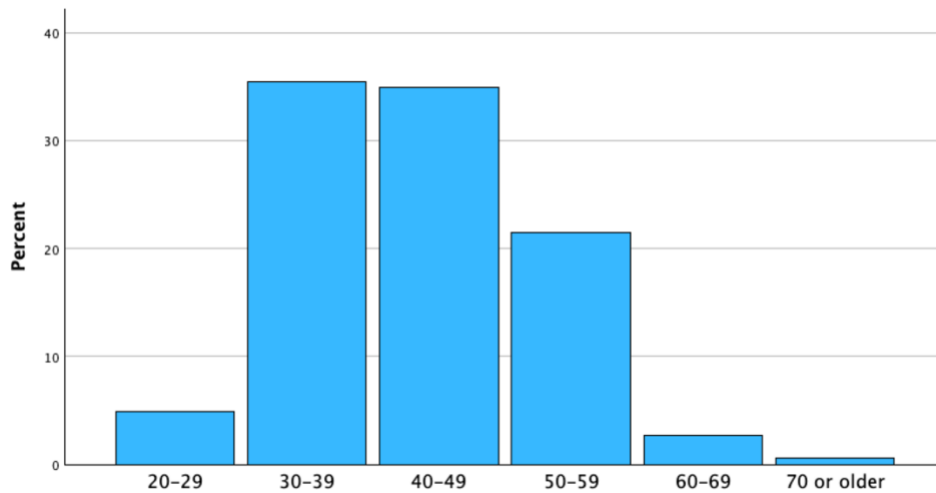
programs reported in 2020 that their student populations were an average of 53% female and 28% male (Carnegie Project on the Education Doctorate, 2020).

Respondents selected their age range. 4.7% were aged 20-29, 34.7% were 30-39, 34.2% were 40-49, 21.1% were 50-59, 2.6% were 60-69, and 0.5% were 70 or older. Most participants (90%) were between the ages of 30 and 59. Additionally, 68.9% of respondents were aged 30 to 49, closely aligning with CPED's 2020 data, which reported that 59% of students were between the ages of 30 and 50 (Carnegie Project on the Education Doctorate, 2020). See Figure 4.

With regard to race and ethnicity, respondents were able to select all categories that applied. The largest proportion of respondents identified as White ($n = 125$, 64.4%). Thirty-two respondents identified as Black or African American (16.5%), 18 as Hispanic or Latino (9.3%), and 8 as Asian (4.1%). Smaller numbers of respondents identified as

Figure 4

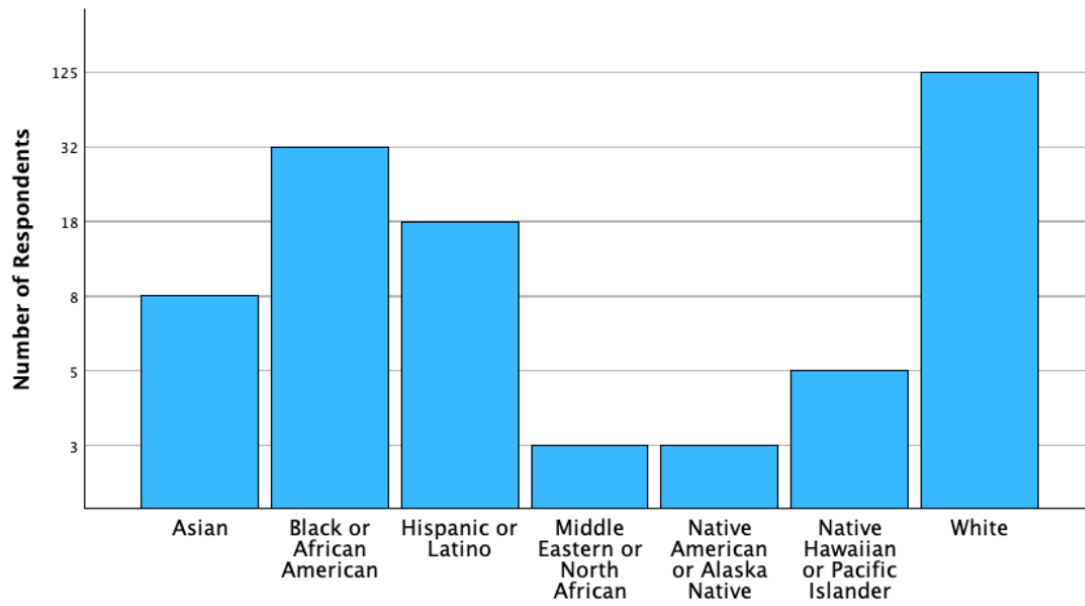
Distribution of EdD Student Age Ranges



Native Hawaiian or Pacific Islander ($n = 5$, 2.6%), Middle Eastern or North African ($n = 3$, 1.5%), and Native American or Alaska Native ($n = 3$, 1.5%). See Figure 5. This distribution of race and ethnicity is generally consistent with CPED's 2020 student statistics, which reported that 51% of students identified as White, 15% as Black or African American, 8% as Hispanic or Latinx, 3% as Asian, and 1% as American Indian or Alaska Native (Carnegie Project on the Education Doctorate, 2020). See Figure 5. Next, I will share results related to the first research question.

Figure 5

Race and Ethnicity Distribution of EdD Students



RQ1: What generative AI tools do doctoral students in CPED institutions use in their academic work, and how do they make decisions about when, how, and to what extent to use these tools?

Results from the survey and focus group sessions showed that generative AI use was prevalent among study participants, which may reflect that generative AI-using students self-selected to participate in this study because of an existing interest versus students that are not interested. The overwhelming majority of participants described using generative AI for academic purposes, with non-users being the minority.

Participants expressed a variety of perspectives on how they used generative AI as part of their academic work. Perspectives range from describing generative AI as an assistant or a tutor, to using it for specifically defined purposes, and to avoiding use for particular situations or avoiding altogether. Students gave several reasons for how they chose to use or avoid generative AI. They often described their decisions in relation to their identities as scholars, which included the desire to be original and maintain ownership, to develop expertise in their studies and research, and to preserve their own voice in their writing.

This research question is well-aligned to the behavioral, cognitive, affective, and metacognitive domains as described by metaliteracy (Mackey & Jacobson, 2022), and also provides insight into students' generative AI literacy. In answering this research question, students' self-reported behavior related to generative AI use will be described. In this section, I will summarize the results from the survey's quantitative items related to patterns of generative AI usage, then I will give results from the study's qualitative items

related to when and how respondents use generative AI, including how they decide to use it.

Overview of Generative AI Usage Patterns

EdD students reported regularly using a range of generative AI tools for academic purposes. *ChatGPT* was the most frequently used tool, with 70.4% of students (n = 133) reporting its use. The next most commonly used tools were *Google Gemini* (19.6%, n = 37) and *Microsoft Copilot* (18.0%, n = 34). *Claude* was used by 11.1% of students (n = 21), while *Perplexity* was reported by 8.5% (n = 16). The survey also allowed respondents to report tools not listed; among these responses, 6.9% of students (n = 13) reported using *NotebookLM* and 4.8% (n = 9) reported using *Grammarly*. Finally, 16.4% of students (n = 31) indicated that they do not use generative AI tools regularly. See Figure 6. Tables for this chapter may be found in Appendix F.

Respondents were asked to report the frequency with which they use generative AI tools. A small subset of respondents reported daily use of generative AI (6.3%, n = 12), while 23.7% (n = 45) indicated frequent use (three to five times per week), and 35.3% (n = 67) reported using generative AI tools occasionally, defined as once or twice per week. Additionally, 26.3% of students (n = 50) reported rare use (once or twice per month), while 7.9% of respondents (n = 15) reported never using generative AI. See Figure 7. Most respondents reported using generative AI tools at least weekly, with 65.3% using them at least once per week.

Figure 6

Distribution of Generative AI Tools Use Among EdD Students (Q1)

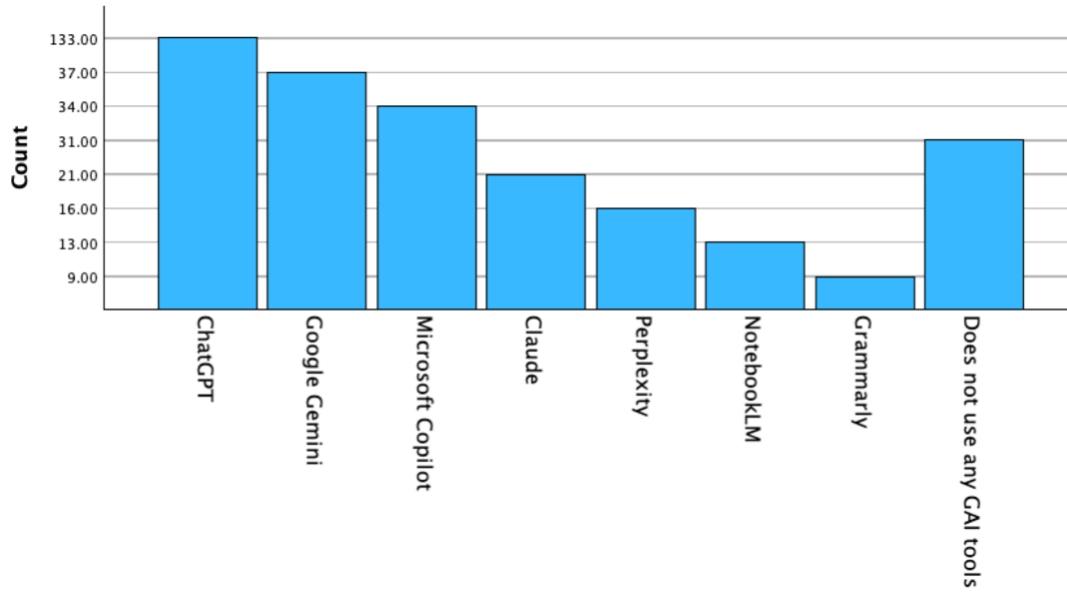
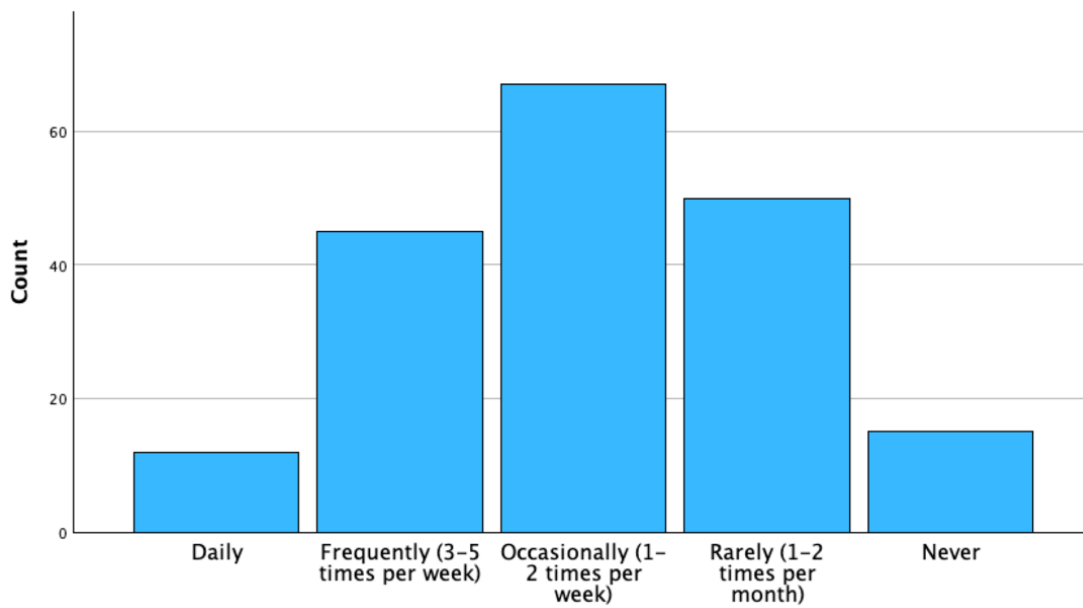


Figure 7

Distribution of Generative AI Usage Frequency Among EdD Students (Q2)



A chi-square test of independence was conducted to examine if there was a relationship between frequency of use and student year in program. To meet the test's assumptions, responses from participants who reported never using generative AI or using it daily were excluded due to low expected cell counts in those categories. The test indicated no statistically significant association between frequency of use and year in program ($p = .296$). See Table 3. This suggests that the frequency of generative AI use does not significantly differ by students' year in the program. For Crosstabulation table see Appendix F.

Table 3

Frequency of Generative AI Use and Year in Program

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	7.272 ^a	6	.296
N of Valid Cases	160		

A chi-square test of independence was conducted to examine the relationship between gender and frequency of generative AI use. All five levels of frequency were included, from Never to Daily. The analysis included only respondents who identified as male or female, as non-binary and "prefer not to say" categories produced low expected cell counts. The association between gender and frequency of generative AI use was not statistically significant ($p = .232$). Two cells (20%) had expected counts below five, but

none were below one, so the test met assumptions. See Table 4. This suggests that frequency of generative AI use does not differ significantly between male and female EdD students.

Table 4

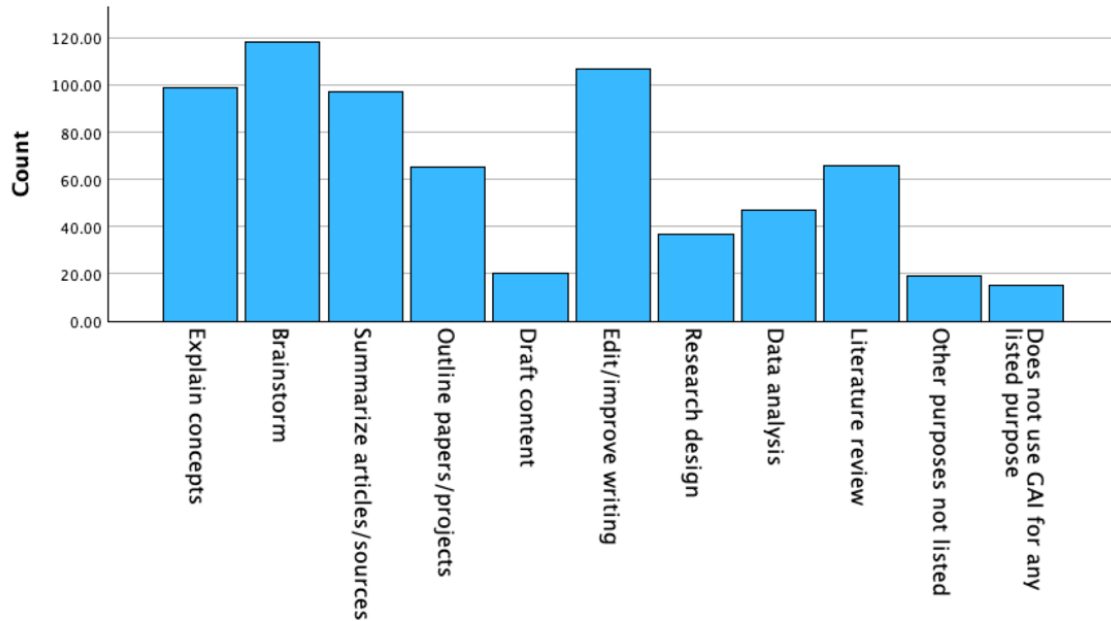
Frequency of Generative AI Use and Gender

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	5.585 ^a	4	.232
N of Valid Cases	180		

EdD students reported using generative AI for a range of academic purposes. The most commonly reported use was brainstorming ideas (62.1%, n = 118), followed by editing and improving writing (56.3%, n = 107), explaining concepts (52.1%, n = 99), and summarizing articles or sources (51.0%, n = 97). Additional uses included literature review assistance (34.7%, n = 66), outlining papers or projects (34.2%, n = 65), data analysis support (24.7%, n = 47), research design assistance (19.5%, n = 37), and drafting written content (10.5%, n = 20). See Figure 8 for more. Open-ended responses from the survey and focus groups were aligned with responses to these items and gave more insight into the nuances of how students are using generative AI.

Figure 8

Distribution of Tasks Using Generative AI (Q3)



How Students Use Generative AI in Practice

In responses to open-ended survey questions, and in focus group sessions, respondents said that they use generative AI to overcome feeling stuck and to be more productive. Respondents said that they use generative AI as an assistant, which includes using it to polish writing, provide feedback on their work, and summarize readings. They also described using generative AI as a 24/7 on-call learning partner and tutor.

When They are Stuck or Want to be Productive

Material coded with **stuck** captured those moments when students described turning to generative AI after encountering obstacles in their academic work. This code was used 33 times across qualitative data. Students described using generative AI to

decide what to do next, to brainstorm, and to regain momentum when they felt unable to move forward independently.

Participants frequently described turning to generative AI when they want to *overcome an obstacle*. Second-year student Aliana wrote that she turns to generative AI, “when I am at a complete loss on how to proceed, I use it to jump-start me with an idea or outline I can follow.” Rona, in her fourth year of her program, stated, “I use a generative AI tool as part of my academic work when I struggle to synthesize a response efficiently, need clarity on a topic or task, or hit a roadblock and need feedback on next steps.” Other students described turning to generative AI in order to *brainstorm* possibilities. Trina, also in her fourth year, said,

I have found great success when I am at a standstill or unsure of what to do, to brainstorm with generative AI to point me in another possible direction. This has allowed me to go to my committee with more work in hand and requiring less direction.

Participants also said that generative AI was a useful tool to overcome *writer's block*. Carlos, who is in his first year of his program, said, “I use it as a jumping board when I am stuck. It has helped me overcome writer's block on many occasions. I'll start with an idea I have circulating in my head, then I'll go from there.” When students feel stuck, they turn to generative AI for help. AI chatbots serve as an immediately accessible tool to help students overcome moments of feeling stalled or uncertainty in how to proceed. The tendencies uncovered by this code align with metaliteracy's cognitive domain, in that participants describe using generative AI to structure tasks, to the affective domain by

reporting a feeling (“stuck”) that prompts this behavior, and to the metacognitive domain by expressing awareness of this feeling.

Similarly to how they use generative AI to overcome obstacles, students stated that they found generative AI to be useful to make themselves more **productive**, which they defined as being able to *save time/be more efficient*. This code was used 28 times. Participants stated that they used generative AI to offload or speed up tasks, such as writing to-do lists or *screening* the relevance of scholarly literature before devoting the time to read. First-year student David said,

I have limited time. When we are assigned literature reviews, or other research based upon a problem of practice, I will use AI to help determine if a selected article is related to the PoP [Problem of Practice]. Being able to weed out research that does not support my work saves me time that I can devote to other aspects of my personal, professional, or academic life.

Using generative AI to screen scholarly literature before reading was a common theme.

Third-year Elise described how generative AI can make the literature review go faster:

“AI has been most useful in helping me find literature that is relevant to my research instead of wading through hundreds of dead-end articles and getting off track and confused.”

Respondents described also turning to generative AI when they wished to offload menial tasks to save time/be more efficient. Grigori, a student in his third year, stated that he uses generative AI “if there is a task I can complete smarter not harder [or in] situations when the manualized [sic] work would take longer, without benefiting my education.” In his survey responses, he reported using generative AI for *summarizing*

readings, editing and improving writing, as well as brainstorming. Blanca, who is in her third year, concurred, “it frees up mundane or repetitive tasks so we can spend our thinking time on deeper topics.” Students valued the ability to save time by using generative AI, believing that this strategy makes them more productive.

One respondent explicitly linked the desire to save time to the pressure of full-time employment and child-rearing. Rona, quoted above as using generative AI when she feels stuck, connected her practice of using generative AI to her desire to save time: “the ability of these tools to respond to specific questions instantaneously is extremely helpful to me as a full-time higher education professional who also has a family with young children to support.” Val, in her fourth year of her program, summarizes this drive, stating that generative AI “helps me get almost everything done faster so there really isn't a decision, it's always helpful.” Being productive is valuable to Doctor of Education students. The patterns of use described under this code align to metaliteracy’s behavioral domain, as participants describe offloading menial information tasks to generative AI, and to the metacognitive domain, as students make strategic decisions about which tasks are important to perform themselves, and which aren’t.

Generative AI as Assistant

Respondents said that they use generative AI tools to edit and improve their written work, receive feedback on their work, and expedite literature reviews. These descriptions were coded as **assistant**. This code was used 78 times to identify and describe lower-level uses of generative AI, in contrast to **thought partner** (described in the next section), which I used to designate higher-level uses that supported learner cognition. The qualitative data aligned with the quantitative result, which showed that

107 respondents reported using generative AI as an assistant to edit and improve their writing (as illustrated in Figure 8).

Second-year student Felcia uses generative AI to assist with *editing* and said that she has no concerns about her use of generative AI because “it is a partnership, AI makes me my thoughts clear and sound more professional, it cleans up my work.” She says that she also turns to *ChatGPT* “if I want to take an idea and describe it using more eloquent words or scholarly words.” Most students stated that they did not use generative AI to write for them, but only to polish what they wrote themselves. As an example, Talissa, who is in her second year, wrote:

AI cannot produce the quality of work that I require for my Ed.D, and doesn't have to contextual knowledge that I do. I can write better and more effectively about my topic than *ChatGPT*, so I know what I'm producing is 95% me and 5% AI polishing what I already have written. It's no different than having a peer or editor go over your work. I do not have concerns about how I'm using AI.

The extent to which students use generative AI to assist in writing is not always so well delineated. First-year student Josie reported using both *Grammarly* and *ChatGPT* for assisting with grammar and spelling as well as suggesting additional material: “after completing a draft for my assignments, I will use *ChatGPT* to request assistance with flow and content additions, based on the prompt. I also use *Grammarly* before putting it into *ChatGPT*.” Overall, respondents described generative AI tools as convenient and useful for improving their writing and, in some cases, for adding additional written content. These tendencies suggest that the boundary between editing and creating written

content with generative AI may be fluid for students, particularly the distinction between revising existing text and generating new content.

Beyond editing their writing, students said that they used generative AI to get *writing feedback* on their work. They ask AI chatbots to evaluate their work to determine whether it's on topic, if it's missing any gaps, and to rate it against expectations or rubrics if it's an assignment for a course. Cameron, a second-year student, gives an example of using generative AI to evaluate his writing that leverages generative AI's ability to summarize:

I don't use AI to create anything new. I ask it to evaluate my own work. For example, I will upload my own writing and ask it to write a concluding paragraph. This paragraph helps me evaluate my writing and if what I am trying to say comes across. If AI is making a claim, I will either just ignore it as I don't want AI changing up my ideas too much.

Cameron is careful to point out that he has a strict boundary to keep his writing and ideas original.

Students also use generative AI to identify content gaps. Fourth-year student Paula, who is currently working on her dissertation, said, "I've used AI to help me summarize proposal content, to review and enhance my writing and to point out what I've missed within my work." Some students also use generative AI to analyze their assignments to ensure that they are complete and ready to turn in. Third-year student Michelle says that she turns to generative AI "when I want to ensure conciseness and clarity, or ensure that a document meets all metrics in a rubric, or when ensuring that the document is politically sensitive and appropriate." Across the data, students described

using generative AI to provide evaluative feedback to confirm alignment, identify gaps, and assess readiness for submission, while maintaining control over their ideas and final revisions.

Participants also used generative AI as an assistant that helps them *manage literature reviews*. When students were asked which generative AI tools they used, 13 (6.8% of students, see Figure 8) reported using one that was not listed as an option: *NotebookLM*, which is a generative AI tool offered by Google. Participants reported using this tool as a personal information retrieval system. *NotebookLM* was described as particularly adept for *summarizing* articles and other literature review sources. Users may upload a wide variety of sources to a “notebook,” which allows the user to query those sources. *NotebookLM* will generate summaries and syntheses of uploaded articles and will also help users locate relevant quotations or information, as well as make connections between uploaded articles. Third-year student Susanna describes how she uses it:

I like to use *Notebook LM* to generate summaries of research articles that I am using for my dissertation. I read the research articles myself, but I use *Notebook* to check and see if I am missing anything, or if there are any emergent themes and links between articles that I have not picked up on.

Susanna reads the articles but also uses *NotebookLM* as an additional strategy to understand her sources and discover commonalities. Second-year student Jed elaborates on his use of *NotebookLM*:

First and foremost, I do not use AI in a way that the models would put my ideas or academic integrity at risk. More than anything, I use *NotebookLM* to reference

and recall notes I have taken. It's an automated way to easily access my original thinking. This allows me to easily click to verify that the output is drawing from a specific piece of original material. When using *perplexity* of [sic] *ChatGPT*, I am working through an exploration process that always results in interacting with primary resources directly. In that way, I see (after the fact) how those LLMs may mistake the context of certain pieces/ideas but not in a way that will end up reflected in my work.

Participants value the ability to stay organized using generative AI tools like *NotebookLM*. This tendency described in the qualitative data aligns with the quantitative result showing 66 respondents reported using these tools for assistance in literature reviews (see Figure 8).

Across the themes under the code **assistant**, respondents described using generative AI in ways that largely supported their academic work without replacing it. They used generative AI tools to edit their writing, get feedback, summarize articles, and manage their literature review, while maintaining authorship of their ideas and work. These tendencies aligned with metaliteracy's behavioral and, to an extent, metacognitive domain. By describing task-specific use of these tools, including for editing, evaluating, and literature organization, they described focused information behavior. By setting clear boundaries for use, they demonstrated self-reflection, which is a metacognitive skill. Their self-reflection and boundary setting also demonstrates their personal ethics, which falls under both metaliteracy and generative AI literacy. Additionally, their use of varied generative AI tools, including *NotebookLM*, demonstrates technical tool knowledge, which is a key component of generative AI literacy.

Generative AI as Thought Partner

Whereas the code **assistant** was used to describe lower-level uses of generative AI that focused on completing discrete tasks or providing editing or organizational support, the code **thought partner** was used to tag instances where generative AI was used to support or improve thinking and learning. This code emerged in vivo from the data (nine participants used this term to refer to generative AI). **Thought partner** was used 50 times across the qualitative data. Participants valued generative AI tools for their 24/7 availability and for its ability to engage in interactive dialogue that allows students to ask questions, think through ideas, and clarify understanding. Under this code, participants described using generative AI as an on-call personal tutor.

The 24/7 availability of generative AI was described as a major point of convenience, as well as its willingness to provide perceived emotional support. Tanja, an English teacher (her year in program was not provided in her focus group session), said that generative AI enhances her learning,

because, I do have someone 24/7 to ask questions to, and I am a questioner. I need to be able to ask questions, and I have some professors who are very open to that, but I have one professor who does not want to engage in that. And so, sometimes I just need to be like, I need a sounding board, and when it's the middle of the night, I'm going to be honest, my husband does not want to hear my doctoral questions.

Generative AI may be used to boost student morale on call. Nancy, a third-year student, describes using generative AI in this way:

We learn in the context of other people. And I didn't have that [as an online student]. And so, in some ways, that thought partnership [of generative AI] got me through...In the middle of the night, when you're doing your deep thinking, who are, you know, who are, how are you, who is the person that you are, using as a sounding board, as a, you know, as a, just somebody to dialogue with. It's not happening at certain hours of the day, it's happening at 12 AM, right? And so, I found, it's possible that in some ways, you know, this doctoral process that, for so many others, has been such a degrading, like, hazing experience, I wonder if AI, in some ways, that sycophantic, sort of, like, incessant praiseworthiness [sic], gets some people through. I mean, it's like, so much of this process is just, gathering the confidence to continue, and to just persist through it. And here you have this little tool that's like, "those are interesting ideas," you know? And, like, you just sort of have to persist on this vague notion that you have an interesting idea, and that you must see it through. Nobody else will say that to you at 12am. You can't just do it in a vacuum. And unfortunately, this program for me was set up to be doing it in a vacuum, which is completely inappropriate for the level of thinking that's happening.

To Nancy, generative AI's sycophancy is a feature, not a bug, and she perceived its output as support. Participants turn to generative AI 24/7 to think through their ideas and receive emotional support, especially when other forms of support were unavailable.

Beyond emotional support, many participants reported using a chatbot to *learn through talking*. Respondents stated that they use generative AI as a partner or as a classmate that they are learning alongside. Second-year student Caitlin wrote:

I primarily use AI when I need a thought partner - I ask it the types of questions I might ask a classmate. For example, I might read an article, jot down my own notes about it, and then ask AI to summarize it to see if it mirrors what I thought or came up with something different, comparable to comparing notes with a classmate.

In these responses, students are describing a drive to learn socially. Similarly, fourth-year student Lara says, “I decide how to use *ChatGPT* when, what I really want, is a critical friend who can help me think through the way I structure my arguments.” Michael, in his third year, went a little further, stating:

I live by the mantra that it's not just a technology, but a team member. In many ways, it acts as a fourth member of my dissertation committee, who is present with me in the daily development process of my ideas.

These students are expressing a desire and a need to learn via social processes. In absence of live classmates or instructors, generative AI fills that void.

In addition to emotional and cognitive support, students use generative AI as a *tutor* to help them better understand new terminology or complex topics. Acacia, a second-year student, said, “as far as development of expertise, I think it has actually benefited me primarily because I might use it to better explain, terminology or concepts that I don't understand as much.” Fourth-year student Franklin said, “I try to digest the information or concepts first, and if I struggle, then I turn to AI to help break it down for me.” He continued, “it has been a great resource for helping me understand complex topics. I have gone back and forth with it on several occasions, and it has challenged my thinking in developmental ways.” Students described using generative AI to improve

their own understanding of a topic and to help them grow as a learner. Third-year student Sandra said,

when using AI, you still have to do the work. AI is a tool. I am the researcher.

This is my work. AI is almost like a think partner, I ask it multiple questions, so I that I have a level of understanding that I understand [sic] and that I can discuss with others.

Across the data, students described using generative AI to help them learn, not to replace their own learning.

These tendencies in the qualitative data align with the quantitative results that 99 respondents that reported using generative AI to explain concepts, as well as the 118 respondents that stated they used generative AI for brainstorming, as illustrated in Figure 8. Students' use of generative AI as a thought partner fall under the behavioral and cognitive domains in metaliteracy, as they show that they ask questions, explore ideas, and test understanding using these tools. In the next section, patterns related to respondents' decision-making will be explored.

Generative AI as Relational Actor

Across both the assistant and thought partner codes, an additional pattern emerged that was not initially captured in task-level descriptions of use. Participants frequently described generative AI using explicitly relational and anthropomorphic language, assigning it roles traditionally occupied by real humans. These labels included tutor, writing coach, critical friend, sounding board, and even "a fourth member of my dissertation committee." Although these labels appeared under both assistant and thought

partner codes, they collectively suggest that students are not merely using generative AI as a tool but are positioning it as a relational actor that assists with their academic work.

Under the **assistant** code, several students compared generative AI's editing and evaluative functions to those of a peer reviewer, writing coach, or tutor. For example, Talissa described AI polishing her writing as "no different than having a peer or editor go over your work." Similarly, when students described asking AI to evaluate their writing against a rubric or identify gaps, they often framed this process as similar to receiving feedback from a human reviewer. These descriptions blur the boundary between tool and collaborator. Even when students emphasized that AI did not replace their thinking, they frequently described it in relational terms that usually apply to human-provided academic support.

This relational framing became even more pronounced within the **thought partner** code. Participants described generative AI as a "sounding board," a "critical friend," and a "classmate" with whom they could compare notes. Caitlin stated that she asks generative AI "the types of questions I might ask a classmate," explicitly aligning AI interaction with peer-based learning. Lara described wanting "a critical friend who can help me think through the way I structure my arguments." These metaphors indicate that students conceptualize their engagement with generative AI as dialogic and socially situated.

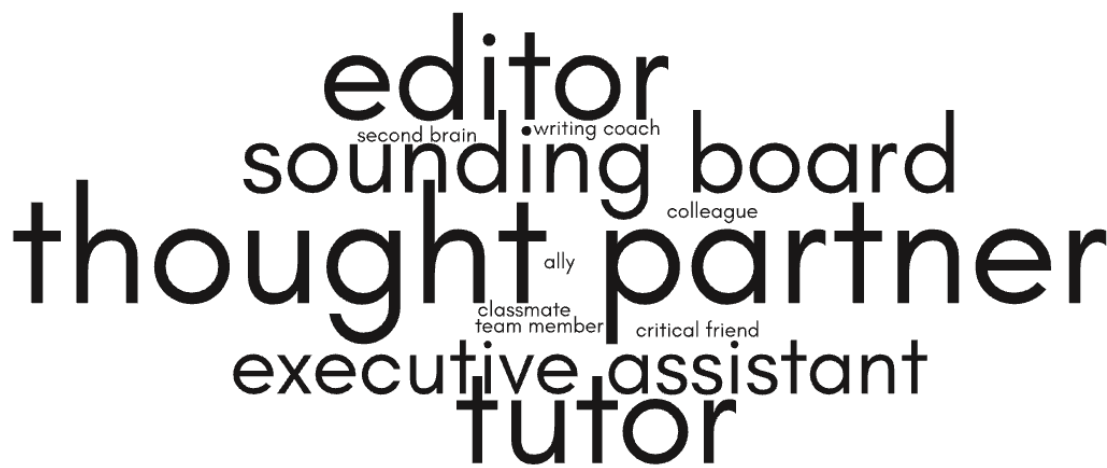
In some cases, the anthropomorphizing language extended beyond peer comparison and into faculty-equivalent roles. Michael stated, "it's not just a technology, but a team member. In many ways, it acts as a fourth member of my dissertation committee." This description assigns generative AI a formalized position within the

doctoral support structure. Similarly, participants referred to AI as a “tutor” or “writing coach,” roles that are forms of academic support typically available from an institution. While students consistently emphasized that they retained authorship and responsibility for their ideas, their language reveals that generative AI is being integrated into the relational ecology of doctoral study.

Importantly, this anthropomorphizing was not isolated to a small subset of participants. Labels such as thought partner, tutor, collaborator, and coach appeared across multiple focus groups and survey responses. Although the assistant and thought partner codes were initially used to differentiate lower-level task support from higher-level cognitive engagement, the relational language embedded within both suggests that students experience generative AI not only as a functional tool but as an anthropomorphized presence within their scholarly development.

Figure 9

Roles Assigned to Generative AI (Weighted by Frequency)



Taken together, these patterns indicate that generative AI is being positioned as a form of frontline academic support that mirrors, supplements, and in some cases overlaps with roles traditionally associated with faculty, peers, or institutional support services. This relational framing provides an important foundation for understanding how generative AI use may intersect with and potentially reshape faculty-student relationships, a topic explored further in Chapter 5.

Decision-Making About When and How to Use Generative AI

In this section, I will present the tendencies and patterns from this study that relate to respondents' decision-making related to when and how they use generative AI. From the previous section, we know more about how respondents describe their behaviors in using generative AI for academic purposes. Now, I will present the results from several quantitative items related to decision-making and then triangulate those results with tendencies and patterns from the survey and focus groups' qualitative responses. Results show that decision-making about when to use generative AI, and the extent to which it is used, is shaped by the affective and metacognitive domains. First, I will present quantitative results for several Likert scale items that relate to metacognition, then I will present relevant qualitative results and triangulate.

Goal Setting, Strategies, and Metacognitive Awareness

On the survey, respondents were asked to use a 5-point Likert scale to describe their agreement with a series of statements related to goal setting, strategies, and metacognition. *Strongly agree* was equivalent to five points and *strongly disagree* to one point. Several of these items were written to gain insight into students' thinking, or

metacognition, related to generative AI. Three of these items were written and included to gain insight into respondents' decision-making related to generative AI:

- When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI (Q4).
- I consider multiple strategies, including whether to use generative AI, when approaching EdD tasks (Q5).
- I use generative AI outputs as starting points rather than finished work (Q18).

Two of these items were written and included to gain insight into respondents' self-reflection and self-monitoring related to generative AI:

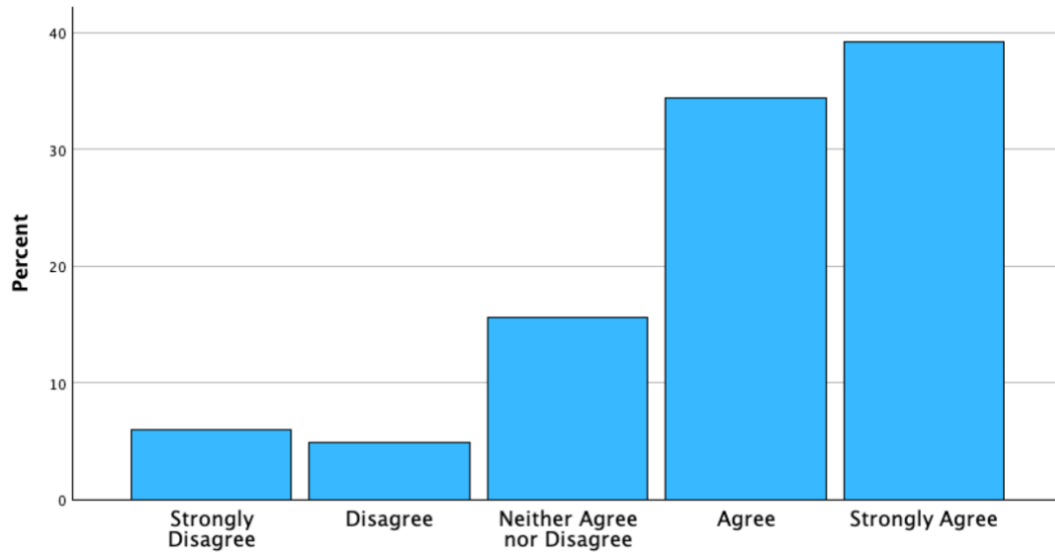
- I regularly reflect on how use of generative AI influences my thinking (Q16).
- I actively monitor how my use of generative AI affects the development of my own expertise (Q17).

This focus on student decision-making and self-reflection corresponds with metaliteracy's metacognitive domain, which describes how students think about their information behavior, and how that thinking relates to their actual behavior (Mackey & Jacobson, 2022). The results for these items show that students say they set goals for their academic work before selecting an appropriate strategy, including use of generative AI, and to an extent, perform self-reflection and self-monitoring when using this technology.

Here's how survey respondents indicated their agreement with the statement, "When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI." For this statement, 5.8% of respondents strongly

Figure 10

When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI (Q4)

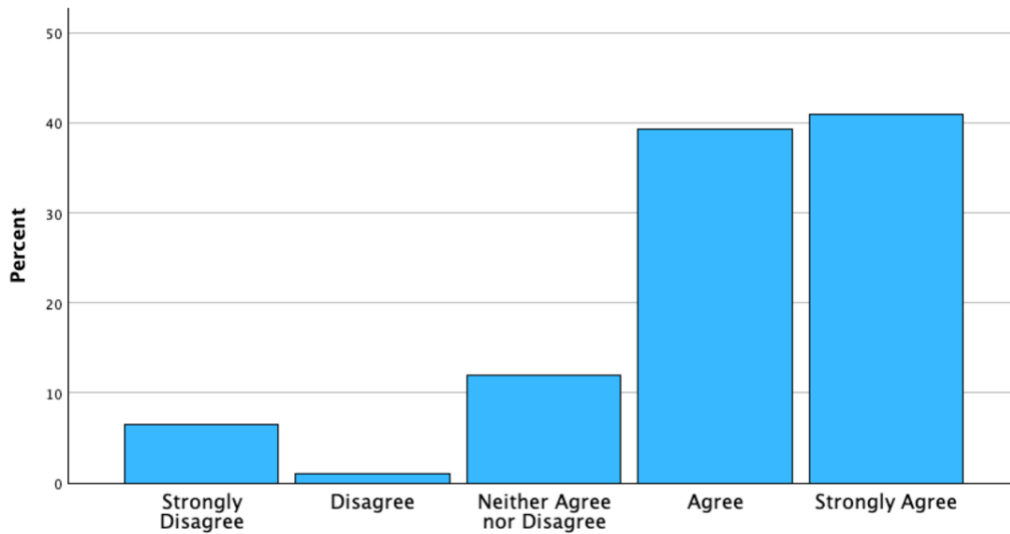


disagreed ($n = 11$), 4.7% disagreed ($n = 9$), 15.3% neither agreed nor disagreed ($n = 29$), 33.7% agreed ($n = 64$), and 38.4% strongly agreed ($n = 73$). Most respondents, 72.1%, either agreed or strongly agreed. The mean for this item was 3.96, and the Standard Deviation was 1.131. See Figure 10 (tables may be found in Appendix F). These results indicate that most students reported that they do set goals for what they need to accomplish before deciding on what to do next.

For the statement, “I consider multiple strategies, including whether to use generative AI, when approaching EdD tasks,” 6.3% of respondents strongly disagreed ($n = 12$), 1.1% disagreed ($n = 2$), 11.6% neither agreed nor disagreed ($n = 22$), 37.9% agreed ($n = 72$), and 39.5% strongly agreed ($n = 75$). Most respondents, 77.4%, either agreed or

Figure 11

I consider multiple strategies, including whether to use generative AI, when approaching EdD tasks (Q5)

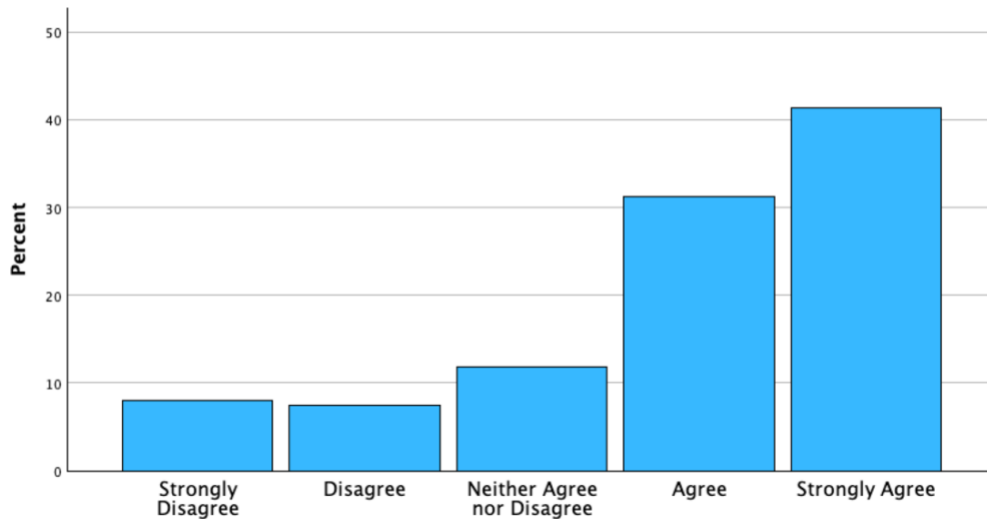


strongly agreed. The mean was 4.07, and the standard deviation was 1.079. See Figure 11. These results indicate that students say they aren't turning automatically to generative AI to accomplish a task. Instead, they identify and weigh the merits of a variety of strategies, with generative AI use potentially being one strategy among them.

Here's how they indicated their agreement with the statement, "I use generative AI outputs as starting points rather than finished work." For this statement, 7.9% of respondents strongly disagreed ($n = 15$), 7.4% disagreed ($n = 14$), 11.6% neither agreed nor disagreed ($n = 22$), 30.5% agreed ($n = 58$), and 40.5% strongly agreed ($n = 77$). Most respondents, 71%, either agreed or strongly agreed. Yet, 15.3% either disagreed or strongly disagreed. The mean was 3.90, and the standard deviation was 1.248. See Figure 12. These results indicate that students may use generative AI as a starting point, perhaps

Figure 12

I use generative AI outputs as starting points rather than finished work (Q18)

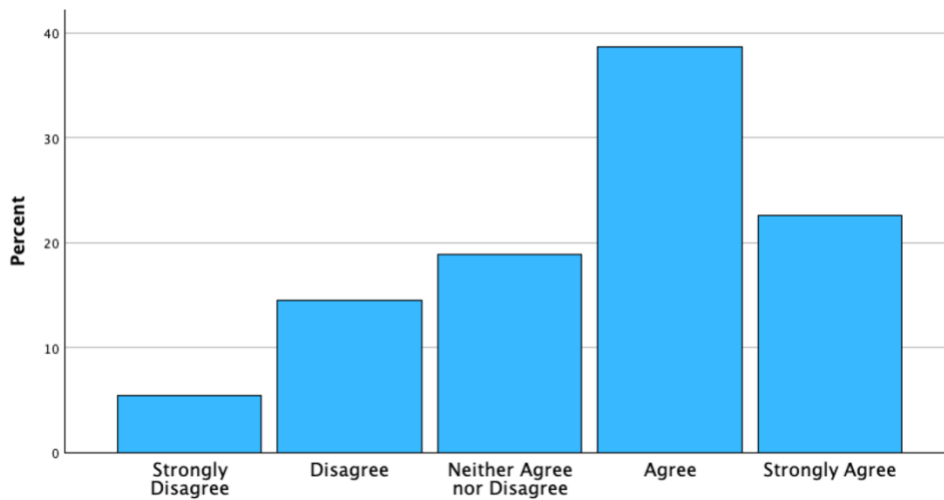


to brainstorm or outline, but do not use it to produce content for their work. Those that disagreed aren't necessarily using generative AI to do their work for them (i.e., cheat). They might be using generative AI to edit their writing, for example, such as asking generative AI to edit a sentence and then copying and pasting that sentence. Respondents may be using generative AI to produce finished work, but generative AI isn't necessarily producing that work in its entirety. Over 100 students stated that they used generative AI to edit or improve their writing, so it's possible they had that task in mind when answering this Likert item.

Respondents were asked whether they regularly reflect on how the use of generative AI influences their thinking. A majority of students agreed (37.9%, $n = 72$) or strongly agreed (22.1%, $n = 42$) with this statement, indicating a high level of metacognitive engagement. An additional 18.4% ($n = 35$) neither agreed nor disagreed,

Figure 13

I regularly reflect on how use of generative AI influences my thinking (Q16)



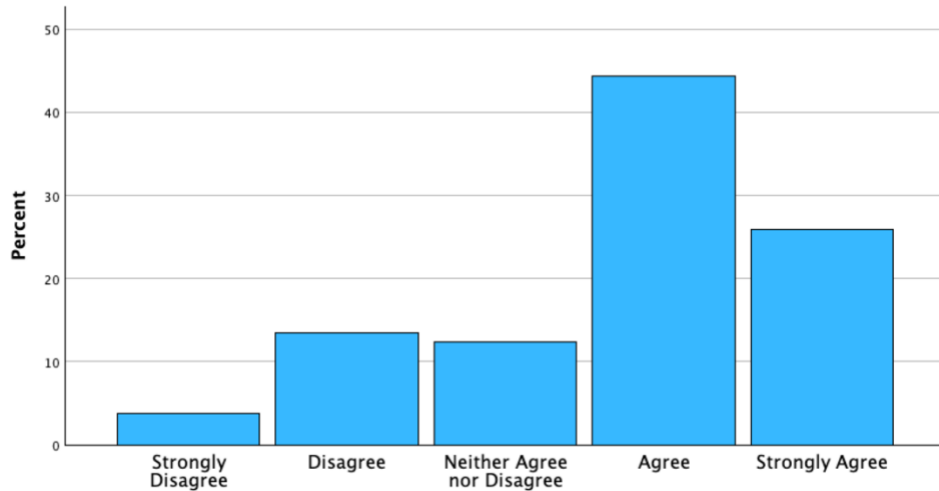
while fewer respondents disagreed (14.2%, $n = 27$) or strongly disagreed (5.3%, $n = 10$).

The mean was 3.59, and the standard deviation was 1.146. See Figure 13. These results show that more than half of students say that they reflect on how generative AI influences their own thinking. This item had more neutral and disagree responses than previous Likert items. This might be because respondents don't feel they are using generative AI in a way that requires self-monitoring. Also, the very act of being asked to respond to a question about metacognitive processes requires students to engage in a metacognitive process. In the context of a survey, students may not have taken the time to carefully consider their answers to this item, and alternatively, it may be that respondents often do not engage in metacognition around their generative AI usage.

In response to the item "I actively monitor how my use of generative AI affects the development of my own expertise," 43.2% of respondents agreed ($n = 82$) and 25.3%

Figure 14

I actively monitor how my use of generative AI affects the development of my own expertise (Q17)



strongly agreed ($n = 48$). A smaller percentage selected neither agree nor disagree (12.1%, $n = 23$), while 13.2% ($n = 25$) disagreed and 3.7% ($n = 7$) strongly disagreed.

The mean was 3.75, and the standard deviation was 1.100. See Figure 14. The results for this item indicate that around two thirds of respondents stated that they monitor development of their own expertise. More respondents indicated “agree” rather than “strongly agree,” showing that they may lack confidence in self-monitoring. However, the overall finding is that students state they engage in self-monitoring.

The quantitative responses above show that students say they are conscientious about generative AI usage, indicating that they use generative AI as one tool among others, and that they say they self-reflect on their thinking and self-monitor development of their own expertise. Qualitative responses to the survey and the discussion in focus group sessions offer additional interpretation of the quantitative results. Themes that

emerged under the codes **lines and boundaries** and **scholar** provided insight into how students say they decide to use generative AI, and the extent to which they use it. Next, I will present results from qualitative responses related to how students decide how to use generative AI, including the boundaries that they set for themselves, as well as offer more insight into how students self-reflect and self-monitor when using generative AI.

Lines and Boundaries

Throughout the data, participants describe drawing personal boundaries around their use of generative AI. **Lines and boundaries**, which was coded 66 times, provides insight into students' ethical decision-making. The lines and boundaries that students set for themselves delineate which academic tasks they view as appropriate for generative AI support and which they consider inappropriate within their coursework.

Acceptable Support vs. Unacceptable Authorship

Students made distinctions between using generative AI for support versus using it for authoring work. Ariadne, a first-year student, said:

I like to think of it [generative AI] as a tutor for my studies. Some articles we are given to read are very lengthy and can be hard to understand. I like to ask AI to help me chunk information into manageable sizes, concise summaries, and maybe alternative definitions of key words to help me better understand. I also feel like I am not the best with grammar, sentence structure, and punctuation. Therefore, I might ask if a sentence sounds coherent and ask what feedback it would offer, like a writing center at school would do. However, I do not copy and paste anything. I use it as a guide or tutor, not my writing tool or idea generator. I want my own voice and thoughts to shine through my work.

Ariadne frames generative AI as appropriate for tutoring and writing support, explicitly comparing its use to services provided by a campus writing center. She draws a clear boundary at copying and pasting AI-generated text and at using generative AI for idea generation, distinguishing between support for comprehension and writing versus the production of original ideas. Second-year student Giselle turns to AI for assistance, but avoids using it to generate text to copy and paste:

It's really appropriate to utilize AI to help in the EdD program because of the stressors of the program and the uncertainty of an online program, before I go bother my professors or a peer. But there's clear inappropriate use. Having it generate any text and inserting that into any of my writing is inappropriate, and simply, just not me.

Giselle describes using generative AI as a form of first-line support in response to the stress and ambiguity of her online doctoral program, positioning AI as an alternative to seeking immediate help from faculty or peers. At the same time, she draws a firm boundary around authorship, rejecting any use of AI-generated text in her writing and framing such use as inconsistent with her identity.

Process vs. Product

Across participants, decisions about generative AI use were shaped by whether students prioritized the learning process or the final academic product. Some participants emphasized developing specific skills through independent work, while others prioritized maintaining ownership of the end product, even when generative AI served as a tool to support its creation. Caitlyn, a second-year student, sets a boundary for herself to only use generative AI after developing her original work:

I think it's important to understand that you shouldn't use AI to accomplish a skill that you are trying to learn before giving it a shot on your own. For example, I am trying to learn how to identify authors to include in a literature review, so I typically work on a review for a while before asking AI for its input. I don't want my ideas to be swayed by AI before I have a chance to form them. However, I am happy to ask AI to help with my grammar, conciseness, and punctuation. I don't delay asking for help with those skills because I've already developed them, and it doesn't benefit me to focus my time primarily on growing my technical writing skills. I need that time to focus on my research skills right now. Still, I pay attention to areas of my writing where AI repeatedly recommends revisions, and I look for themes so that I can improve.

Caitlyn sets learning goals and then decides to use generative AI accordingly, first attempting tasks that develop her research skills before turning to AI for support with writing mechanics. She uses generative AI selectively to manage time while protecting independent thinking in areas she is still learning.

Similarly, second-year student Caspar decides to use generative AI based on developing his understanding of his own work:

So I think, like, for me, the product is knowing things, right? Like, I, we just, did a big re-read of our lit review, and, understanding, like, yeah, I know the information that's here, and I know how it's sewn together because it came out of my hands, is a different level of knowing than when I sometimes, like, use it to stitch together things at work. And so it feels uncomfortable to me to have to stand on writing that I can't know exactly how it got pieced together. I did try

some of that early on with some smaller assignments, and I was, like, turning them in. I was like, man, this is not, it's not right.

Caspar regulates his use of generative AI based on whether it helps him develop understanding and maintain ownership. After experimenting with using generative AI to assist in writing smaller assignments, Caspar found that using generative AI to assemble text limited his ability to fully know and stand behind the work, leading him to more carefully monitor and restrict his use in academic contexts, particularly in contrast to how he uses AI in professional settings.

Another student, Lida, does use generative AI to help assemble her work. Lida is also in her second year and participated in the same focus group as Caspar. She also uses a sewing metaphor in her response to a focus group question on when you can copy and paste from generative AI, and when you shouldn't:

Yeah, so I would say I definitely try to put everything into my own words, and, like, read through, and be sure that I'm, like, weaving things together, and, I have, I start by copying and pasting, but nothing ever gets, like, that's never the version that ends up making it into the paper. It's always, like, an iteration to get it going, and, so, and it does come from, again, like, me pulling the sources and pulling the quotes and adding the pieces together, so I do feel like there's a, I don't know, like a, maybe I'm trying to make a quilting metaphor. Like, if it's the back fabric, like, I'm doing a lot of my own stitching on top of it, but never, like, just handing the one piece of cloth over to the other person.

While Caspar perceives AI-assisted assembly as producing work he cannot fully stand behind, Lida treats generative AI output that is grounded in her own sources and ideas as

a scaffold for iterating a final product she claims as her own. Both students prioritize ownership, but they diverge in their process to reach their goals.

Following these examples, similar distinctions between learning and production appeared consistently across the data. Participants articulated lines and boundaries that centered on whether generative AI supported understanding or replaced the demonstration of learning. Fourth-year student Lucia explained, “if what I'm getting from generative AI is not essential to the learning or understanding, then I'll use it. If what is generated from AI is the demonstration of learning, I do not.” Another participant, third-year student Edin, framed the boundary in terms of labor and intent, noting that using generative AI to reorder ideas or brainstorm still constituted doing the work, while using it to make up for lost time did not:

The decision for using GenAI for me has to do with who is doing what work. If I am using it because I'm running behind, that's a bad use of AI. If I'm using it to reorder or brainstorm with, I am doing the 'work.'

Taken together, these examples demonstrate that students consistently relied on self-defined lines and boundaries to regulate generative AI use, using distinctions between process and product as a guide. For more examples of moments in the qualitative data where participants described their lines and boundaries in terms of process versus product, see Appendix G.

When Uncertainty Leads to Avoidance

Across the qualitative data, participants described moments of uncertainty about ethical or appropriate use of generative AI that led them to limit their use or avoid the technology altogether. Rather than experimenting and adjusting, many students defaulted

to nonuse when boundaries felt unclear. Second-year student Aliana said, “I likely underutilize it because I worry that using AI for more than just organizational tasks and grammatical error detection might be unfair or unethical.” Similarly, third-year student Wendy said,

I believe I could probably use AI more than I do but I struggle with what is appropriate and allowable and what is crossing a line in the academic world. I always default to not using it if I am questioning the appropriateness of my AI usage.

For some participants, this restraint was explicitly tied to fear of accidental academic dishonesty. First-year student Muriel articulated a lack of confidence in their own AI literacy,

I have maintained a personal philosophy that I do not know enough about generative AI to use it 'safely' in my work. I fear using it without proper training could put me in a position to commit accidentally [sic] academic dishonesty.

Therefore I only use it (*ChatGPT* free version) to explain terms or concepts to me if I cannot understand them fully from my lessons or text.

Together, these accounts suggest that uncertainty, rather than clear policy violations, often drives reduced use or avoidance of AI altogether, positioning ethical ambiguity as a barrier to confident use of generative AI.

But there was one respondent that stated that they regretted not using generative AI to do at least some of their assignments. Third-year student Alonzo said,

A big part of the EdD program involves writing discussion posts. Most of the discussion posts are time-consuming, not rewarding, labored, and formulaic

('create one post and reply to two classmates'). Because many of my classmates used AI to generate/augment their responses, it was not a big time-suck for them (this is something they have openly discussed), but it took me hours every week, with little pay-off. I lost so much time to these posts that I could've used for papers/projects. NOT using AI harmed me.

These accounts suggest that reduced or avoided use of generative AI was often driven less by clear policy violations and more by uncertainty about ethical boundaries. For many students, the absence of clarity led to conservative decision-making, with nonuse functioning as a barrier against potential academic dishonesty. However, as Alonzo's reflection illustrates, reducing or avoiding use may seem to have consequences as well. In contexts where peers were quietly using generative AI to complete routine academic tasks, choosing not to use these tools sometimes resulted in lost time and diminished capacity to focus on more meaningful scholarly work. Notably, participants did not describe these decisions as being guided by formal instruction or program-level expectations. As Nancy observed, "I don't think any instructor in any part of my program has ever offered guidelines on the usage of AI." The lines and boundaries that students draw for themselves, along with Nancy's quote, suggest that students were left to navigate ethical use largely on their own.

Across the code **lines and boundaries**, participants reported consistent self-regulation of generative AI use by drawing personal lines and boundaries grounded in ethics, ownership, and learning goals. These decisions reflect the behavioral and metacognitive domains of metaliteracy, as students actively monitored how and when they used AI in relation to process versus product, and adjusted their practices to protect

understanding and authorship. Participants' emphasis on maintaining voice, identity, and comfort with their work highlights affective metaliteracy, while distinctions between comprehension support and idea generation align with cognitive metaliteracy. However, uncertainty about acceptable use, often in the absence of formal guidance, revealed uneven generative AI literacy, particularly around ethical use and technical confidence, leading some students to avoid AI altogether.

Scholarly Identity as a Driver of Generative AI Use

One factor that played into decision-making related to generative AI was if students expressed values related to being a **scholar**, coded 61 times across the qualitative data. The themes *originality and ownership*, *expertise*, and *voice* were uncovered under this code. Students often cited their scholarly identity or values as guiding their decision-making about when and how to use generative AI. These values are likely related to CPED's focus on developing scholar-practitioners (*The CPED Framework*, 2022), as well as to the structure of a Doctor of Education program which often includes high-pressure features like oral exams, multiple defenses, and a dissertation.

Originality and Ownership

Across the data, participants described making decisions about generative AI use in ways that reflected deeply held scholarly values, particularly related to *originality and ownership*. Rather than defining originality in terms of producing entirely novel ideas, students more often framed it as maintaining control over their thinking, voice, and academic work. Participants emphasized the importance of being able to recognize their work as their own, stand behind it, and defend it in academic contexts. As with the lines

and boundaries described earlier, these values shaped how and when students chose to engage with generative AI, guiding decisions about acceptable support versus uses that felt unaligned with their sense of scholarly responsibility.

Several participants described preserving originality by sequencing their use of generative AI. Tilly, a second-year student, explained, “I do not use generative AI until I have developed my own intellectual content. I do not introduce AI until it is the editing process.” Similarly, third-year student Lydia described using generative AI as a form of cognitive support,

I prefer to talk through and collaborate and it’s been a great tool to provide me support with that: I also sometimes get stuck and AI can help with that unstuck. I do believe when I use AI the thoughts and outcomes are mine it’s just helping me process my own ideas.

Lydia states that she uses generative AI as a tool to help her think through her original ideas, with generative AI serving as cognitive support rather than coming up with ideas for her.

Others articulated originality primarily through statements of authorship and accountability. Shukriya, a third-year white student, stated, “I always want to be very clear that no matter how I use AI, the work (paper, dissertation, etc) that I am submitting is my work.” Theresa, a fourth-year student, makes a similar assertion in her statement, “I don’t want there to be any question as to the authorship of my dissertation.” Third-year student Michelle was similarly declarative: “It is NOT the author of my documents or papers.” Together, these accounts illustrate how participants operationalized originality

as the ability to claim, defend, and stand behind their academic work, even when generative AI played a supporting role in the process.

Expertise

Under the theme of *expertise*, participants described making decisions about generative AI use based on whether it supported or undermined their development as knowledgeable scholars. Expertise was consistently framed in terms of being prepared to explain, elaborate on, and defend one's work in academic settings. Many students placed clear limits on how much they allowed generative AI to affect their learning and production. Under the theme *expertise*, second-year student Alyn spoke of the importance of being prepared to defend as shaping their generative AI use:

What can I stand behind and be able to explain? So, if...someone's asking me a follow-up question in my proposal, in my defense. I'm able to elaborate and speak, speak on it, because the whole point of at least my university's model is you're making a contribution to your field. And so I guess that's where I draw the line. So if your use of generative AI is leading you to not make a contribution to your field, or you're using it to the point where it's, it's doing more of the work for you, like a saying is, you know, use AI, don't let it use you. That's what, that's where I draw the line. What can I stand behind? What can I elaborate on?

Other participants expressed similar concerns, particularly around using generative AI to summarize readings. Edin reflected on using generative AI to summarize readings, "I also think long term not having actually read and only getting the TLDR version means I will be less prepared for my defense/future work." First-year student Sandrine echoed this

concern, and agreed that using generative AI to summarize readings does her a disservice:

I want to learn the content myself, and I know that if I use genAI to summarize articles, then I will miss things. So, I think of how can it augment my work (such as creating an infographic for a presentation) in a skill that I am not as strong at, but I can still review/approve.

Sandrine described using generative AI in ways that helped make up for skills in which she was weaker, such as creating visuals, while still being sure to personally review and approve. Rico stated that he uses generative AI to assist in his work but stated that “I can stand by anything that I do. When I submit, if I present at a conference, I feel very comfortable that I can defend every piece of work that I have there.” Across these accounts, expertise was defined by depth of understanding and readiness to defend one’s thinking. These students’ responses show how much they value being knowledgeable and prepared to defend their work, and their belief that overusing generative AI would only hurt their preparation.

Voice

As part of their scholarly identity, respondents described concerns they had about losing their *voice* if they were to overuse generative AI. Voice was framed as an expression of identity, understanding, and presence within academic work. For these students, maintaining voice was closely tied to being recognizable in their writing and ensuring that their work reflected their own thinking rather than that of a generative system.

Belinda, a third-year student, emphasized this distinction when describing work submitted for formal evaluation, noting that “when it comes time to something I'm turning in for a grade, or I'm turning in my doctoral writing, that needs to be my own authentic voice and my own understanding of the research.” Acacia concurred, “it was very, very important to me that everything be in my own voice.” Acacia underscores how voice functioned as a non-negotiable boundary in her academic work. Giselle elaborated on this concern by drawing parallels between her expectations as an English instructor and her practices as a doctoral student. She described refusing to submit AI-generated writing not only because it felt unethical, but because it erased her presence from the work:

When I think of what is, what I would consider an appropriate or inappropriate use of AI in the program, it's similar to the, to the guidelines that I would give my students. As an English instructor, I give a lot of guidelines when it comes to writing, and in this program, we do a lot of writing. Every course, there's, there's papers to write. So, I would never use AI, I would never feed a writing prompt from one of our assignments in the course, and have AI just produce some writing. Not just because it's unethical, but because what generative AI produces is not my voice, and when I have my committee read my dissertation, I want them to be able to see me in that writing, which is the same requirement I have for my students, that every writing that we do is personal to us so that we can see each other in our writing. As people, as humans, not just fulfilling the requirement. For Giselle, voice is part of cementing her humanity in her academic writing, rather than simply fulfilling course requirements.

Other participants described deliberately restricting generative AI use to protect their voice. First-year student April stated that she uses generative AI only for grammar and spelling corrections, stating,

I haven't used that much. One thing I have used it for is to make spelling and grammar corrections, I give it clear directions not to change the wording. I worry if I rely on AI I will lose my writing voice (which is way better than my talking voice).

Eugene, a first-year student agreed, “I am always careful not to allow AI to replace my voice and words. I use AI for assistance only, not to directly write anything for me,” positioning generative AI as a support tool rather than a writing tool. These respondents want to be able to stand behind their academic work, maintain and uphold their identities, including when using generative AI, and hold on to their own unique writing voice. Voice functioned as both a personal and scholarly value, shaping how students determined appropriate boundaries for generative AI use while striving to remain visible and recognizable in their work.

Scholarly Values

These tendencies suggest that students’ decisions about generative AI use were closely tied to how they thought of themselves as scholars. Across the themes of originality and ownership, expertise, and voice, participants consistently described regulating their use of generative AI in ways that allowed them to maintain ownership of their thinking, prepared to defend their work, and remain recognizable in their writing. They described making deliberate choices about when and how to use these tools so that generative AI supported their development as doctoral scholars. These decisions often

reflected students' understandings of the expectations of doctoral study and their future roles as scholar-practitioners. This framing was summarized by Kelly, who is ABD:

Doc students should really be careful with their use of AI in that, you know, we, we're the experts of tomorrow. We're the leaders. We should be, I believe, well-versed in generative AI. But, as everyone has mentioned, we're all going to be able to stand on our work. AI didn't write our dissertations in practice, we did, with assistance, you know, from AI.

Kelly's reflection captured a recurring tension across the data: the importance of becoming well-versed in generative AI while still being able to "stand on" one's scholarly work.

Neverusers

While the majority of respondents described some level of generative AI use, a notable subset reported that they did not use generative AI at all or restricted their use to very narrow, non-writing tasks. The **neveruser** code, used 24 times, captured instances in which participants described complete avoidance of generative AI, refusal to use it for writing or idea generation, or rejection of AI-generated output altogether. These accounts provide insight into how values related to creativity, originality, and ethics shaped decisions to avoid using generative AI.

Several participants described *complete avoidance of generative AI* because they viewed it as a threat to creativity and originality. During a focus group session, Cyn explained:

I don't want *ChatGPT* to stifle your creativity, or AI, I should say, to stifle your creativity, because if you depend on it, and you go to it, and you need it, then

you're, you're just not, you're not being your creative self, you're letting somebody else create for you. So that, for me, is why I choose not to use it at all, whatsoever, for any reason.

Cyn wants to preserve their sense of creativity and as well as their claim to authorship, and thus, avoids generative AI usage.

Other participants framed complete avoidance primarily in ethical terms. First-year student Melissa stated, “I don't use it. I think it's unethical for many reasons. I'm a librarian in my day job. I don't need it.” Melissa's professional background informed her position on generative AI. Similarly, third-year student Tamara described AI as unethical:

AI seems like cheating to me. I don't use it because I think a person reading work from AI can tell that it's not human...When I read posts from other students that sound like AI, I am annoyed and don't want to respond to them because it doesn't seem to be their original thoughts.

When Tamara identifies peers' writing as AI-generated, her reaction is to lessen her engagement.

A smaller subset of participants identified as neverusers but said they allowed exceptions for tasks they did not conceptualize as “doing the work.” First-year student Maura says she *never uses it – except*:

I have decided to never use generative AI - even for assignments that allow it specifically. I see no purpose in using it and have developed all the tools necessary to complete my work without. General exception - using a website to help create APA accurate citations.

Likewise, second-year white male Micah wrote, “I do not use generative AI at all. All my work is from my brain and my wife's editing skills. If you consider looking for research articles using AI, I do that.” These responses suggest that these two students define “using generative AI” to mean using it to produce work for them, like writing and editing, while other uses that fall outside of those tasks do not count as using generative AI.

These accounts indicate that avoiding or defining only narrow uses of generative AI reflected values related to originality, voice, and ethical academic practice. Consistent with Minimo and Bueno (2024), these patterns highlight how affective orientations and metacognitive commitments, particularly those tied to scholarly identity, play a significant role in shaping students’ information behaviors and decisions about generative AI use.

RQ1 Summary

The results presented in this section describe information behaviors of EdD students in relation to generative AI and demonstrate that affective, metacognitive, cognitive, and behavioral domains of metaliteracy shape these behaviors (Mackey & Jacobson, 2022), along with uneven development of generative AI literacy. Participants reported using a variety of generative AI tools regularly, with *ChatGPT* cited most frequently, and most students indicated that they used these tools at least weekly. Students use generative AI to overcome feeling stuck, to increase their productivity, to polish writing, provide feedback, and summarize readings. They described using generative AI as a 24/7 on-call learning partner and tutor, showing that they value convenience, as well as the affective support and social dynamics of learning with a

partner, even if that partner is a chatbot. Students say that they set goals for their academic work before selecting an appropriate strategy, such as generative AI, to accomplish that goal, and reported that they regularly self-reflect and self-monitor their learning and development of expertise when using generative AI. They also reported anthropomorphizing generative AI, as illustrated through the various roles they assigned it.

However, students described nuanced decision-making around their use of generative AI. Participants described an array of lines and boundaries that shaped their use of generative AI, distinguishing between acceptance and unacceptable uses, or using for process versus product. In the face of uncertainty, some students refrained from generative AI use or used only for very specific tasks. The extent to which students used generative AI was further shaped by their stated scholarly values related to originality and ownership, expertise, and voice. Students reported using generative AI to a lesser extent and more conscientiously when prioritizing and preserving these values, suggesting that metacognition may play a greater role in shaping information behavior when tied to personal values and identity. In the next section, I will discuss tendencies and patterns related to how students weigh academic integrity, describe responsible usage, and express ethical decision-making related to generative AI.

RQ2: What concerns do doctoral students in CPED institutions have regarding academic integrity, ethics, and the responsible use of generative AI in academic work?

This research question focuses on exploring Doctor of Education student concerns related to academic integrity, ethics, and responsible use of generative AI in their academic work. Patterns indicate that while many students report confidence in their ability to use generative AI appropriately, they also express uncertainty, concern, and hesitation related to policy, acknowledgment practices, and potential consequences of misuse. Students indicate that unclear or lacking institutional policy and training is partly to blame. The results in this section stand in contrast to those for RQ1, as results here emphasized students' reported concerns and perceived risks associated with generative AI use.

In addressing RQ2, this section examines students' emotional responses to generative AI use (metaliteracy's affective domain), their understanding of institutional policy and expectations (cognitive domain), and how uncertainty shapes self-regulation and transparency (metacognitive and behavioral domains). Quantitative survey results related to policy awareness and concern are presented first, followed by qualitative patterns that further contextualize and triangulate these patterns. In this section, I will summarize the results from the survey's quantitative items related to student concerns about and knowledge of institutional policy and practice related to generative AI, then I will give results from the study's qualitative items related to these topics and triangulate them.

Perceived Understanding of Ethical and Policy Expectations for Generative AI Use

On the survey, respondents were asked to use a 5-point Likert scale to describe their agreement with a series of statements related to generative AI and academic integrity. *Strongly agree* was equivalent to five points and *strongly disagree* to one point. The following four items were written and included to better understand student knowledge of academic integrity practices related to AI, as well as gauge their level of concern:

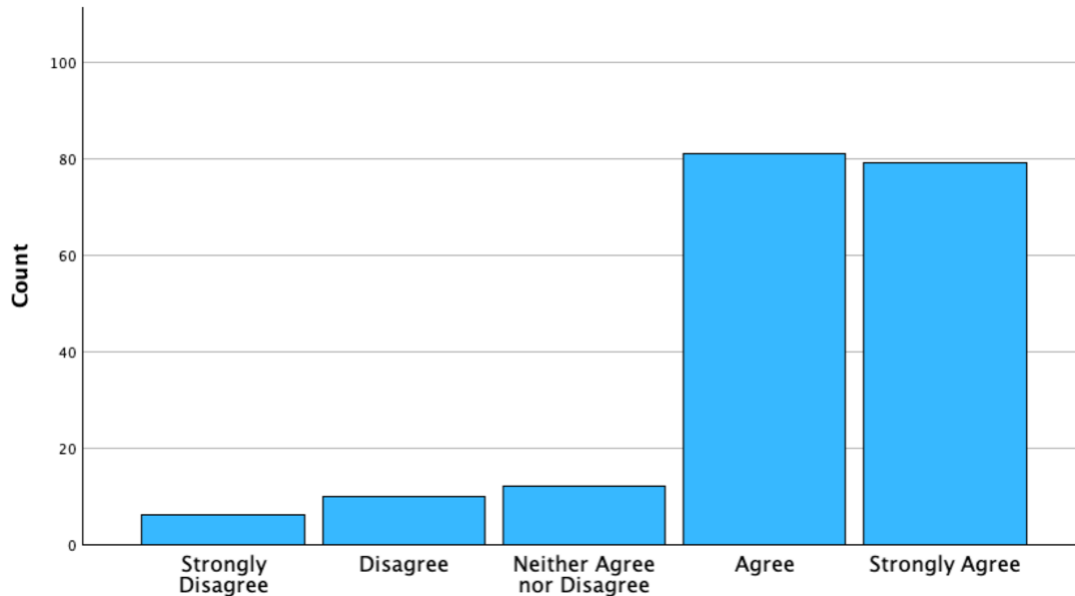
- I understand when it is appropriate to use generative AI as part of my EdD coursework and research (Q7).
- I am concerned about potential academic integrity issues when using generative AI (Q8).
- I know what my institution's policies are regarding generative AI use (Q9).
- I understand when to acknowledge my use of generative AI (Q10).

These items may be categorized into the behavioral, cognitive, and affective domains as described by metaliteracy (Mackey & Jacobson, 2022). In order to be able to adhere to an institution's academic integrity policy (behavioral domain), students need to know what it is (cognitive domain). Naturally, academic integrity can spark deep emotions in students, which categorizes students' level of concern in the affective domain.

For the item “I understand when it is appropriate to use generative AI as part of my EdD coursework and research,” 3.2% of respondents strongly disagreed ($n = 6$), 5.3% disagreed ($n = 10$), 6.3% neither agreed nor disagreed ($n = 12$), 42.6% agreed ($n = 81$),

Figure 15

I understand when it is appropriate to use generative AI as part of my EdD coursework and research (Q7)

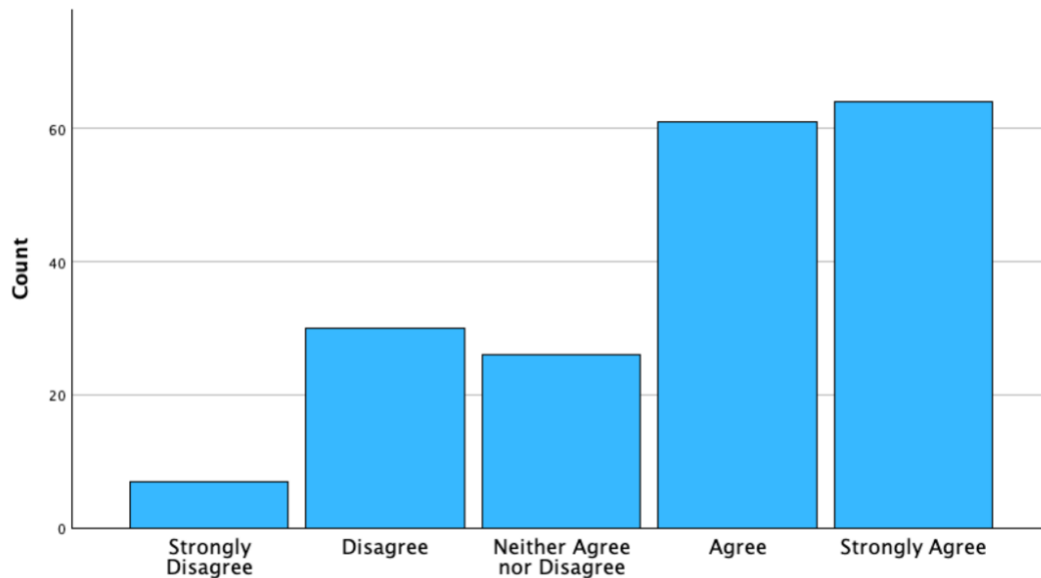


and 41.6% strongly agreed ($n = 79$). See Figure 15. The mean response was 4.15 ($SD = 0.98$). These results suggest that respondents felt confident in their use of generative AI. However, this item did not define “appropriate,” and thus, students may have had their own interpretation of the term and what it means (e.g., what uses adhere to official policy vs. what uses feel ethical vs. and what uses feel relevant to a student’s task at hand).

For the item “I am concerned about potential academic integrity issues when using generative AI,” 3.7% of respondents strongly disagreed ($n = 7$), 15.8% disagreed ($n = 30$), 13.7% neither agreed nor disagreed ($n = 26$), 32.1% agreed ($n = 61$), and 33.7% strongly agreed ($n = 64$). See Figure 16. The mean response was 3.77 ($SD = 1.19$), which

Figure 16

I am concerned about potential academic integrity issues when using generative AI (Q8)



indicates an overall tendency towards concern about academic integrity issues related to generative AI use. However, a substantial number of respondents (33.2%) were neutral or disagreed on this item, in contrast to 65.8% that agreed or strongly agreed, showing high variability in responses. This indicates that students may be weighing academic integrity risks differently, or may have varying knowledge of their institution's policies, if their institutions have existing policies.

A chi-square test of independence was conducted to examine the relationship between gender and concern about academic integrity when using generative AI. The analysis included only respondents who identified as male or female. The test revealed no statistically significant association between gender and level of concern ($p = .442$). One cell (10%) had an expected count less than 5, with a minimum expected count of 1.63,

but this falls within acceptable limits. See Table 5. These results suggest that concern about academic integrity does not differ significantly by gender among EdD students.

Table 5

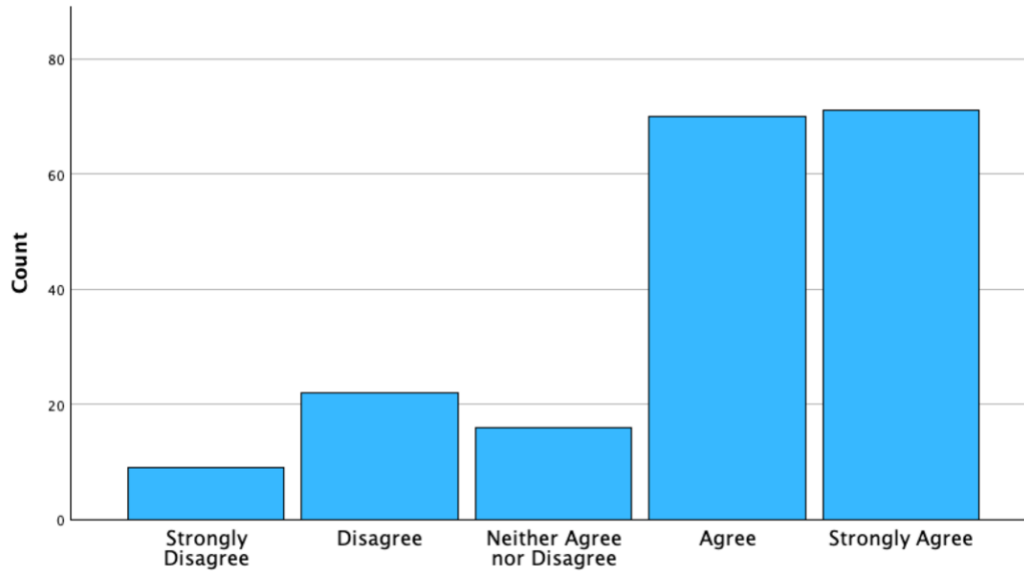
Concerned About Academic Integrity and Gender

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.744 ^a	4	.442
N of Valid Cases	180		

For the item “I know what my institution’s policies are regarding generative AI use,” 4.7% of respondents strongly disagreed ($n = 9$), 11.6% disagreed ($n = 22$), 8.4% neither agreed nor disagreed ($n = 16$), 36.8% agreed ($n = 70$), and 37.4% strongly agreed ($n = 71$). See Figure 17. The mean response was 3.91 ($SD = 1.17$), suggesting that most students felt confident they understood their institution’s generative AI policy. However, more than one quarter of respondents either disagreed or were unsure. This may indicate that students do not know their institutional policies, that those policies are not well-communicated, that those policies are not clear, or that their institutions do not have policies. This result is unsurprising as institutions are still setting generative AI policies, and these policies may be in flux (Buss et al., 2025). Additionally, this item asked whether students knew their institutional policies, not whether they are clear or not, so that those students that agreed or strongly agreed may not be clear on how to put their institution’s policies into practice. This finding is especially interesting juxtaposed with

Figure 17

I know what my institution's policies are regarding generative AI use (Q9)

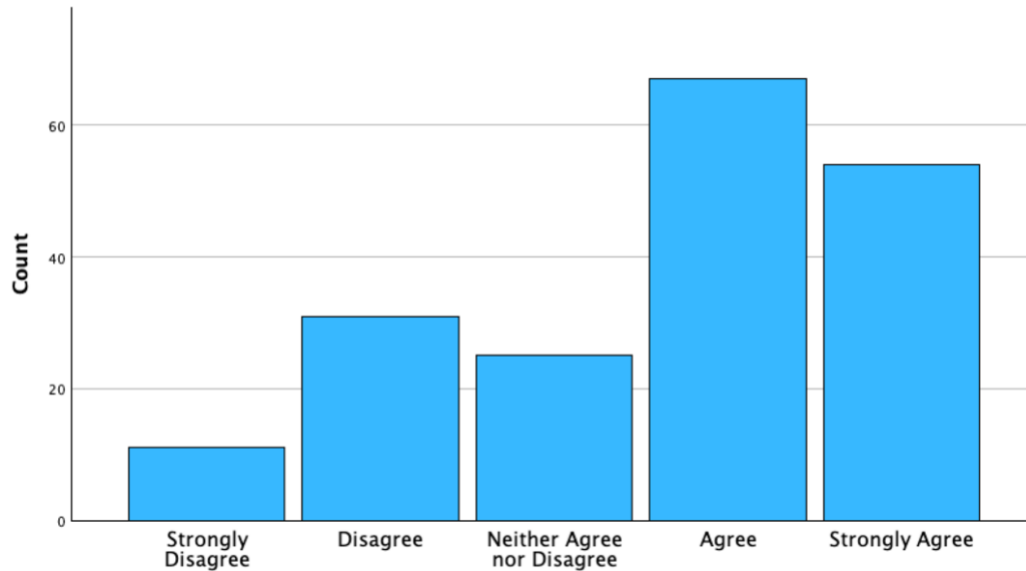


the previous, which shows that two thirds of students are concerned about academic integrity, even though over 70% also say they know what their institutional policy is related to generative AI. Qualitative responses will shed more light into this in the next section.

For the item *“I understand when to acknowledge my use of generative AI,”* 5.8% of respondents strongly disagreed ($n = 11$), 16.3% disagreed ($n = 31$), 13.2% neither agreed nor disagreed ($n = 25$), 35.3% agreed ($n = 67$), and 28.4% strongly agreed ($n = 54$). See Figure 18. The mean score was 3.65 (SD = 1.22). While the majority agreed or strongly agreed with this statement, over 20% disagreed or strongly disagreed, showing that many students are unsure of when they should acknowledge. Students are unsure of what uses of generative AI require acknowledgement, possibly because they haven’t

Figure 18

I understand when to acknowledge my use of generative AI (Q8)



received training, or their institutional policies are unclear, or both. In the next section, I will present qualitative results that are relevant to RQ2, and I will triangulate them with quantitative results.

Generative AI Policy, Training, and Guidance

Overall, students report uncertainty about how to adhere to institutional and instructor policy on generative AI. The code **GAI policy** was used 34 times across the qualitative data to identity instances of policy discussion. Building on the finding that over 70% of respondents reported familiarity with institutional policies on generative AI (Figure 17) while 66% expressed concern about academic integrity (Figure 16), qualitative responses suggest that many view existing policies as vague or insufficiently actionable in practice. Awareness and understanding of generative AI policy falls under

metaliteracy's cognitive domain. Under the theme *no clear policy*, fourth-year student Jona said, "I use my best judgment but it is not yet institutionally clear what the expectations are." Furthermore, under the theme *policy varies*, students reported that individual faculty may have their own policy on generative AI, which sometimes caused frustration. Jacek stated:

One [instructor] is, she does such a good job in the syllabus. Every assignment tells you the extent of what AI can do for you for that assignment...And then I have another faculty member this semester that is 100% against AI. She told us the first night of the class that she will, like, hunt us down, if she thinks that we're using AI for any assignments...She set up her class to be very, like, anti-AI. We had a timed midterm exam where we took it with our cameras on. I've never done that before. Even going back to undergrad, it was an interesting experience. I get it, but it almost, I feel like she's fighting something that is inevitable.

Yet, if the policy is that no generative AI use is allowed, students may *use even though it's banned*. "I've had one syllabus that said, just don't use AI at all. And I was like, well, I'm just gonna ignore that," said Cass. While students could often identify institutional or instructor policies on generative AI use, these policies did not necessarily shape how students described their own use practices.

Beyond policy, respondents expressed that they had *not been trained* on generative AI but had a desire for it. Tanja said, "we have not had direct training on how to use it." The best practices for Doctor of Education students may still be settling, such that institutions and faculty are still figuring out how to provide such training. Fourth-year student Lucia *wants training*, stating:

All students would benefit from greater instruction & guidance on how/when to use generative AI. There seems to be no agreed-upon practices in place for doctoral work and given that many students are working full time while pursuing this degree, making the use of AI to complete assignments tempting, a guided approach for use would benefit both the students and the academic integrity of the courses.

Students expressed a desire for clearer, program-specific guidance on how to use generative AI ethically and transparently in doctoral-level academic work.

Uncertainty Around Acknowledging Generative AI Use

Just as over 60% of students reported that they know when to formally acknowledge use of generative AI, while 20% disagreed or strongly disagreed (Figure 18), qualitative responses revealed considerable uncertainty about when and how such acknowledgment should occur in practice. The qualitative data in this section were uncovered by the code **acknowledging use**, which was used to tag 31 comments, and aligns with metaliteracy's cognitive and behavioral domains. First, students were *unsure how to acknowledge*. For example, Jona said, "My EdD program does not yet have clear ethics guidelines around AI use or when to acknowledge use." First-year student Noelle said, "It is not clear when to cite AI when used for editing with products that it is built into. Similar to spell and grammar checking." Lydia stated,

I am not clear on how to cite the use of AI. I know I can use it for brainstorming, editing and helping organize and analyze but I also know I'm supposed to cite that somehow and I have no clue where or how that should look.

These responses illustrate uncertainty about what constitutes acknowledgment of generative AI use and how such formal acknowledgement should be conducted.

Some respondents questioned whether generative AI use required formal acknowledgment, particularly when they understood it as a tool rather than a contributor to their academic work. These comments fall under the theme *don't have to acknowledge*. For example, Cass said, “do we also credit SPSS, do we credit, like, like, do we have to credit all of the technology?” Several students said they would not cite a person that helped them, so it didn't make sense to cite generative AI. Students often drew on familiar academic practices, such as peer feedback or writing center support, to reason through whether acknowledgment was necessary. Connor, a second-year student, said he plans on using generative AI for brainstorming, editing his writing, and helping with APA, and stated:

I don't see that sort of use being any different from working with a real person, like a peer or someone at the Writing Center, and so I don't see the need to declare any of that, because if I were doing that with a person, there would be no need to cite that, you know, I worked with this person on it, and so, I, I don't see that as being necessary with, you know, generative AI help with it. I do think, though, that it really, like, it's very case-dependent, and it would depend on your level of use.

Cass agreed that using it as one would use a person's help muddies the acknowledgment waters, though he found it so helpful he wants to be sure to give it credit:

So, I mean, I don't cite my partners or my family. You know, like, I think, and I've thought about this a lot, like, in my dissertation, when I'm giving credit and,

like, acknowledgements, I'm definitely gonna, say, like, AI was useful for this, in this way, and the ways that, the ways that it was helpful, because there's things that AI does with me that no one else can do, because I'm taking together such diverse fields...So, while I don't have, like, a reference section, because I'm not actually, like, sourcing it or quoting it in my papers, I'm definitely gonna give it credit in some way, like, just recognize what, what the technology did for me, you know, but then what?...But I've benefited so much from conversations with the, with the chatbot that I feel like I, I, I want to give it acknowledgement, anyway. These differing interpretations highlight the absence of shared norms for distinguishing between generative AI as a tool and as a contributor.

While students feel the pressure to formally acknowledge use, others felt hesitant about explaining how they used it in their academic work or worry that their work won't be seen as original. This fell under the theme "*bad optics*." Second-year student Erich said, "I think that generally our instructors are fine with us using it (I think?), but I don't, for example, particularly like the idea of citing it in the references for my dissertation because I think it's bad optics." Similarly, third-year student Augustina notes concern about how use might be perceived:

As far as I know, my cohort is the first to be encouraged to interweave the use of AI into most aspects of our work, I am concerned that the field may judge the work as lesser for the inclusion. I also know that we may be cutting edge and that the use and acknowledgement of AI is helping me go deeper in some aspects that I would have.

These responses reflect concern that acknowledging generative AI use could prompt negative judgments about the legitimacy or originality of students' work.

Beyond stigma, students also expressed concern that disclosure of generative AI use could lead to misinterpretation of their work as academically dishonest or diminish their ownership. This fell under the theme *AI assistance erodes ownership*. This aligns with the 66% of students that reported agreeing or strongly agreeing about being concerned with academic integrity when using generative AI (Figure 16). Some are concerned that formally acknowledging use of generative AI will open the door to such accusations. First-year student Anthea stated that she is worried that if their instructors know that she uses generative AI, “that it will be perceived as cheating or not entirely my own work even if the AI does not generate the actual writing and is just a thought partner.” Other students are concerned about maintaining ownership of their work, like Champa, a second-year student, who said: “I am concerned that AI will get credit for my thinking if I disclose I used it.”

Even when policy clearly allows use of generative AI for academic purposes, students are concerned about how disclosure might be perceived. These comments fell under the code **fear of being accused**, which was used 16 times. Students were concerned about *policy violations*. Fourth-year student Annamarie stated, “although we’re encouraged to state when we use AI, I can’t help but worry that it might still be held against us.” Cameron echoed this concern:

My concern is my program handbook explicitly states there is no use of AI. I never copy and paste, or even paraphrase, but I still worry about being 'caught'

using AI since it not allowed in any capacity in my program according to the handbook.

Even when institutional policy allowed generative AI use, students described concern that disclosure could result in accusations of academic dishonesty or loss of ownership over their work. In some cases, this concern extended beyond immediate coursework to how current generative AI use might be judged in the future under the theme *retroactive punishment*. Nicola, a third-year student, wrote that she is concerned “that at some point some rule or person will decide that use of AI was a violation of academic integrity and nullify my degree.”

Concern About Overuse

Students described concerns about overusing generative AI that extended beyond issues of academic dishonesty to questions about learning, self-regulation, and responsible use. The code **concerned about overuse** appeared 16 times across the qualitative data. This code aligns with metaliteracy’s affective and metacognitive domains. Several respondents expressed uncertainty about whether reliance on generative AI might undermine their own intellectual development, or, *where the line is*. Erich wrote, “I’m unsure of the extent to which using it is cheating myself out of learning and growth.” Similarly, second-year student Dot reflected on the need for self-monitoring:

I think the use of AI is very helpful but it can be harmful as well. If not used appropriately it will take away your ability to think for yourself. It can be very easy to just let AI do everything, but you have to monitor yourself and ensure that you are getting out of your classes what you intended.

Students also described tension between their intentions for ethical use and the ease with which generative AI offers to take over academic tasks. Cass explained:

It, like, offers, like, it just automatically writes the paper for you, or it tells me, like, “would you like me to draft this for you?” And it just, like, automatically offers to do something unethical, I find that, kind of annoying, because, like, everyone, most people that I know are not on board with using AI for, like, anything. And then when it does that, and I'm like, stop, stop doing that! This is what, like, everyone I know doesn't like about you. Like, I wish it, I wish I could just have it not, have it stay in its lane, you know?

The willingness of generative AI to help students with their work raised concerns for students about maintaining boundaries between assistance and overreliance.

Several students described patterns of personal use that led them to question whether generative AI was diminishing their motivation, stamina, or confidence in their own abilities, as seen in the theme *feel dependent on AI*. Gabby, a third-year student wrote:

I always wonder if it is affecting my motivation/stamina to learn/think as I increasingly include it in my thinking process. I find that things I used to do earlier in my studies, like undergraduate school or graduate school, now seem like tasks that would be exhausting to do myself without AI and I wonder if it because I was younger and less tired in general or because now I rely on AI for shortcuts to tasks so I lost my energy to do that for myself and became 'lazier.'

Third-year student Kaipo reflected on her use of generative AI, and decided to use it less as a result:

Honestly, sometimes I feel like I use it too much. Fortunately, I feel that the content generated is not very accurate or useful for 'the big stuff' so I stopped trying to use it for everything. Recently, I don't even like how it revises my writing, so I have used it less and less frequently as I progress in my research. It is still helpful for getting through our coursework, but it is less helpful in the dissertation process.

Across these responses, students articulated concern that overuse of generative AI could interfere with learning, thinking, or the development of scholarly skills. Rather than deciding to turn away from generative AI altogether, many described efforts to regulate their use to align with their educational goals.

Preparing Scholarly Practitioners and Leaders

Students described concern that limited guidance on generative AI use had implications beyond their immediate academic work, particularly given their roles as current or future educational leaders. Under the code **scholar**, the theme *we will lead on AI* uncovered comments from participants that stated they viewed understanding responsible generative AI use as integral to their preparation as scholarly practitioners. This theme aligns with metaliteracy's affective domain. Kelly reflected on this expectation:

Given the goal is for us to be scholarly practitioners within our field of practice, I would say really help train EdD Graduates on how we can utilize this to advance our, our, you know, practitioner piece post-graduation. For many of us serving the community...it really can help advance the things that we would like to do and ensure that we're efficient. I really want to focus on differentiating our degree

from the PhD, so, generative AI can help us do that in ways that we may not realize it, even at this point, as it evolves so rapidly.

Other students also emphasized leadership responsibility. Third-year student Evita wrote:

As educational leaders we need to understand how to use these tools and guide others to use these tools. AI is not going away. Our future workforce will be expected to use these tools and it's our job to prepare them for that future. To not use AI in education is to set up future generations for struggle. I don't think my university program has done enough to prepare me for educational leadership in the age of AI.

Kiki, a second-year student, echoed Evita's concern, "as future administrators in higher education, we should be learning to correct way to use AI and how to share that with students."

Participants also offered specific ideas about what effective guidance might include. In a focus group session, Jen said that while policy should be set at the institutional level, professors should offer guidance on using it within each class, for instance, ways that past students used it appropriately, or helpful ways it can be used on specific assignments. Similar, Natalia said, "if they can really teach how to stay within those ethical boundaries and use it for really good resources, I think that will really help." These students point out that training would be useful not just on policy, but on how to put the policy into practice. In addition, the space to be able to talk about how students use generative AI without being punished would be welcomed. In a focus group session, Giselle stated that, "I think education as a whole would be able to progress a lot faster if we gave people just the opportunity to comfortably talk about their use of AI without

being afraid of getting in trouble.” These comments suggest that training would not just help students be successful academically and, in their careers, but may also effect a cultural shift that encourages conversation about how students use generative AI.

RQ2 Summary

The results for RQ2 highlight the role of concern, uncertainty, and perceived risk in shaping Doctor of Education students’ engagement with generative AI. Across both quantitative and qualitative data, students reported substantial concern about academic integrity, alongside uneven understanding of institutional policies and limited clarity about how those policies should be enacted in practice. Although many students indicated familiarity with institutional expectations, qualitative patterns revealed difficulty translating that knowledge into confident and transparent academic behavior, particularly with regard to acknowledging generative AI use.

Students reported multiple concerns, including uncertainty about how and when to acknowledge generative AI use, concern that disclosure could prompt negative judgments about originality or authorship, and fear of being accused of academic dishonesty, both under current policies and under potential future policy changes. Some students also expressed concern about overusing generative AI in ways that might undermine learning or scholarly development, leading them to intentionally regulate or reduce their use. Others emphasized the importance of guidance on generative AI as part of their preparation as scholarly practitioners and educational leaders, noting the relevance of these tools in their current and future professional roles.

These patterns indicate that students’ concerns about generative AI are not rooted in disregard for academic integrity, but rather in uncertainty about expectations and fear

of misinterpretation. While students continue to use generative AI, these affective concerns shape how openly they talk about that use and how confidently they engage with it. In this way, the patterns for RQ2 complement those for RQ1 by illustrating how concern, uncertainty, and perceived risk influence not only decisions about use, but also decisions about transparency. The next section presents tendencies and patterns related to RQ3, which examines factors that influence students' ability to critically evaluate generative AI output in their academic work.

RQ3: What factors influence doctoral students' ability to critically evaluate generative AI output as part of their work in CPED EdD programs?

RQ3 examines the factors that influence doctoral students' ability to critically evaluate generative AI output in CPED EdD programs. Survey responses indicate that students generally perceive themselves as engaging in effective evaluation practices, particularly in relation to verifying AI-generated information, recognizing hallucinations, and understanding technical limitations. These practices align with the cognitive and behavioral domains of metaliteracy, as well as with generative AI literacy's technical knowledge dimension. However, self-reported evaluation ability reflects more than technical knowledge alone. Together, the quantitative and qualitative data suggests that several interrelated factors shape students' evaluative practices, including awareness of AI limitations, verification behaviors, assumptions embedded in prompting strategies, and the development of a scholarly identity. Consistent with the sequential mixed methods design, the quantitative results are presented first to describe patterns in students' self-perceived evaluation ability, followed by qualitative results that further illuminate how students describe evaluating generative AI output in practice.

On the survey, respondents were asked to use a 5-point Likert scale to describe their agreement with a series of three statements related to evaluate practices around generative AI. *Strongly agree* was equivalent to five points and *strongly disagree* to one point. These items were written to gauge students' self-perception of evaluation skills, and their self-identification of technical knowledge of generative AI:

- I can effectively evaluate the quality and accuracy of AI-generated content (Q12).

- I verify AI-generated information against other sources (Q13).
- I understand the technical limitations of generative AI (e.g. hallucinations, knowledge cutoff dates) (Q14).

These items may be categorized into the behavioral and cognitive domains as described by metaliteracy (Mackey & Jacobson, 2022). In a qualitative item, respondents were asked about the evaluation practices in which they engaged. In this section, students report what they know and what they do, and by analyzing their self-reports, some insight may be gained into real-world practices.

Evaluation and Generative AI Knowledge

For the item *“I can evaluate the quality and accuracy of AI-generated content,”* 3.7% of respondents strongly disagreed ($n = 7$), 6.3% disagreed ($n = 12$), 12.1% neither agreed nor disagreed ($n = 23$), 47.9% agreed ($n = 91$), and 27.9% strongly agreed ($n = 53$). The mean was 3.92 (SD = 1.00), suggesting that most students believed they had the ability to critically assess the quality and accuracy of generative AI output. See

For the item *“I verify AI-generated information against other sources,”* 1.6% strongly disagreed ($n = 3$), 6.3% disagreed ($n = 12$), 8.4% neither agreed nor disagreed ($n = 16$), 32.1% agreed ($n = 61$), and 48.9% strongly agreed ($n = 93$). The mean for this item was 4.24 (SD = 0.97). See Figure 20. This suggests that students report that they regularly verify AI-generated information.

For the item *“I understand the technical limitations of generative AI (e.g., hallucinations, knowledge cutoff dates),”* 5.8% strongly disagreed ($n = 11$), 10.0% disagreed ($n = 19$), 6.8% neither agreed nor disagreed ($n = 13$), 34.7% agreed ($n = 66$),

Figure 19.

For the item “I verify AI-generated information against other sources,” 1.6% strongly disagreed ($n = 3$), 6.3% disagreed ($n = 12$), 8.4% neither agreed nor disagreed ($n = 16$), 32.1% agreed ($n = 61$), and 48.9% strongly agreed ($n = 93$). The mean for this item was 4.24 ($SD = 0.97$). See Figure 20. This suggests that students report that they regularly verify AI-generated information.

For the item “*I understand the technical limitations of generative AI (e.g., hallucinations, knowledge cutoff dates)*,” 5.8% strongly disagreed ($n = 11$), 10.0% disagreed ($n = 19$), 6.8% neither agreed nor disagreed ($n = 13$), 34.7% agreed ($n = 66$),

Figure 19

I can effectively evaluate the quality and accuracy of AI-generated content (Q12)

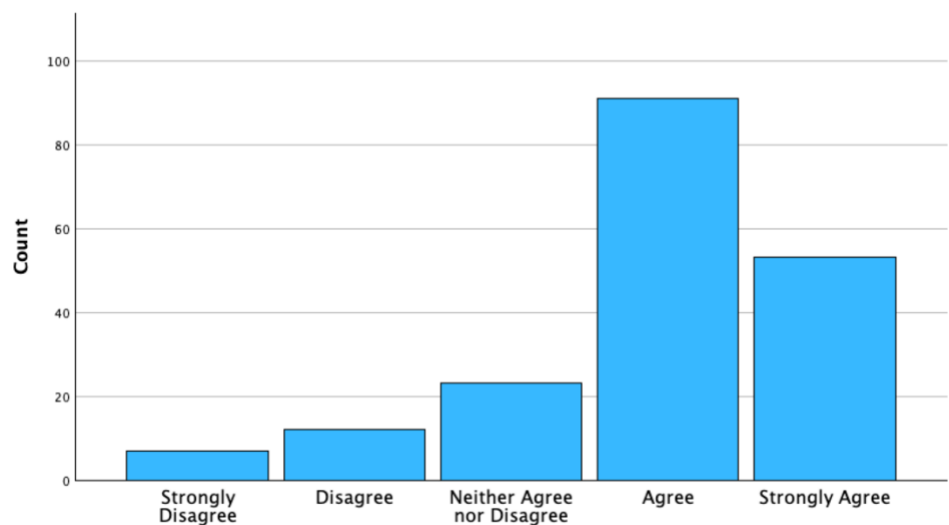


Figure 20

I verify AI-generated information against other sources (Q13)

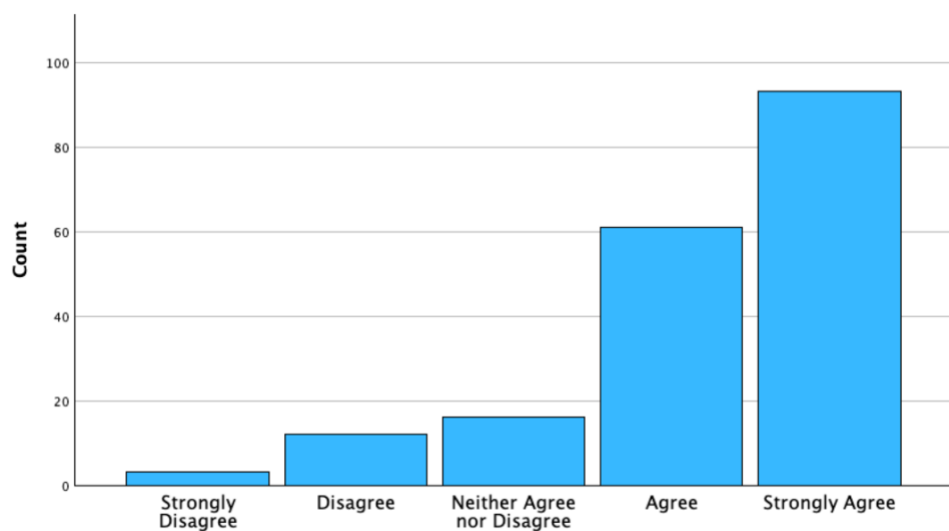
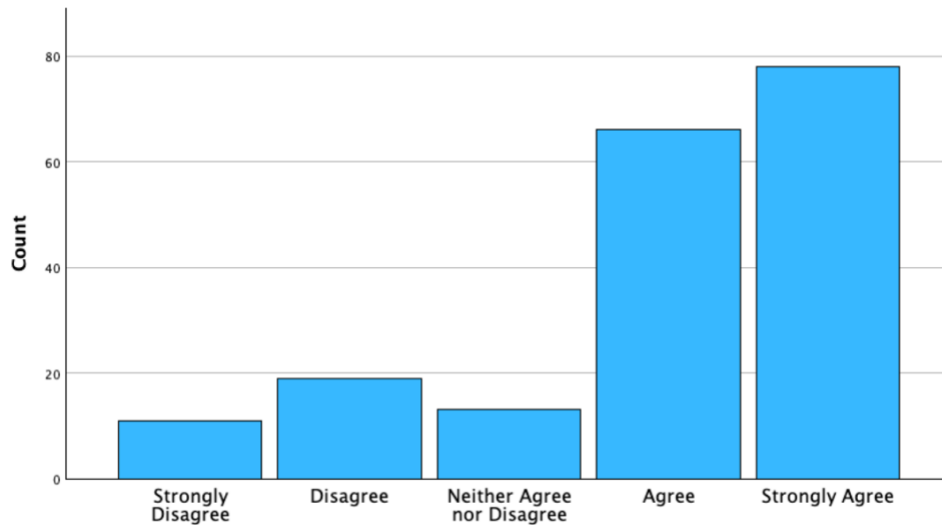


Figure 21

I understand the technical limitations of generative AI (e.g. hallucinations, knowledge cutoff dates) (Q14)



and 41.1% strongly agreed ($n = 78$). The mean was 3.97 ($SD = 1.20$), suggesting that students believe they understand the technical limitations of generative AI. See Figure 21. These quantitative results suggest that students report high evaluation abilities when it comes to utilizing generative AI. A chi-square test of independence was not run on these Likert-scale questions because the data didn't meet the assumptions needed.

Some of the response categories, specifically "Strongly Disagree" and "Disagree," had very few responses, which made the results unreliable (i.e. more than 20% of cells had values less than 5). Because of that, valid conclusions couldn't be drawn from those items, and it was not possible to test for correlations between demographics and how students responded to these Likert items. Next, I will triangulate these results with the qualitative results.

Evaluation Practices

The qualitative responses provide more detail into how students describe evaluating generative AI output in practice. Across open-ended survey items and the focus groups, participants described a range of strategies used to assess the accuracy, reliability, and usefulness of AI-generated content, particularly in relation to research-related searches and tasks. Under the code **verification practices**, the theme *verifies information* was seen 43 times to describe instances of participants describing corroboration practices. The theme *hallucinations* appeared 15 times across qualitative survey responses addressing student concerns and evaluation strategies, indicating broad awareness of this limitation. This code and theme align with the behavioral and cognitive domains of metaliteracy.

Students frequently linked this awareness of hallucinations to specific behaviors, most notably verifying AI-generated information against published sources. This pattern is consistent with survey responses in which participants reported regularly verifying AI-generated content. For example, second-year student Ren explained,

I find articles and books for research in journals and double check anything 'cited' by AI. I will do the work and use AI to confirm or catch something I might have missed but still compare to what I have.

Similarly, first-year student Timothy double-checks what generative AI produces, writing, “I spot check to evaluate the quality and accuracy of AI-generated content by looking up the research article myself, looking up the quote myself, prompting it to double check for accuracy.” Several additional students reported similar practices,

emphasizing the importance of referring back to original or referenced texts in order to ensure accurate information.

Perceived Control and the Limits of Prompting

Several students described relying on specific prompting strategies as a means of controlling the accuracy and trustworthiness of generative AI output, as tagged 25 times by the code **GAI knowledge and prompting strategies**. Under the code's theme *questionable practices*, these strategies were often intended to reduce hallucinations or increase transparency in AI-generated content but, in some cases, reflected assumptions about generative AI's capacity to monitor or regulate its own accuracy and output. This theme aligns with metaliteracy's behavioral and cognitive domains as it describes both practice and knowledge (or misconceptions) that shaped that behavior. These patterns contrast with the quantitative results wherein students reported high awareness of technical limitations of generative AI.

Some students attempted to control accuracy directly through prompts intended to prevent hallucinations or to report changes from input to output. First-year student Octavia goes on the offense against hallucinations in her prompting as part of her verification practices: "I review content against sources. I, also, include 'do not hallucinate' in my prompts." April asks their chatbot to make a list of how it changed their writing:

The only thing I worry about is that AI makes changes to my work I don't know about when it proofs it. I don't even want AI to change words. This is why I ask AI to make a list of all the errors they changed so I know if they changed this I did not ask for.

Although these prompting strategies show skepticism toward generative AI output, they are not effective safeguards, as generative AI systems do not possess awareness of the accuracy of their responses and may generate inaccurate or fabricated explanations of their own behavior (OpenAI, 2025).

Other students described prompting strategies that relied on the chatbot's apparent ability to explain, justify, or correct its own output. Kaipo reported asking the chatbot to double-check its work: "sometimes, I will ask it to cite, prove, or defend its own content and it will tell on itself. I ask for page number [sic] references and I go into the source to check." Second-year student Clarissa uses a similar strategy, as they "ask the AI to explain its reasoning and to provide evidence of accuracy. That often leads to evidence or the AI admitting that it made up the response." These descriptions suggest a degree of anthropomorphization, as students attributed epistemic agency or self-awareness to the chatbot. In such cases, apparent admissions of error are more likely explained by sycophancy, an inherent feature in LLMs in which generative AI systems produce responses aligned with user expectations, rather than engaging in genuine self-evaluation (Cheng et al., 2025). Additionally, generative AI chatbots like ChatGPT are designed to be anthropomorphic, as seeming more human serves as a commercial selling point by making chatbots appear as accessible and helpful assistants (Ji, 2024; van Es & Nguyen, 2025). When chatbots are humanized, the technology that underpins them is obscured, which likely fosters these students' perceptions of the chatbots as "thinking" instead of perceiving this technology's inherent limitations (Ji, 2024).

In contrast, a smaller number of students described prompting practices intended to limit generative AI output to specific, known sources. Evita strives to ensure output

accuracy by providing only preselected, credible texts that she wants to query, and giving careful instructions in her prompts:

I do not ask AI to fully generate any papers. I provide specific sources that I already know to be credible and ask questions of the sources. I am surgically precise in my prompts ensuring I provide a role for the AI, a goal, ensure it only references the provided articles or sources, and there is a clear product, outcome, or question.

Two other students reported a similar technique but using *NotebookLM*, which may be used to create a sort of personal information retrieval database powered by generative AI. While these approaches may reduce the likelihood of hallucinations, generative AI systems may still produce inaccurate or fabricated content even when constrained to provided texts (Hagar et al., 2025).

Across these responses, students demonstrated strong motivation to control and evaluate generative AI output, often through increasingly specific prompting strategies. However, these practices varied in their effectiveness and reveal differing assumptions about how generative AI systems generate and validate information. Notably, several respondents expressed concern that overreliance on AI, even when carefully prompted, could interfere with the development of their own expertise and scholarly judgment, a theme that is taken up more fully in the following section.

Scholarly Identity as an Evaluative Lens

Several respondents described concerns that reliance on generative AI could interfere with the development of their own expertise and identities as scholars. Rather than focusing solely on the accuracy of AI-generated output, these students focused on

opportunities for developing their thinking and growth as scholars. These patterns were uncovered through the theme *personal expertise* under the code **scholar** and aligned with metaliteracy's affective and metacognitive domains. For example, second-year Jila expressed:

I am very aware AI can and will influence us bases on what was put in the computer program. I want my ideas to be what I work on and grow. AI always tried to write my work or summarize my reading. I tell it to turn off its automatic re-write and summarizations. I need the article read word for word because I do my thinking on my own and will ask when I have a question. And even then I clarify the answer to my questions is correct and refer AI to search the article I was reading. I do not want AI to do my thinking, writing or to take away my learning moment.

For these students, evaluation of generative AI output was tied to protecting their own intellectual development.

Beyond routine verification practices, many students pointed to their own expertise as a way to evaluate generative AI output. Bobbie wrote that, in evaluating generative AI output, "I compare it to other articles or other information i already know." Sandra used her own research to verify, stating that she would "refer back to my own research to make sure it is accurate." Third-year student Ashanti elaborated, "I typically only use it when I have a strong understanding of the content and can verify if it's accurate. I wouldn't have it explain a totally novel concept to me and not check it against other sources." Giselle echoed this stance, stating that, "I would never use AI, with information, outputting information that I didn't already know. That way, I can verify it

based on my knowledge and my experience and my expertise.” These responses indicate that students frequently positioned their own scholarly judgment as a benchmark against which AI output was assessed.

As students progressed in their programs, several described increasing confidence in their ability to identify inaccuracies in AI-generated content. Kelly articulated this shift, stating, “we're training to become the experts within our fields.” She continued, “you get so deep into your research, and, even though you may be studying a niche area, you somewhat become more well-rounded, just generally on a topic.” For Nami, this growing expertise functioned not only as an evaluation tool but also as a source of scholarly confidence:

I think how it's built my identity as a researcher, as a scholar, is that it was a lovely reminder that I'm smarter than it. That we all are smarter than it. Because of all of the errors that I was finding, all of the checking, there's no way that a robot can do what we are doing. And so using the AI for me, was a little bit of, in some ways, a confidence boost, because it's just so clearly not, the human experience, and not the experience of my community, which is what I'm trying to share in my dissertation, is that experience, and the personal, the human, so there's no way that I think that AI could replace us and the work that we are doing.

Nami emphasized the importance of real human experience, embedded in a particular community context, as a research tool and expertise that cannot be replicated by generative AI.

Other respondents similarly emphasized the limits of generative AI in producing doctoral-level work. Talissa stated, “AI cannot produce the quality of work that I require for my Ed.D, and doesn't have to contextual knowledge that I do. I can write better and more effectively about my topic than *ChatGPT*.” Kelly framed AI use as potentially unaligned with scholarly goals: “I mean, we're in this, we're going through these programs to, you know, essentially be scholarly practitioners, and so I'm doing my writing.” Taken together, these perspectives illustrate how scholarly identity and developing expertise shaped students’ evaluation of generative AI output. Rather than viewing generative AI as an authoritative source, they looked at it as a tool that needed to be supplemented by their own expertise.

RQ3 Summary

The tendencies and patterns for RQ3 illustrate how doctoral students describe their capacity to evaluate generative AI output and the factors that shape these practices. Students commonly reported cognitive awareness of generative AI’s limitations and described behavioral verification aligned with that awareness. At the same time, qualitative responses revealed uneven technical understanding of how generative AI systems function, particularly in relation to prompting strategies that assume AI can regulate or assess its own accuracy. Importantly, many students positioned their developing scholarly identities and developing expertise as central to their evaluative judgment, using their own knowledge to assess AI-generated content. These patterns suggest that critical evaluation of generative AI among EdD students is influenced not only by technical knowledge, but also by scholarly identity, which together shape how students interpret, constrain, and ultimately trust AI output.

Themes

Above, I presented the results of this study organized by research question. In this section, I synthesize the patterns that cut across research questions to highlight the major themes that emerged and the ways in which they interact. While each theme was introduced within specific codes, taken together they illustrate a broader reorganization of academic support, ethical decision-making, and relational dynamics within EdD programs. The following cross-cutting themes emerged:

- *GenAI Policy and Guidance Gaps*: Participants consistently reported that institutional policy and program-level guidance related to generative AI were absent, inconsistent, or difficult to operationalize. Even when policies existed, students described them as vague, faculty-dependent, or lacking practical examples of acceptable use. As a result, institutional guidance was often experienced as ambiguous. This ambiguity shaped how students interpreted risk, responsibility, and appropriate engagement with generative AI.
- *Fear and Perceived Risk*: Across research questions, students described fear of being accused of academic dishonesty, concern about “bad optics,” and anxiety that acknowledgment of generative AI use might erode perceptions of authorship. Fear functioned as a regulating force, influencing not only whether students used generative AI, but how openly they disclosed that use. Even when policies permitted use, perceived reputational risk shaped transparency practices.
- *Personalized Ethical Rules of Engagement*: In the absence of consistent institutional guidance, students constructed individualized lines and boundaries to regulate their use of generative AI. These rules of engagement were often

identity-driven and grounded in distinctions such as process versus product, acceptable support versus unacceptable authorship, and augmentation versus replacement of learning. Students described making deliberate decisions to preserve ownership, understanding, and accountability. These personalized ethical rules served as a substitute for shared institutional norms.

- *Scholarly Values and Identity*: Students' decisions about generative AI were intertwined with their identities as emerging scholars and scholar-practitioners. Themes of originality and ownership, expertise, and voice appeared across research questions and shaped not only how students used generative AI, but how they evaluated it and whether they trusted its output. Scholarly identity functioned as both a boundary-setting mechanism and an evaluative lens. Rather than viewing generative AI as authoritative, students positioned themselves as responsible for defending and standing behind their work.
- *Generative AI as Frontline Academic Support*: Across both **assistant** and **thought partner** codes, participants described turning to generative AI as an immediately available source of support. Students used it to overcome obstacles, increase productivity, receive writing feedback, clarify understanding, and engage in dialogic learning. Its 24/7 availability and responsiveness were cited as defining features. Importantly, participants frequently used relational language, such as tutor, writing coach, collaborator, critical friend, team member, and "fourth member of my dissertation committee," to describe this engagement. This anthropomorphizing suggests that generative AI is not experienced merely as a tool, but as an interactive presence within students' academic work. In this way,

generative AI functions as frontline academic support, often accessed before faculty or peers.

- *Transparency Practices*: Uncertainty around acknowledgment practices intersected with fear, policy ambiguity, and personalized ethical rules of engagement. Students struggled to determine when generative AI functioned as a tool that required no citation and when it functioned as a contributor requiring acknowledgment. Some resisted formal citation by analogizing generative AI to functioning as a tool or a person, while others expressed a desire to credit it in some capacity. These varied transparency practices reveal a lack of shared norms and reflect the relational ambiguity surrounding generative AI use.

Taken together, these themes suggest that generative AI use among EdD students reflects more than isolated behaviors. Participants described institutional policy and guidance as unclear or uneven. In response, they constructed personalized ethical rules of engagement grounded in scholarly values such as originality, expertise, and voice. Within this context, generative AI emerged as a readily accessible source of frontline academic support. Students used it to overcome obstacles, clarify understanding, and receive feedback, frequently describing it in relational terms such as tutor, collaborator, or “fourth member” of their committee. This language suggests that generative AI is experienced not only as a tool, but as an interactive presence within academic work. At the same time, fear and uncertainty shaped transparency practices, influencing how openly students disclosed their use. Together, these patterns indicate that, in the absence of consistent institutional direction, students are independently integrating generative AI

into their scholarly development. In Chapter 5, I examine how this integration may have implications for faculty-student relationships in CPED-aligned doctoral programs.

Summary

Chapter 4 examined how Doctor of Education students in CPED-aligned programs engage with generative AI across patterns of use, ethical concerns, evaluative practices, and relational positioning. Collectively, the results show that students use generative AI regularly and strategically to support learning, productivity, writing, and cognitive development, while actively self-monitoring their use through goal setting, reflection, and boundary-setting. Students described using generative AI both as an assistant for discrete tasks and as a thought partner for dialogic learning, frequently emphasizing its 24/7 availability as a defining feature.

Across qualitative data, participants also used explicitly relational language, such as tutor, collaborator, critical friend, and “fourth member of my dissertation committee,” to describe their engagement with generative AI. This anthropomorphizing suggests that generative AI is not experienced solely as a neutral tool, but as an interactive presence embedded within students’ academic workflows and scholarly development.

Students’ decisions about generative AI use were closely tied to scholarly values such as originality, ownership, voice, and the development of expertise, leading many to regulate or limit AI use in ways that preserved their sense of authorship and preparedness. At the same time, students described substantial concern and uncertainty related to academic integrity, institutional policy, and acknowledgment practices. In the absence of clear and actionable guidance, many constructed personalized ethical rules of

engagement to govern their use. These affective and metacognitive processes shaped not only how generative AI was used, but how openly that use was disclosed.

Although students expressed confidence in their ability to evaluate AI-generated output and reported frequent verification behaviors, their descriptions revealed uneven technical understanding of how generative AI systems function. Overall, the tendencies and patterns described in this chapter illustrate that EdD students' engagement with generative AI is shaped by the interaction of scholarly identity, perceived risk, evaluative judgment, and limited institutional guidance. Together, these themes suggest that generative AI is becoming integrated into the everyday academic support structures of EdD students, a development that is examined further in Chapter 5 in relation to faculty-student relationships.

CHAPTER 5

DISCUSSION

Introduction

In this chapter, I move beyond description to interpret the findings presented in Chapter 4 and to situate them within broader conversations about doctoral education in an AI-mediated environment. While the results were organized by research question, several cross-cutting patterns emerged that point to a structural shift in how academic support is accessed and regulated within CPED-aligned EdD programs. Participants described using generative AI not only as a tool for specific tasks, but as 24/7 frontline academic support under conditions of institutional policy and guidance gaps. In response to this ambiguity, students constructed individualized ethical rules of engagement grounded in scholarly identity, which shaped both their generative AI use and their transparency practices. Taken together, these patterns suggest a reorganization of academic support pathways rather than merely the adoption of a new educational technology.

In this chapter, I situate these findings within existing scholarship on generative AI and metaliteracy. I introduce a conceptual model that explains how institutional ambiguity and identity-driven regulation contribute to the integration of generative AI into doctoral support structures. I then consider the structural implications of this reorganization for CPED programs and conclude with recommendations for future research.

Discussion

The findings of this study both corroborate prior research on generative AI use in higher education and extend it by identifying a structural pattern in how EdD students

integrate generative AI into their academic workflows. While much of the existing literature focuses on frequency, productivity, or ethical concern, this study suggests that generative AI is becoming embedded as frontline academic support under conditions of institutional ambiguity. In this section, I organize the discussion around areas of alignment with existing research and then consider how the cross-cutting themes identified in Chapter 4 form a broader explanatory model.

Frequency, Timing, and Purposes for Generative AI Usage

EdD students in this study reported frequent generative AI use, with 65.3% indicating at least weekly engagement, a rate consistent with emerging national and institutional data (Shaw, 2025; UCD Center for Educational Effectiveness, 2024). As in prior research, students primarily used generative AI for writing support, brainstorming, summarization, and productivity enhancement (Buss et al., 2025; Chen et al., 2024). However, this study extends existing literature by demonstrating that such usage is not merely functional but ethically negotiated. Participants described establishing individualized lines and boundaries in response to institutional ambiguity, suggesting that generative AI integration among EdD students is shaped less by formal policy and more by identity-mediated ethical self-regulation. In CPED contexts, where scholarly practitioner identity is central, these findings suggest that generative AI use is filtered through commitments to originality, expertise, and voice rather than governed solely by institutional directives (Zambo et al., 2015). Beyond frequency and purpose, an important extension of the literature lies in the timing and sequencing of use. Participants described turning to generative AI as a first-line source of feedback, clarification, and idea development, which are functions traditionally associated with faculty mentorship or peer

collaboration. This suggests that generative AI is not simply supplementing existing support structures but is becoming integrated into the front end of doctoral help-seeking processes. Such patterns indicate a redistribution of mentoring-related functions within EdD programs.

Challenges in Using Generative AI

Participants' concerns about shifting policies, academic integrity, and stigma align with prior research documenting widespread uncertainty in higher education (Buss et al., 2025; Minimo & Bueno, 2024). This study extends that literature by illustrating how such uncertainty shifts ethical responsibility onto individual students, raising equity concerns in CPED programs. When institutional guidance is ambiguous, students not only assume ethical responsibility but also reorganize their academic support strategies independently. In this context, generative AI can function as compensating for inadequate infrastructure, filling perceived gaps in clarity, availability, or immediacy.

Verification Practices and Impact of Limited Technical Knowledge

Although participants expressed high confidence in evaluating generative AI output, similar to patterns observed in prior information literacy research, qualitative data revealed gaps between perceived and demonstrated technical understanding (Mahmood, 2016; Nierenberg & Dahl, 2023). Many students described verifying information by checking cited sources or comparing output to what they already knew. However, some prompting strategies suggested incomplete understanding of how generative AI systems function, particularly when students relied on the chatbot to “double-check” itself or prevent hallucinations through specific phrasing. These responses indicate that while

students are motivated to evaluate AI-generated content carefully, their technical understanding of generative AI's limitations varies.

At the same time, students frequently relied on their own developing expertise as a benchmark for evaluating generative AI output. Rather than treating generative AI as authoritative, they compared its responses to their own knowledge, research, and disciplinary understanding. In this way, evaluation was shaped not only by technical knowledge, but by scholarly identity. Students positioned themselves as responsible for determining accuracy and appropriateness, even when institutional guidance was unclear.

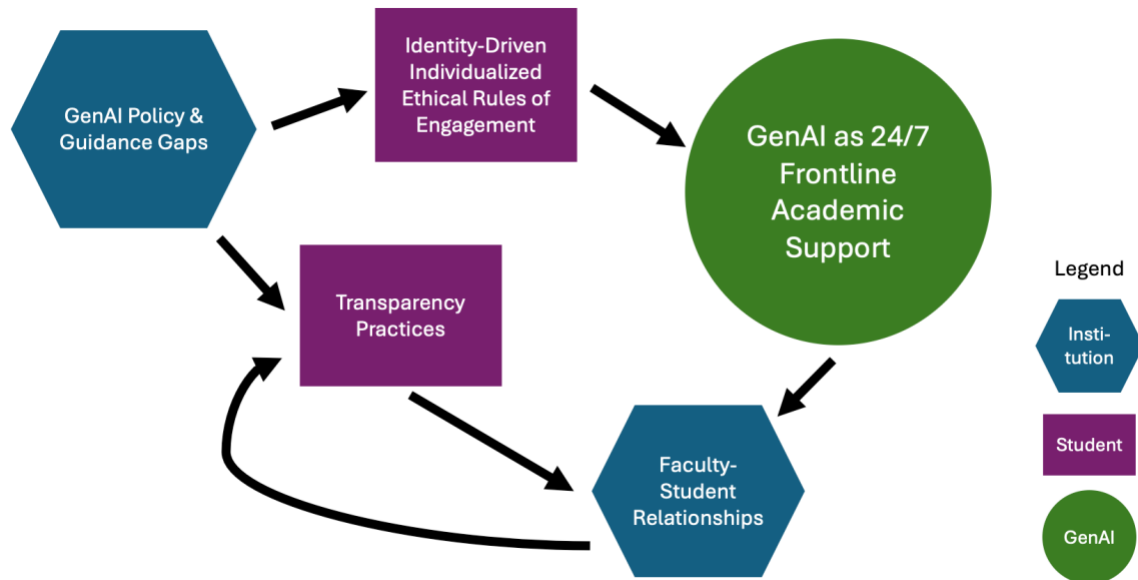
This pattern of identity-driven evaluation reinforces generative AI's role as frontline academic support. When students rely on their own expertise to validate AI output, they are able to use generative AI independently, without necessarily seeking confirmation from faculty. Over time, this independence may influence the sequencing of faculty-student interaction, as students resolve many lower-level evaluative and feedback needs before engaging their advisors or instructors.

Conceptual Model: Shifting Pedagogical Interactions and Relational Instructional Ties (SPIRIT)

Synthesizing findings across research questions, this study suggests that EdD students' generative AI practices are best understood not only as individual ethical decision-making, but as part of a broader reorganization of academic support when generative AI policy and guidance are ambiguous. Figure 22 presents a conceptual model illustrating how policy and guidance gaps interact with identity-driven ethical regulation to position generative AI as 24/7 frontline academic support, with implications for faculty-student relationships.

Figure 22

Shifting Pedagogical Interactions and Relational Instructional Ties (SPIRIT Model)



At the left of the model are *Generative AI Policy and Guidance Gaps*. Participants consistently described institutional expectations as unclear, inconsistent across faculty, or difficult to operationalize. Even when policies existed, students often experienced them as abstract rather than actionable. This ambiguity created uncertainty about acceptable use and acknowledgment.

In response, students developed *Identity-Driven Individualized Ethical Rules of Engagement*. Rather than relying primarily on shared program norms, participants described constructing personal boundaries grounded in scholarly values such as originality, expertise, and voice. These rules functioned as internal governance systems that guided when and how generative AI could be used.

These individualized ethical rules of engagement shape the emergence of *GenAI as 24/7 Frontline Academic Support*. Participants reported turning to generative AI first when they felt stuck, needed clarification, or sought feedback. Its immediacy and availability distinguished it from faculty or peer support. Moreover, students frequently described generative AI in relational terms, such as tutor, collaborator, critical friend, or “fourth member” of their committee, indicating that it was not experienced merely as a tool, but as an embedded academic support presence.

The SPIRIT model also includes *Transparency Practices*, which are influenced directly by institutional ambiguity and shaped indirectly by generative AI’s integration into academic workflows. Participants described uncertainty about when and how to acknowledge use, and in some cases, reluctance to disclose due to concerns about perception or stigma. Transparency practices therefore reflect the intersection of institutional guidance, reputational risk, and individualized ethical reasoning.

Together, these dynamics contribute to shifts in *Faculty-Student Relationships*. When students routinely consult generative AI for feedback, clarification, idea development, and organizational support before engaging faculty, the sequencing and distribution of mentoring-related functions changes. This does not imply replacement of faculty mentorship. Rather, it suggests a redistribution of academic support pathways, in which generative AI functions as compensatory infrastructure within doctoral education.

SPIRIT Model Summary

Under conditions of institutional policy and guidance gaps, EdD students construct identity-driven individualized ethical rules of engagement to regulate generative AI use. These rules facilitate the integration of generative AI as 24/7 frontline

academic support while shaping transparency practices. As students increasingly rely on generative AI for functions traditionally associated with faculty mentoring, academic support pathways are redistributed, contributing to a reorganization of faculty-student relationships within CPED-aligned programs.

This model suggests that generative AI is not merely a new tool within existing doctoral structures. Rather, under conditions of institutional ambiguity and evolving norms, it becomes embedded within the academic support system itself. When students consistently access generative AI as a first-line source of feedback and cognitive support, mentoring functions are redistributed. This redistribution reflects a structural reorganization of how academic support is accessed and sequenced within CPED programs.

Structural Implications for CPED Doctoral Programs in the Age of Generative AI

When I began this study, much of the literature on AI literacy emphasized knowledge and technical skills, often drawing on Bloom's taxonomy (Jin et al., 2024; Ng et al., 2021). Since then, the conversation has shifted. More recent scholarship increasingly centers ethics, metacognition, attitudes, and values as foundational rather than supplemental to AI literacy (Frau-Meigs, 2024; Ma et al., 2025; Yang et al., 2025).

These developments resonate strongly with Mackey and Jacobson's (2022) metaliteracy framework and help illuminate what this study suggests for CPED doctoral education: generative AI literacy should not be framed solely as a matter of technical competence. Instead, it should be situated within the broader development of epistemic agency in emerging scholar-practitioners. Epistemic agency refers to students' capacity to take ownership of their thinking, exercise critical judgment, and accept responsibility for

the knowledge they produce (Yan et al., 2025). In doctoral education, this capacity is central. EdD students are being prepared not only to consume knowledge but to contribute to it. Generative AI introduces new efficiencies and supports, but it also reshapes the conditions under which intellectual ownership and responsibility develop.

Shared Norms and Ethical Infrastructure

The conceptual model presented in this study suggests that, in the absence of clear and stable institutional guidance, students engage in individualized ethical self-governance. While this self-regulation reflects thoughtful metacognitive engagement, it also creates inconsistency. Students interpret acceptable practice on their own, which may advantage those with stronger mentorship, confidence, or prior expertise. For CPED programs, this points to the importance of shared norms. Encouraging student reflection remains essential, but it should be accompanied by clear, collective guidance regarding generative AI use and acknowledgment. Reducing ambiguity does not remove agency; rather, it provides a more equitable foundation for exercising it.

Scholarly Identity and Responsible AI Use

Another strong implication concerns scholarly identity. Participants consistently framed their AI decisions through commitments to originality and ownership, expertise, and voice. These identity-based commitments served as internal regulators of use. CPED programs, which explicitly aim to develop scholarly practitioners, are well positioned to make these connections explicit (Perry, 2015; Zambo et al., 2015). Conversations about what it means to “stand behind” one’s work in an AI-mediated environment can help students align generative AI use with their developing professional identities. At the same time, identity alone cannot substitute for program-level clarity. Without shared

conversations and norms, students are left to interpret individually what responsible use looks like.

Relational Learning in an AI-Mediated Environment

The results raise structural questions about relational learning in CPED programs. Many participants described turning to generative AI first when they felt stuck, needed clarification, or sought feedback. The immediacy and availability of generative AI lowers barriers to engagement and increases efficiency. However, this shift also alters the sequencing of academic interaction. When early-stage feedback, idea development, and clarification occur through AI-mediated dialogue, faculty engagement may move further downstream in the learning process. Doctoral education has traditionally relied on relational mentorship and critique. If generative AI absorbs some of these mentoring functions, programs may need to reconsider how faculty time and attention are structured. The question is not whether generative AI should be used, but how CPED programs can intentionally design relational touchpoints so that mentoring remains developmental rather than reactive.

Practical Considerations for CPED Programs

In the absence of clear and actionable guidelines for generative AI use, EdD students are creating personalized ethical rules of engagement guided by scholarly values, but also by their fear. Based on these patterns, CPED programs might consider:

- Developing clear and transparent guidance regarding generative AI use and acknowledgment.
- Providing training on technical affordances and limitations, including hallucinations and sycophancy.

- Integrating structured reflection on generative AI use into coursework and dissertation milestones.
- Making explicit connections between scholarly practitioner identity and responsible generative AI integration.
- Re-examining faculty advising structures in light of AI-mediated frontline support.
- Designing intentional, structured mentoring interactions that account for AI use rather than ignoring it.

Importantly, such efforts should extend beyond technical skills. Attention to affective and metacognitive dimensions is necessary if programs aim to cultivate metaliterate, ethically grounded scholar-practitioners.

A Reflexive Perspective

Because this study examines generative AI use among EdD students, it is important to acknowledge my own position as both a researcher and a generative AI user. I matriculated into my EdD program shortly after the public release of ChatGPT. Initially, I did not engage with generative AI tools. Over time, particularly in professional contexts where exploration of these tools was encouraged, I began using generative AI for writing support and ideating.

Like many participants in this study, I found myself constructing a personalized ethical set of rules of engagement in the absence of clear program-level guidance. I have used generative AI to assist with editing and improving clarity in my writing. However, the analytic decisions, conceptual framing, coding processes, and development of the

model presented in this dissertation are entirely my own. Generative AI did not generate findings, conduct analysis, or construct theoretical arguments.

Table 6

A Proposed Framework for Student Transparency Practices

Tool-Level Support	May Warrant Formal Disclosure
Using generative AI or AI-powered platforms for assistant-level tasks, such as: • Project management (e.g., to do lists) • Correcting grammar and spelling (e.g., Grammarly) • Explaining concepts (e.g., Google) • Brainstorming or information generation when corroborated with scholarly sources • Finding literature (e.g., Research Rabbit or LitMaps) • Organizing literature that you have read (e.g., NotebookLM) • Identifying connections between literature that you have read (e.g., NotebookLM) • Any task that requires little to no cognitive effort or that	Using generative AI or AI-powered platforms for tutor or thought-partner level tasks, such as: • Organizing writing • Editing writing • Generating writing (including first drafts that are edited) • Summarizing literature in lieu of reading • Brainstorming or information generation when <i>not</i> corroborated with scholarly sources • Analyzing data • Any offloading of cognitive effort or any task that influenced your own cognitive effort or presentation of your ideas

Tool-Level Support	May Warrant Formal Disclosure
would not impact generation or presentation of your ideas	

Engaging in this dual role, as both a user and a researcher of generative AI, heightened my awareness of the tensions described by participants. Their concerns about ownership, voice, expertise, and transparency were not abstract. They were recognizable and, at times, personally resonant. This reflexive awareness informed my interpretation of the data while also reinforcing the importance of transparency in my own scholarly practice. In the absence of formal guidance from my program, I elected to include a generative AI acknowledgment in this dissertation. That decision reflects my own ethical rules rather than an institutional requirement.

Based on both participant reasoning and my own decision-making process, Table 6 illustrates one possible framework for distinguishing between generative AI use that functions as background assistance or tool-level support, and use that meaningfully influences intellectual production. This framework is not intended as prescriptive policy, but as a starting point for discussion within CPED programs.

Implications for Future Research

Future research should extend this study by examining how structural features of EdD programs shape student usage of generative AI. This study suggests that generative AI becomes frontline academic support when policy and guidance are unclear, but additional research is needed to determine how usage might vary depending on program design. Comparative studies examining fully online, hybrid, and in-person EdD programs

could shed light into whether modality influences the extent to which students rely on generative AI as a first-line source of feedback, clarification, and idea development. Further research should also analyze faculty availability, advising structures, cohort models, and dissertation supervision practices to better understand how generative AI intersects with existing mentoring infrastructures. If generative AI functions as compensatory academic support, then variations in program structure may predict differences in how and when students turn to AI rather than faculty.

Longitudinal research would also be valuable in examining whether generative AI use changes as students progress through doctoral milestones, particularly during the dissertation phase. Studies that track shifts in help-seeking behavior over time could clarify whether generative AI primarily supports early-stage coursework, later-stage independent research, or both.

Finally, while this study relied primarily on self-reported behavior, future research could incorporate observational or mixed method designs to examine how generative AI is integrated into real-time academic workflows and advising interactions. Such work would deepen understanding of how generative AI contributes to, or reshapes, relational learning processes within doctoral education.

Conclusion

This study explored how Doctor of Education students in CPED-aligned programs report using generative AI in their academic work, with attention to patterns of usage, decision-making, concerns, and evaluative practices. While the findings were organized around research questions, taken together they suggest a broader system shaping generative AI use in doctoral education.

Participants consistently described institutional ambiguity regarding expectations for generative AI. Policies were often unclear, inconsistent, or perceived as absent. In this context, responsibility for ethical decision-making shifted to students themselves. Many responded by constructing personalized ethical rules of engagement grounded in their own scholarly values, resulting in individualized and largely private systems of regulation.

Scholarly identity emerged as a central organizing force. Commitments to originality, voice, and expertise shaped how students sequenced, limited, and justified their generative AI use. At the same time, uncertainty about transparency and acknowledgment practices created discomfort around open disclosure. Rather than reflecting disregard for ethical considerations, this pattern suggests defensive and aspirational ethical self-governance enacted under conditions of perceived risk.

Participants expressed confidence in their ability to evaluate generative AI output and described corroborating AI-generated information with scholarly sources. Yet qualitative descriptions of prompting strategies revealed uneven technical understanding. This gap highlights the need to approach generative AI literacy as more than technical skill acquisition.

Overall, the findings suggest that generative AI use among EdD students is not primarily governed by formal policy but by identity-mediated ethical self-governance shaped by institutional ambiguity and reputational risk. In CPED contexts, where developing scholar-practitioners is central, generative AI literacy must therefore be understood as intertwined with epistemic agency, relational learning, and the cultivation of shared ethical norms.

Beyond ethical self-governance, the findings of this study suggest that generative AI is becoming embedded within the academic support infrastructure of CPED doctoral programs. As students increasingly turn to generative AI as a first-line source of feedback, clarification, and idea development, mentoring-related functions are redistributed and the sequencing of faculty-student interaction shifts. This structural reorganization does not signal the replacement of faculty mentorship. Rather, it reflects an evolving ecology of support in which generative AI operates alongside, and sometimes prior to, human relational engagement. CPED programs must therefore move beyond policy clarification alone and intentionally design doctoral structures that account for this new support landscape.

GENERATIVE AI ACKNOWLEDGMENT

Across the dissertation, *Claude 3.7 sonnet*, and later, *ChatGPT 4o* and *ChatGPT 5.2*, were used to advise on writing style and phrasing and to edit writing.

Chapter 2: *Claude 3.7 sonnet* was used to advise on organization of and wording in the version of chapter as presented in the proposal. *Claude 4.5 sonnet* was used very sparingly to provide advice on word choice. For the dissertation, *ChatGPT 4o* was used to offer critique of my writing and for brainstorming.

Chapter 3: *Claude 3.7 sonnet* was used to advise how to tighten up connections between my research questions, my constructs, and my methodologies as part of my proposal. It also advised on methodology selection and data analysis, which I cross-referenced with reliable sources.

Chapter 4: *ChatGPT 4o* was used to generate instructions on how to use SPSS to calculate chi-square tests of independence, including how to configure variables in SPSS in order to make such tests possible. It was used to calibrate writing style of chapter content, including remaining at findings-level and not conceptual-level. It was NOT used to analyze data or conduct any thematic analysis.

Chapter 5: *ChatGPT 5.2* was used to advise on organization and to edit writing, including to calibrate writing style to conceptual-level, and to avoid duplication of content from Chapter 4.

Survey: *Claude 3.7 Sonnet* was used to revise the survey. I created an original draft based on secondary research and my study goals. I used *Claude* to help better align items with my constructs, and to decide which items to keep or remove. I further edited survey items after running a pilot.

Focus Group Protocol: *Claude 3.7* Sonnet was used to format the protocol and to create a first draft of questions. I edited and revised.

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APPENDIX A

ASU PROGRAM PERMISSION TO CONDUCT RESEARCH

Thursday, December 19, 2024 at 14:24:08 Mountain Standard Time

Subject: Re: Dissertation Project Approval
Date: Thursday, December 19, 2024 at 11:59:04 AM Mountain Standard Time
From: Josephine Marsh
To: Lindsay O'Neill

You have to program committee's approval for your project! Keep this email in your file.

Josephine Peyton Marsh, Ph.D.
Associate Director, Doctoral (EdD) Programs
Associate Professor, Literacy Education
Graduate College Faculty Fellow
Mary Lou Fulton Teachers College
Arizona State University
[Online Leadership and Innovation EdD Information](#)
[General Leadership and Innovation EdD Information](#)

APPENDIX B
IRB EXEMPTION

EXEMPTION GRANTED

Gustavo Fischman
MLFTC: Educational Leadership and Innovation, Division of
(480) 965-5225
fischman@asu.edu

Dear [Gustavo Fischman](#):

On 5/29/2025 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Exploring Student Usage of Generative AI in CPED Doctor of Education Programs
Investigator:	Gustavo Fischman
IRB ID:	STUDY00022258
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• Focus Group Consent, Category: Consent Form; • Focus Group Protocol, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • Focus Group Recruitment, Category: Recruitment Materials; • Protocol, Category: IRB Protocol; • supporting_documents_18-05-2025.pdf, Category: Recruitment materials/advertisements /verbal scripts/phone scripts; • Survey Consent, Category: Consent Form; • Survey Recruitment, Category: Recruitment Materials; • survey_instrument_17-05-2025.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions);

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2)(ii) Tests, surveys, interviews, or observation (low risk) on 5/20/2025.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

If any changes are made to the study, the IRB must be notified at research.integrity@asu.edu to determine if additional reviews/approvals are required. Changes may include but not limited to revisions to data collection, survey and/or interview questions, and vulnerable populations, etc.

It is the research team's responsibility to notify the IRB of 'reportable new information.' (an RNI) During a research study, any adverse events, unanticipated problems involving risk, and non-compliance **must** be reported to the IRB as an RNI. Please see the following link for details: <https://researchcompliance.asu.edu/human-subjects/reportable-events/>. This does not include risks previously identified and listed in the IRB protocol and consent. Any serious events **must** be reported within **24 hours**. Non-serious adverse events **must** be reported within 5 business days.

Sincerely,

IRB Administrator

cc: Lindsay O'Neill
Lindsay O'Neill

APPENDIX C

SURVEY

Draft Survey

Note: For this survey, the term “generative AI tools” refers to text-based chatbots (such as ChatGPT, Claude, or Gemini), image generators, music generators, and similar technologies that create content based on user prompts.

For all questions in this survey, please respond based only on your use of generative AI for your Doctor of Education (EdD) program work, including coursework, assignments, research, and dissertation. Do not consider your professional work outside the program.

Which of the following generative AI tools do you regularly use for your EdD coursework and research? (Select all that apply)

1. ChatGPT
2. Google Gemini
3. Claude
4. Perplexity
5. Microsoft Copilot
6. Other
7. I do not regularly use any generative AI tools for academic purposes

How frequently do you use generative AI tools for your EdD coursework and research?

1. Never
2. Rarely (1-2 times per month)
3. Occasionally (1-2 times per week)
4. Frequently (3-5 times per week)
5. Daily

For what purposes do you use generative AI when it comes to your EdD coursework and research? (select all that apply)

1. Explaining concepts
2. Brainstorming ideas
3. Summarizing articles or sources
4. Outlining papers or projects
5. Drafting written content
6. Editing and improving writing
7. Research design assistance
8. Data analysis support
9. Literature review assistance
10. Something else
11. None of the above

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI.	☐	☐	☐	☐	☐
I consider multiple	☐	☐	☐	☐	☐

strategies, including whether to use generative AI, when approaching EdD tasks.					
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How do you decide when to use a generative AI tool as part of your EdD work?

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I understand when it is appropriate to use generative	☐	☐	☐	☐	☐

AI as part of my EdD coursework and research.					
I am concerned about potential academic integrity issues when using generative AI.	☐	☐	☐	☐	☐
I know what my institution's policies are regarding generative AI use.	☐	☐	☐	☐	☐

I understand when to acknowledge my use of generative AI.	☐	☐	☐	☐	☐
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What, if any, concerns do you have about use of generative AI related to your EdD coursework and research?

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I can effectively evaluate the quality and accuracy of	☐	☐	☐	☐	☐

AI-generated content.					
I verify AI-generated information against other sources.	☐	☐	☐	☐	☐
I understand the technical limitations of generative AI (e.g. hallucinations, knowledge cutoff dates).	☐	☐	☐	☐	☐

What strategies do you use to evaluate the quality, accuracy, or usefulness of AI-generated content?

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I regularly reflect on how use of generative AI influences my thinking.	☐	☐	☐	☐	☐
I actively monitor how my use of generative AI affects the development of my own expertise.	☐	☐	☐	☐	☐
I use generative AI outputs as starting points	☐	☐	☐	☐	☐

rather than finished work.					
-------------------------------	--	--	--	--	--

Is there anything else you would like to share about your use of generative AI for your EdD coursework and research?

What is your gender?

1. Male
2. Female
3. Non-binary
4. Prefer to self-describe:
5. Prefer not to say

What is your age range?

1. 19 or younger
2. 20-29
3. 30-39
4. 40-49
5. 50-59
6. 60-69
7. 70 or older

What is your race/ethnicity? (Select all that apply)

1. Asian
2. Black or African American
3. Hispanic or Latino
4. Middle Eastern or North African
5. Native American or Alaska Native
6. Native Hawaiian or Pacific Islander
7. White
8. Prefer to self-describe:
9. Prefer not to say

What year are you in your doctor of education program?

1. 1st year
2. 2nd year
3. 3rd year
4. 4th year or beyond
5. Not applicable

Final Survey

Note: For this survey, the term “generative AI tools” refers to text-based chatbots (such as ChatGPT, Claude, or Gemini), image generators, music generators, and similar technologies that create content based on user prompts.

For all questions in this survey, please respond based only on your use of generative AI for your Doctor of Education (EdD) program work, including coursework, assignments, research, and dissertation. Do not consider your professional work outside the program.

Q1 Which of the following generative AI tools do you regularly use for your EdD coursework and research? (Select all that apply)

- ChatGPT
- Google Gemini
- Claude
- Perplexity
- Microsoft Copilot
- Other
- I do not regularly use any generative AI tools for academic purposes

Q2 How frequently do you use generative AI tools for your EdD coursework and research?

- Never

- Rarely (1-2 times per month)
- Occasionally (1-2 times per week)
- Frequently (3-5 times per week)
- Daily

Q3 For what purposes do you use generative AI when it comes to your EdD coursework and research? (select all that apply)

- Explaining concepts
- Brainstorming ideas
- Summarizing articles or sources
- Outlining papers or projects
- Drafting written content
- Editing and improving writing
- Research design assistance
- Data analysis support
- Literature review assistance
- Something else
- None of the above

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Q4 When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI.	☐	☐	☐	☐	☐
Q5 I consider multiple strategies, including whether to use generative AI, when approaching EdD tasks.	☐	☐	☐	☐	☐

Q6 How do you decide when to use a generative AI tool as part of your EdD work?

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Q7 I understand when it is appropriate to use generative AI as part of	☐	☐	☐	☐	☐

my EdD coursework and research.					
Q8 I am concerned about potential academic integrity issues when using generative AI.	☐	☐	☐	☐	☐
Q9 I know what my institution's policies are regarding generative AI use.	☐	☐	☐	☐	☐
Q10 I understand	☐	☐	☐	☐	☐

when to acknowledge my use of generative AI.					
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Q11 What, if any, concerns do you have about use of generative AI related to your EdD coursework and research?

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Q12 I can effectively evaluate the quality and accuracy of AI-generated content.	☐	☐	☐	☐	☐
Q13 I verify AI-generated information against other sources.	☐	☐	☐	☐	☐
Q14 I understand the technical limitations of generative AI (e.g. hallucinations,	☐	☐	☐	☐	☐

knowledge cutoff dates).					
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Q15 What strategies do you use to evaluate the quality, accuracy, or usefulness of AI-generated content?

For the following items, please indicate your level of agreement:

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
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Q16 I regularly reflect on how use of generative AI influences my thinking.	☐	☐	☐	☐	☐
Q17 I actively monitor how my use of generative AI affects the development of my own expertise.	☐	☐	☐	☐	☐
Q18 I use generative AI outputs as starting points rather than finished work.	☐	☐	☐	☐	☐

Q19 Is there anything else you would like to share about your use of generative AI for your EdD coursework and research?



Q20 What is your gender?

- Male
- Female
- Non-binary
- Prefer to self-describe:
- Prefer not to say

Q21 What is your age range?

- 19 or younger
- 20-29
- 30-39
- 40-49
- 50-59
- 60-69
- 70 or older

Q22 What is your race/ethnicity? (Select all that apply)

- Asian
- Black or African American
- Hispanic or Latino
- Middle Eastern or North African
- Native American or Alaska Native
- Native Hawaiian or Pacific Islander
- White
- Prefer to self-describe:
- Prefer not to say

Q23 What year are you in your doctor of education program?

- 1st year
- 2nd year
- 3rd year
- 4th year or beyond
- Not applicable

APPENDIX D

FOCUS GROUP PROTOCOL

Focus Group Protocol: Doctoral Students' Generative AI Usage (Zoom Format)

Technical Setup for Moderator

- Test Zoom connection and recording capabilities in advance
- Enable closed captioning if needed
- Turn on cloud recording (*only cloud recording includes transcript*)
- Have participant list available

Introduction Script (10 minutes)

Welcome and thank you for joining our virtual focus group today. My name is Lindsie and I will be facilitating our discussion.

Before we begin, in the interest of anonymity, I'd like you all to select pseudonyms. To that end, please change your name in Zoom to a pseudonym. To do this, open the Participants pane, hover over your name, select More, then Rename. Type in your pseudonym.

[give them a few moments to change to pseudonyms, help as necessary]

Thanks for doing that! Here are a few participation notes for today's session.

- You can use the raise hand feature if you'd like to speak
- We encourage you to keep your camera on if possible, but it's not required
- Please stay muted when not speaking to minimize background noise

The purpose of today's focus group is to understand how doctoral students in education use generative AI tools in their academic work. We're interested in learning about your experiences, decision-making processes, and thoughts about these technologies. The information you share will help better understand current practices and potentially inform guidance for students and faculty.

Important points to note:

- The session will last approximately 90 minutes
- This session will be recorded and transcribed, but only the transcript will be provided to the researcher, not the video or audio recording
- Your participation is voluntary, and you may decline to answer any question or leave at any time
- While we'll take steps to protect confidentiality, we ask all participants to respect each other's privacy
- The information you share will be used for research purposes only, with all identifiers removed
- Your participation is completely voluntary, and you may choose not to answer any question or leave at any time
- There are no right or wrong answers. We value your honest perspectives, even if they differ from others
- To ensure everyone has a chance to speak, I may occasionally call on those who haven't shared as much

Did you all read and comprehend the informed consent, and agree to participate in this study?

[Pause and ensure each participant consents]

Does anyone have any questions before we begin?

[Pause for questions]

I'll now start the recording. By remaining in this session, you are consenting to participate under these terms.

[Start recording to cloud]

Introductions (5 minutes)

Let's start with brief introductions. Please share your year in your doctoral program, and briefly, something you do for fun outside of your academic studies.

Section 1: Prior Knowledge and Initial Exposure (15 minutes)

Let's begin by discussing how you first learned about generative AI tools.

- **Q1 Opening Question:** What prompted you to try using generative AI for your EdD work?
 - *Probing question:* Did you learn about these tools from peers, faculty, or other sources?
 - *Probing question:* Were you hesitant to use these tools at first? Why or why not?
- **Q2 Follow-up Question:** What do you believe is appropriate or inappropriate use of generative AI for your EdD work?
 - *Probing question:* How did you form these boundaries or guidelines for yourself?

Section 2: Institutional and Program Guidance (15 minutes)

Now let's discuss what kind of guidance you've received about using generative AI.

- **Q3 Key Question:** What formal guidance or training, if any, have you received from your doctoral program about using generative AI in your academic work?
 - *Probing question:* Did your program provide specific policies, guidelines, or statements?
 - *Probing question:* How was this guidance communicated to you?

Section 3: Current Academic Use Practices (15 minutes)

Let's talk about how you currently use generative AI in your academic work.

- **Q4 Key Question:** Can you walk us through your decision-making process for when you use generative AI?
 - *Probing question:* What factors help you determine whether using AI is appropriate for a specific task?
 - *Probing question:* Are there certain academic tasks where you deliberately avoid using these tools? Why?

- **Q5 Key Question:** When can you use output from generative AI in your work? For example, when can you copy and paste from generative AI into your work, and when shouldn't you?
- **Q6 Key Question:** How do you handle citation and acknowledgment of generative AI use in your academic work?
 - *Probing question:* What determines whether you formally cite AI use in your work?
 - *Probing question:* How do you approach transparency about AI use with your faculty and peers?
- **Q7 Follow-up Question:** How do you evaluate and verify the quality of content generated by AI tools?
 - *Probing question:* Can you describe a time when you identified inaccurate or problematic AI output?

Section 4: Broader Impact and Future Implications (15 minutes)

Finally, let's explore the broader impact of generative AI on your doctoral experience.

- **Q8 Key Question:** Has generative AI affected the development of your own expertise and scholarly identity, and if so, how?
 - *Probing question:* Do you think these tools enhance or potentially limit your learning in certain ways?
 - *Probing question:* Has your relationship with these tools evolved as you've progressed in your program?

Conclusion (5 minutes)

- **Q9 Ending Question:** If you could give one piece of advice to the leadership of your doctoral program about how to approach generative AI, what would it be?
- **Q10 Final Question:** Is there anything else about your experiences with generative AI in doctoral education that you'd like to share that we haven't covered?

Wrap-Up

Thank you all for your time and thoughtful contributions today. Your insights will be extremely valuable for this research. As mentioned at the beginning, everything shared today will remain confidential, and your identities will be protected in any reporting.

I will now stop the recording and end our session. The transcript will be provided to the researcher, but not the video recording itself. If you have any additional thoughts after today's session or questions about the research, please feel free to contact the research team: Gustavo Fischman, fischman@asu.edu, or Lindsay O'Neill, lindsay.oneill@asu.edu.

Thank you again for your participation!

[end meeting]

Post-Session Instructions

Download the recording transcript. Ensure that the transcript is accurate, pseudonyms are assigned, and email the transcript to Lindsay O'Neill. Once you receive confirmation from Lindsay that the transcript is complete and coherent, please permanently delete any session recordings and other files generated from the session.

APPENDIX E

QUALITATIVE CODEBOOK

Table 7*Codebook*

Code	Group	Description
Acknowledging use	How students use	How are students being transparent about use? Or formally acknowledging their use? What do they know about how to acknowledge? Doesn't know how to properly acknowledge, or when to acknowledge.
Assistant	How students use	LOWER LEVEL OF USE, used as helper (lower level cognition). Assists in a task, doesn't produce final output. Helps organize. Edits writing.
Concerned About Other Students	Policy, Training, Guidance	Thinks other students are overusing; feels distrust of other students' work, especially discussion posts; feels resentful
Concerned About Overuse	Policy, Training, Guidance	Worries that they rely on GAI too much, or that it's easy to cross a 'line' into using too much.
Fear of Being Accused	Concern	Whether they use GAI or not, they are concerned about being accused of using it or overusing it. Worried about overall integrity of programs, degrees.
GAI Knowledge and Prompting Strategies	Evaluating	Notes concern about technical limitations of GAI (e.g. hallucinations, sycophancy). Description of strategies used to prompt GAI to achieve preferred output.

GAI Policy	Policy, Training, Guidance	Expresses clear understanding of GAI policy and how to adhere to it. Feels confident in use according to policy. States that there is no clear GAI policy in their class/program/institution, or that it's difficult to understand or put to use, or that it varies too much by instructor/etc. to be useful.
GAI Sometimes Isn't Worth the Trouble	How students use	Explanation of occasions in which GAI isn't worth using (e.g. too much work to prompt, too much work to evaluate, too much work to acknowledge use)
Lines and Boundaries	How students use	Description of how students use and don't use GAI
Neveruser	Identity	Doesn't use GAI, or chooses specific times to avoid using GAI
Productive	How students use	Use GAI to speed up tasks, work more efficiently, when they have limited time.
Scholar	Identity	Sees themselves as a scholar, as adhering to academic integrity. Values personal voice, their ideas, ownership of their work. May avoid using GAI for output in order to ensure complete ownership of work. Using GAI for outlining, brainstorming, and other lower level tasks or roles is acceptable.
		Values learning, sees themselves as a learner. Would not use GAI to shortcut learning.

		Thinks that GAI inhibits critical thinking or scholarly growth, growth as a scholarly practitioner, results in cognitive offloading
Stuck	How students use	Students use to overcome obstacles or blocks
Thought Partner	How students use	HIGHER LEVEL OF USE, supports learning. Used more like an on-call thought partner or tutor. Helps explain coursework, helps students learn.
Training and Guidance	Policy, Training, Guidance	Opinions or experiences about training and guidance in use of GAI. May have questions about how to use GAI.
Verification Practices	Evaluating	Verifies that source GAI provides exist/say what GAI says they do. Use AI for research and information, but verify what it says with external sources before using in scholarly work.

APPENDIX F
ADDITIONAL TABLES

Research Question 1

Table 8

Year in EdD Program

	N	%
1st year	51	26.8%
2nd year	52	27.4%
3rd year	54	28.4%
4th year or beyond	30	15.8%

Table 9

Gender

	N	%
Male	42	22.1%
Female	138	72.6%
Non-binary	5	2.6%

Table 10*Age Ranges*

	N	%
20-29	9	4.7%
30-39	66	34.7%
40-49	65	34.2%
50-59	40	21.1%
60-69	5	2.6%
70 or older	1	0.5%

Table 11*Race and Ethnicity*

	N	%
Asian	8	4.1%
Black or African American	32	16.5%

Hispanic or Latino	18	9.3%
Middle Eastern or North African	3	1.5%
Native American or Alaska Native	3	1.5%
Native Hawaiian or Pacific Islander	5	2.6%
White	125	64.4%

Note. Respondents could select more than one race/ethnicity.

Table 12

Descriptive Statistics for Generative AI Tools Used by EdD Students (Q1)

Tool	N	%
<i>ChatGPT</i>	133	70.4%
<i>Gemini</i>	37	19.6%
<i>Copilot</i>	34	18.0%
<i>Claude</i>	21	11.1%
<i>Perplexity</i>	16	8.5%

<i>Notebook LM (Other)</i>	13	6.9%
<i>Grammarly (Other)</i>	9	4.8%
Don't regularly use GAI tools	31	16.4%

Table 13

Frequency of Generative AI Use (Q2)

	N	%
Never	15	7.9%
Rarely (1-2 times per month)	50	26.3%
Occasionally (1-2 times per week)	67	35.3%
Frequently (3-5 times per week)	45	23.7%
Daily	12	6.3%

Table 14

Year in Program and Frequency of Generative AI Use Crosstabulation

			Frequency of GAI use					Total
			Never	Rarely (1-2 times per month)	Occasionally (1-2 times per week)	Frequently (3-5 times per week)	Daily	
Year in EdD Program	1st year	Count	7	12	15	14	3	51
		% within Year in EdD Program	13.7%	23.5%	29.4%	27.5%	5.9%	100.0%
	2nd year	Count	3	10	21	15	3	52
		% within Year in EdD Program	5.8%	19.2%	40.4%	28.8%	5.8%	100.0%
	3rd year	Count	3	16	22	10	3	54
		% within Year in EdD Program	5.6%	29.6%	40.7%	18.5%	5.6%	100.0%
	4th year or beyond	Count	2	12	8	5	3	30
		% within Year in EdD Program	6.7%	40.0%	26.7%	16.7%	10.0%	100.0%
	Total	Count	15	50	66	44	12	187

	% within Year in EdD Program	8.0%	26.7%	35.3%	23.5%	6.4%	100.0%
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Table 15

Gender and Frequency of Generative AI Use Crosstabulation

236	Gender	Male	Count	Frequency of GAI use					
				Never	Rarely (1-2 times per month)	Occasionally (1-2 times per week)	Frequently (3-5 times per week)	Daily	Total
				4	10	12	10	6	42
			Expected	3.5	10.7	14.7	10.3	2.8	42.0
			Count						
		Female	Count	11	36	51	34	6	138
			Expected	11.5	35.3	48.3	33.7	9.2	138.0
			Count						
	Total		Count	15	46	63	44	12	180
			Expected	15.0	46.0	63.0	44.0	12.0	180.0
			Count						

Table 16*Generative AI Tasks (Q3)*

Purposes	N	%
Brainstorming ideas	118	62.4%
Editing and improving writing	107	56.6%
Explaining concepts	99	52.4%
Summarizing articles or sources	97	51.3%
Literature review assistance	66	34.9%
Outlining papers or projects	65	34.4%
Data analysis support	47	24.9%
Research design assistance	37	19.6%
Drafting written content	20	10.6%
Something else	19	10.1%
None of the above	15	7.9%

Table 17*Mean and Standard Deviation for Q4, Q5, Q16, Q17, Q18*

			Std.
	N	Mean	Deviation
Q4: Sets goals before using GAI	186	3.96	1.131
Q5: Considers strategies incl. GAI use	183	4.07	1.079
Q16: Reflects on GAI's impact on thinking	186	3.59	1.146
Q17: Monitors GAI's impact on own expertise	185	3.75	1.100
Q18: Uses GAI as a starting point	186	3.90	1.248

Table 18

When working on an EdD task, I set clear goals for what I want to accomplish before deciding whether to use generative AI (Q4)

	N	%
Strongly Disagree	11	5.8%
Disagree	9	4.7%
Neither Agree nor Disagree	29	15.3%
Agree	64	33.7%
Strongly Agree	73	38.4%

Table 19

I consider multiple strategies, including whether to use generative AI, when approaching EdD tasks (Q5)

	N	%
Strongly Disagree	12	6.3%
Disagree	2	1.1%
Neither Agree nor Disagree	22	11.6%
Agree	72	37.9%
Strongly Agree	75	39.5%

Table 20

I regularly reflect on how use of generative AI influences my thinking (Q16)

	N	%
Strongly Disagree	10	5.3%
Disagree	27	14.2%
Neither Agree nor Disagree	35	18.4%
Agree	72	37.9%
Strongly Agree	42	22.1%

Table 21

I actively monitor how my use of generative AI affects the development of my own expertise (Q17)

	N	%
Strongly Disagree	7	3.7%
Disagree	25	13.2%
Neither Agree nor Disagree	23	12.1%
Agree	82	43.2%
Strongly Agree	48	25.3%

Table 22

I use generative AI outputs as starting points rather than finished work (Q18)

	N	%
Strongly Disagree	15	7.9%
Disagree	14	7.4%
Neither Agree nor Disagree	22	11.6%
Agree	58	30.5%
Strongly Agree	77	40.5%

Research Question 2

Table 23

Mean and Standard Deviation for Q7, Q8, Q9, and Q10

	Q7: Understands when GAI is appropriate	Q8: Concerned about academic integrity	Q9: Knows institution's GAI policy	Q10: Knows when to acknowledge GAI use
Mean	4.15	3.77	3.91	3.65
Std. Deviation	.983	1.186	1.167	1.221

Table 24

I understand when it is appropriate to use generative AI as part of my EdD coursework and research (Q7)

	N	%
Strongly Disagree	6	3.2%
Disagree	10	5.3%
Neither Agree nor Disagree	12	6.3%
Agree	81	42.6%
Strongly Agree	79	41.6%

Table 25

I am concerned about potential academic integrity issues when using generative AI (Q8)

	N	%
Strongly Disagree	7	3.7%
Disagree	30	15.8%
Neither Agree nor Disagree	26	13.7%
Agree	61	32.1%
Strongly Agree	64	33.7%

Table 26*Concerned About Academic Integrity and Gender Crosstabulation*

			Concerned or not concerned		Total
			.00	1.00	
Gender	Male	Count	13	29	42
		% within Gender	31.0%	69.0%	100.0%
	Female	Count	47	91	138
		% within Gender	34.1%	65.9%	100.0%
	Non-binary	Count	2	3	5
		% within Gender	40.0%	60.0%	100.0%
	Prefer not to say	Count	1	2	3
		% within Gender	33.3%	66.7%	100.0%
	Total	Count	63	125	188
		% within Gender	33.5%	66.5%	100.0%

Table 27*I know what my institution's policies are regarding generative AI use (Q9)*

	N	%
Strongly Disagree	9	4.7%
Disagree	22	11.6%
Neither Agree nor Disagree	16	8.4%
Agree	70	36.8%
Strongly Agree	71	37.4%

Table 28

I understand when to acknowledge my use of generative AI (Q10)

	N	%
Strongly Disagree	11	5.8%
Disagree	31	16.3%
Neither Agree nor Disagree	25	13.2%
Agree	67	35.3%
Strongly Agree	54	28.4%

Research Question 3

Table 29

Means and Standard Deviation for Q12, Q13, Q14

			Std.
	N	Mean	Deviation
Q12 Can evaluate GAI	186	3.92	1.002
quality/accuracy			
Q13 Verifies GAI info with	185	4.24	.971
other sources			
Q14 Understands technical	187	3.97	1.195
limits of GAI			

Table 30*I can effectively evaluate the quality and accuracy of AI-generated content (Q12)*

	N	%
Strongly Disagree	7	3.7%
Disagree	12	6.3%
Neither Agree nor Disagree	23	12.1%
Agree	91	47.9%
Strongly Agree	53	27.9%

Table 31*I verify AI-generated information against other sources (Q13)*

	N	%
Strongly Disagree	3	1.6%
Disagree	12	6.3%
Neither Agree nor Disagree	16	8.4%
Agree	61	32.1%
Strongly Agree	93	48.9%

Table 32

I understand the technical limitations of generative AI (e.g. hallucinations, knowledge cutoff dates) (Q14)

	N	%
Strongly Disagree	11	5.8%
Disagree	19	10.0%
Neither Agree nor Disagree	13	6.8%
Agree	66	34.7%
Strongly Agree	78	41.1%

APPENDIX G

SUPPLEMENTAL QUALITATIVE DATA

Supplemental data from participants on how they set personal lines and boundaries based on process versus product.

- Survey participant 124: I do not use generative AI until I have developed my own intellectual content. I do not introduce AI until it is the editing process.
- Survey participant 30: I believe it [generative AI] is a great starting point for brainstorming, summaries, grammar checks, etc. However, the 'meaty' part of the work should still be done by us the students.
- Survey participant 143: I have personal boundaries concerning AI use, and if GAI falls within them, I may use it. I do not ask it to generate information or analyze data. I will, however, ask GAI to group codes, or check a paragraph for fluency.
- Survey participant 6: I only utilize AI as a way to improve my understanding of concepts and topics, but I've made the intentional choice not to have AI draft any part of my work/research. I won't utilize it beyond creating an initial outline to help organize my ideas.
- Survey participant 127: I do not use AI to write for me or create content. I use AI as a 'google' entity that helps me locate resources and information at a faster pace than typical search engines.
- Survey participant 60: I do not use it to draft or write content, rather use it to assist in brainstorming, and flow of papers.

- Survey participant 71: I use AI to help me think, not write. It is great to bounce ideas off of, help to outline papers or projects, and help with finding articles and literature to support what I am writing.
- Survey participant 169: I do not copy and paste anything. I use it as a guide or tutor, not my writing tool or idea generator. I want my own voice and thoughts to shine through my work.
- Survey participant 33: I will never use AI to generate an initial or final output, but rather to suggest revisions and refinements that I selectively incorporate based on my own judgement.