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Instructional Designers' Perceptions on Generative AI Integration in Higher Education

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This is to certify that the doctoral study by

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Walden University
2025

Abstract

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by

Alison McLaughlin

MBA, Wayne State University, 2010

BS, Central Michigan University, 2005

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Education

Walden University

February 2026

Abstract

The problem addressed through this study is that the rapid evolution of generative artificial intelligence (AI) tools has created challenges for online higher education instructional designers, who must evolve pedagogically and continually evaluate and refine the balance between the use of generative AI tools and human development. The purpose of this basic qualitative study was to explore the perceptions of online higher education instructional designers on what challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development, and how these experiences have shaped their current perceptions about teaching and learning. Guided by Mishra and Koehler's technological pedagogical content knowledge framework, semistructured interviews with 10 geographically dispersed instructional designers were conducted and the data analyzed using Braun and Clarke's reflexive thematic analysis approach. Overall, functional limitations and negative perceptions posed challenges for participants and sparked complex philosophical questions pertaining to education, but successes were found when generative AI tools helped participants in their processes and beyond. Perceptions about teaching and learning are shifting with calls for best practices, adaptable policies, and a balance between human expertise and generative AI tool use. This study contributes to positive social change in that the information gathered can be used to develop guidance and best practices for instructional designers to use generative AI tools in a meaningful, ethical, and responsible way. Evidence-based guidance would be advantageous to the instructional design community and could lead to improved course development, thereby being valuable to faculty and, in turn, might improve students' learning, satisfaction, and outcomes.

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Dedication

With love and gratitude, I dedicate this study to my family. To my incredible husband, Derek: your unwavering belief in me has helped to make me a better person every single day. You are my perfect partner and the best man I know. This milestone belongs to both of us.

To Dougie: your quiet confidence and steady strength inspire me every single day. Resilience often whispers instead of shouts, but that doesn't diminish the power of who you have the potential to be. Keep doing you, buddy!

To Remy: your radiant personality and boundless curiosity are truly remarkable. Keep being an incredible light, baby girl – you are capable of being anyone you want to be.

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Author Stacie Martin wrote, "It's an amazing woman who use her fire to light up the world instead of burn it down." This dissertation is a testament to the light and strength of the extraordinary and uniquely brilliant women who have walked beside me every step of the way. To my tribe, you make the world a better place, and I am honored to call you all my friends.

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As a final acknowledgement, to Mitch and Morgan: I win.

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Chapter 1: Introduction to the Study

In this study, I explored the perceptions of online higher education instructional design professionals on what successes and challenges they are experiencing in integrating rapidly evolving generative artificial intelligence (AI) tools in course design and development. In November 2022, when OpenAI released the ChatGPT chatbot on an open and free platform, it commenced a rapid popularization of generative AI tools that has persisted for several years. Although it certainly was not the beginning of the integration of generative AI tools in the workplace, this event accelerated that process. For example, in 2021 and 2022, about 50% of organizations were using AI tools (Chiu et al., 2022), and in 2025, McKinsey reports that 92% of companies plan to invest more in generative AI in the next several years (Mayer, 2025). Higher education has been a part of this rapid expansion both within institutions and with students, and the perception of this evolution has not always been seen by all as positive and beneficial. Across education, opinions have varied from fear to optimism, from outrage to relief. Some feared that the ease with which these tools could produce text could lead to major issues with plagiarism and loss of critical thinking skills (Elkhodr et al., 2023; Rahman & Watanobe, 2023). Others saw immediate benefits like reducing the time needed for laborious tasks, freeing up mental energy to be creative and innovative (DaCosta & Kinsell, 2024; Sáez-Velasco et al., 2024). Instructional designers, similar to other stakeholders across higher education, have a wide range of opinions and experiences related to generative AI use in their work, and this facet of higher education has yet to be studied thoroughly.

Generative AI tools came into education, and specifically into instructional design very quickly (Kumar et al., 2024; Meron & Araci, 2023). Almost immediately after ChatGPT was released, some higher education institutions began to rapidly develop policies, procedures, and recommendations for their use by both faculty and students. Others chose to wait. Some instructional designers were encouraged to try the tools and explore their uses, while others were not. Still other instructional designers were given mixed messages about expectations around generative AI tool use. This initial period of discovery was challenging for many and led to varying experiences. This study was needed to understand the varying experiences and the successes and challenges that instructional designers noted throughout the process of integrating generative AI tools in their daily work. In gaining a better understanding of experiences, instructional designers can regulate their processes with the new tools, create policies and integrations that work within their processes, and facilitate the use of generative AI tools in a meaningful, efficient, and responsible way.

In this chapter, I will begin by explaining the background of the study and an overview of the results from the literature about the topic. This will be followed by a full description of the problem statement, the purpose of this study, and the research questions that I used to direct the study. From there, I will introduce the conceptual framework that was used to guide this study. I will then describe the nature of the study, the assumptions that need to be considered when reading the results, and the scope and delimitations, limitations, and significance of the study.

Background

To better understand the current state of generative AI tools, it is beneficial to examine the historical milestones that have shaped the field and contributed to its innovation and advancement. From the broad field of AI that stemmed from Alan Turing's question about whether machines can think (Delipetrev et al., 2020; Muggleton, 2014) to the official inception of the field at the 1956 Dartmouth conference, the 1950s are considered the birth of AI (Mijwel, 2015). Over the next several decades, scientists and researchers advanced the field rapidly building tools that could complete increasingly difficult tasks like solving mazes (Roser, 2022), playing chess and Go (Grzybowski et al., 2024; Mijwel, 2015), proving mathematical theorems (Grzybowski et al., 2024), processing language (Haenlein & Kaplan, 2019), and mapping complex organic compounds (Grzybowski et al., 2024). In the 1980s, the focus of the AI field shifted to modern machine learning, and further innovations advanced the field, like the study of neural networks, advanced algorithms, and robots that could mimic certain aspects of humanity (Copeland & Proudfoot, 2007; Fradkov, 2020; Mijwel, 2015). Machine learning technology shifted to deep learning in the 2000s, although the concept was discussed rudimentarily much earlier than that. During this period of growth, AI tools were trained in a different way that better mirrored the human brain (Ganatra & Patel, 2018; Marr, 2016). Deep learning methods have significantly decreased errors, leading to AI tools that are more effective and accurate. Generative AI, like machine learning and deep learning, can be traced back primitively to the early 1950s (Kilinç & Keçecioğlu, 2024), but the current understanding of the technology dates back to the early 2010s

when big data and computing power also sharply increased (Dasgupta et al., 2023). This time period from the 2010s to 2022 saw the release of increasingly complex and accurate tools that could converse with people, create imagery, and draft text at a faster rate than ever before (Bengesi et al., 2024; Foote, 2024). Then in November 2022, OpenAI released the free and simple to use ChatGPT, which contributed to the mass popularization of the technology (Al-Amin et al., 2024; Bengesi et al., 2024; Grzybowski et al., 2024). Since this event, countless generative AI tools have been released that can perform myriad tasks across nearly all fields, including education. Although not a true part of identifying the gap that is addressed in this study, having an understanding of the evolution of the field illustrates this continued and constant change, making pinpointing best practices challenging for instructional designers.

The integration and popularization of generative AI tools in higher education have prompted a considerable amount of research exploring the perspectives of students, educators, and institutions. Much of this research has unveiled a dichotomy of opinions and expectations. Students found the tools easy to use and beneficial (Chan, 2023; Tlili et al., 2023; Tzirides et al., 2024), but they also recognized the limitations of generative AI (Denecke et al., 2023; Essien et al., 2024; Li et al., 2024; Stojanov, 2023). They were motivated to adopt the tools and use them to complete their work (Alammari, 2024; Yeh, 2024), but issues of accuracy (Michalon & Camacho-Zuñiga, 2023; Yusuf et al., 2024), bias (Denecke et al., 2023; Essien et al., 2024; Rahman & Watanobe, 2023), and plagiarism (Chaudhry et al., 2023; Habib et al., 2024) caused concern and trepidation. This is similar to the attitudes that educators hold around adopting generative AI tools

within the classroom. Educators saw many potential benefits like personalization of learning (Kadaruddin, 2023; Schneider & Haried, 2024; Yusuf et al., 2024), improvements to pedagogy (Alshraah et al., 2024; Chiu, 2024), and task automation (Alammari, 2024; Denecke et al., 2023), but they were wary of generative AI tools becoming so powerful that they render their jobs obsolete (Alammari, 2024; Kohnke et al., 2023). They also worried about the ease with which these tools allow students to cheat (Alshraah et al., 2024; Rejeb et al., 2024; Yusuf et al., 2024) and the lack of adequate detection tools (Alexander et al., 2023; Chan, 2023; Chaudhry et al., 2023). At the institutional level, several of the same positive and negative sentiments were expressed. Generative AI tools cannot be ignored by higher education institutions (Schneider & Haried, 2024), and strong guidance and policy are needed to ensure responsible and appropriate use (Chaudhry et al., 2023; Yusuf et al., 2024). At this level, there were various suggestions for what ought to be included in an institutional policy like training (Alshraah et al., 2024; Chiu, 2024; Elkhodr et al., 2023), security (McDonald et al., 2024; Ngo et al., 2024), ethics (Chan, 2023; Nguyen et al., 2024), and equity (Essien et al., 2024; Foung et al., 2024), but there was no full agreement on what that list ought to include. It is crucial to understand the diverse opinions of these various stakeholders in higher education, as they relate directly to the same concerns and positive thoughts shared by instructional designers.

Narrowing further to instructional design professionals, the literature contained several studies that describe case studies and other experiences with using generative tools within the instructional design process. Many of these studies included mentions of

potential benefits to instructional designers like time savings (Bolick & da Silva, 2023; Davis & Lee, 2024; Kostikova et al., 2024; Kumar et al., 2024; McNeill, 2024; Tupper et al., 2025), strengthening of creativity (Choi et al., 2024; DaCosta & Kinsell, 2024; Mikeladze, 2023), increased quality of content (Hu et al., 2024; Mangaroska et al., 2024; Morales-Chan et al., 2023), and personalization and customization (Karpouzis et al., 2024; Mikroyannidis et al., 2024; Ryall & Abblitt, 2023). They also, however, emphasized that generative AI tools are not capable of replacing humans within the instructional design process (Amando-Salvatierra et al., 2023; Kostikova et al., 2024; Meron & Araci, 2023) and that they should be used to support and strengthen human work (Morales-Chan et al., 2023; Sridhar et al., 2023). The literature on the perspectives and experiences of instructional design professionals was, however, light in many areas, and no empirical, peer-reviewed research existed that synthesized the perspectives of this group from a broad viewpoint on their professional practice. In addition, no study analyzed instructional design perspectives of their experiences with generative AI tools within the online higher education course design process. In conducting this research, which fills gaps in the literature and professional practice related to the use of generative AI, I aim to gain a deeper understanding of the successes, challenges, and needs of instructional designers. This will enable me to contribute to the development of best practices and proven techniques that enhance efficiency and quality.

Problem Statement

The problem addressed through this study was that the rapid evolution of generative AI tools has created challenges for online higher education instructional

design professionals who must evolve along with them pedagogically and continually evaluate and refine the balance of the use of generative AI tools with human development. To explore this problem, I interviewed instructional designers about their experiences, both positive and negative, in using generative AI in their daily work. Research shows that this problem is current, relevant, and significant. To begin, I will explain how this problem is current. Generative AI tools spiked in popularity in November 2022, and since their popularization, they have continued to be refined, expanded, and developed within higher education and outside the field. The growth of generative AI cannot be understated. For example, a large-scale report on the generative AI market as a whole reported that in 2022, the generative AI market was valued at $191 million and grew to $25.6 billion in 2024 (Fernandez, 2025). The applications of generative AI tools have grown and continue to grow exponentially as well. The exact number of tools that are currently available is impossible to know, as more are developed each day. The fact that additional tools are developed daily and are growing so rapidly that the exact number is not known demonstrates the current relevance of the topic.

This study was also relevant. Within the instructional design field, the use of generative AI tools is thought by some to become expected as a way to increase efficiencies (McNeill, 2024; Ryall & Abblitt, 2023; Tupper et al., 2025), improve the quality of content (Davis & Lee, 2024; Morales-Chan et al., 2023; Sridhar et al., 2023), and diversify information used in course development (Choi et al., 2024; DaCosta & Kinsell, 2024; Mikeladze, 2023). However, guidance and best practices for instructional designers are noticeably absent and often contradictory in scholarly literature. This

represents another literature gap regarding professional instructional design practice. The existing publication most pertinent to this study examined the perceptions of corporate and educational on integrating generative AI tools into their daily work (Kozan et al., 2025). In their study, the authors recruited a variety of instructional designers from corporate, primary and secondary education, and higher education. In focusing on the experiences of online higher education instructional designers, I gathered critical information needed to develop guidance and best practices for ethical, meaningful, responsible generative AI tool use. Not only could this study benefit the instructional design community, but its results could yield improved course developments, thereby benefiting faculty and students as well.

Within the broader field of higher education, this study was significant to the instructional design discipline. There are a large number of generative AI-related studies that pertain to higher education as a whole. Most are geared toward students, educators, and institutions, and how generative AI tools have affected each group. Instructional designers are a smaller set of stakeholders in higher education, and the amount of published research that relates to this group is similarly smaller. Much of instructional design-focused scholarly research is case studies describing an attempt at using the tools to design a lesson or course. Very few collect perceptions of multiple instructional designers, particularly on their experiences, successes, and challenges. In conducting this research, I contributed to the body of literature specific to instructional design and expanded what is understood about the practices that work best for course design.

Perhaps when this is better understood, institutions can provide their instructional designers with more specific and applicable guidance and best practices.

Purpose of the Study

The purpose of this qualitative study was to explore the perceptions of online higher education instructional design professionals on what challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development, and how these experiences have shaped their current perceptions about teaching and learning. To fulfil that purpose, in this study, I conducted semistructured interviews with online higher education instructional design professionals who have experience with using generative AI tools in creating course content. In the interviews, I explored the perceptions of instructional designers related to their experiences with successes and challenges with using generative AI tools in their daily work.

Research Questions

To address the problem and purpose of integrating generative AI tools into online higher education instructional design, the following research questions were used to guide the study.

RQ1: What are online higher education instructional design professionals' perceptions of the challenges they are experiencing in integrating rapidly evolving generative AI tools in course design and development?

RQ2: What are online higher education instructional design professionals' perceptions of the successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development?

RQ3: How have online higher education instructional designers' experiences with generative AI tools formed their current perceptions about teaching and learning?

Conceptual Framework

The framework that supports this study is the technological pedagogical content knowledge (TPACK) technology integration model. This model was initially developed by Mishra and Koehler (2006) as a result of a 5-year study on teacher professional development. The first iteration of the model describes three types of foundational knowledge that teachers need to successfully integrate technology into the classroom. They are content knowledge (CK), pedagogical knowledge (PK), and technological knowledge (TK), and the model includes both the foundational knowledge domains and the interplay between them, represented by blended knowledge domains. Although context was included loosely in the original model, the fourth type of knowledge, contextual knowledge (XK), was officially added as a separate domain later (Mishra & Koehler, 2008).

The logical connections between the framework presented and my study are that, in using generative AI tools to create academic content, instructional designers also require these different foundational and blended knowledge domains. Therefore, for this study, TK will refer to knowing how generative AI tools work and how best to integrate them. When applied to instructional design rather than teaching, CK will be the subject matter knowledge that is gleaned from working alongside a subject matter expert (SME), conversing on the topic throughout the instructional design process, and engaging with resources on the topic. PK is understanding the various instructional strategies, models,

and techniques that can be used and how to best select them. In addition to these three knowledge domains are the blended knowledge domains that represent the interplay between each. They are pedagogical content knowledge (PCK), technological content knowledge (TCK), technological pedagogical knowledge (TPK), and TPACK, a combination of all three foundational knowledge domains, which gives the framework its name (Mishra & Koehler, 2009). Finally, encompassing each foundational knowledge domain and the overlapping blended knowledge domains is XK. This broad circle includes a wealth of considerations around generative AI use, including institutional requirements, policies, student needs, and ethical considerations under which educators have little control (Mishra et al., 2023). I used this framework to undergird my study by querying participants about their generative AI experience from the perspective of some of the knowledge domains. In doing so, I explored meaningful uses of generative AI in the instructional design process that can be used to improve the practice of course development. This also provided information that could be used for training and education of instructional designers. In Chapter 2, I will explain in more detail how these knowledge domains will apply to this study.

Nature of the Study

A basic qualitative research paradigm was used for this research study. This approach was justified for a number of reasons. The exploration of experiences and perceptions is better aligned to the interpretive, contextualizing nature of qualitative research rather than statistical analysis, making a qualitative design the most appropriate choice for this study (see Ravitch & Carl, 2021). Percy et al. (2015) also suggested that

when a researcher has existing knowledge and understanding of a topic and wants to explore participants' experiences further, a basic qualitative design is appropriate. As I have past experience and knowledge of the instructional design practice, I found this approach relevant and appropriate. Finally, this is the type of approach other researchers have taken when addressing similar problems. For example, Kumar et al. (2024) used a general qualitative approach to examine the roles of instructional designers in integrating generative AI tools into their institutions and daily work. Although not addressing the exact problem that will be addressed in this study, the similarities between the two studies help to justify the use of the same methodological approach.

To gather this information, I conducted semistructured interviews with 10 online higher education instructional design professionals who had significant experience using generative AI tools in course development. I identified participants using the Walden participant pool and my LinkedIn network, ensured that each participant met the inclusion criteria, and asked a series of questions about their experiences to gather information to analyze. To conduct the data analysis, I employed the six phases of reflexive thematic analysis as described by Braun and Clarke (2022). I used both manual and technological tools throughout data analysis to code the data, identify clusters and themes, and draft a narrative to tell the story of the data. Chapter 3 provides additional detail about the methodological choices made in this study.

Definitions

The following definitions helped to guide this study:

Generative AI: Machine learning systems that are capable of generating seemingly new text, images, audio, or video, drawing upon training data and based on human-drafted prompts (Feuerriegel et al., 2024; Francis et al., 2025; Jaboob et al., 2025).

Instructional design: Refers to an inherently complex set of systematic processes aimed at creating educational curricula and facilitating student learning and development (Amando-Salvatierra et al., 2023; Choi et al., 2024; Hu et al., 2024). Although instructional design can also include the creation of training material, for the purposes of this study, instructional design refers only to the development of higher education curricula.

Instructional designer: An individual who, in conjunction with a faculty SME, specializes in creating and delivering learning experiences, analyzing and redesigning courses, developing full courses and programs, and evaluating courses across disciplines and levels (Kumar et al., 2024; McNeill, 2024; Morales-Chan et al., 2023). In this study, the term instructional designer was used as an overarching term for anyone in this type of role, regardless of their actual title. Actual job titles held by participants included instructional designer, learning experience designer, and senior manager of learning experience design.

Assumptions

This study was based on two major assumptions. First, it was assumed that participants accurately and truthfully recalled their experiences with using generative AI in course design. The phenomenon of generative AI tools in education is so new that it

can cause trepidation and mystification amongst instructional designers. Recalling experiences and putting them into words can also be challenging for some participants. There may also be a temptation for some to embellish or exaggerate the usefulness or lack thereof of generative AI tools based on their own opinions or preconceived notions about the tools. To help ensure that I was able to make my interview subjects comfortable in collecting their thoughts and sharing, I conducted a practice interview and modified my behaviors and questions as needed. To promote truthfulness, I have built questions into my interview protocol that ask participants to describe both positive and negative experiences in using generative AI tools. The second major assumption was that generative AI tools will continue to evolve and permeate the field. The future can never really be known by anyone. There are certainly trends and forecasts that predict this continued evolution and increase, but it is only an assumption.

Scope and Delimitations

In this study, I chose to research the very specific phenomenon of using generative AI tools in creating online higher education course content. In doing so, I narrowed the scope of the study by imposing delimitations that focused solely on generative AI tools and a select group of instructional designer participants. First, I chose to only study the use of generative AI tools rather than the larger set of AI tools. AI tools are a much broader category of tools with a diverse set of functions. In choosing the smaller set of tools, I narrowed the functions that the tools could perform to only those that involved the creation of new materials. Second, I chose to only select participants whose main job function is creating course content for an online institution of higher

learning. This excluded several other groups like instructional designers who work primarily on creating training materials, those that write curricula for brick-and-mortar institutions, and faculty who create course content that they then teach. I chose to only study this group of individuals because their experiences and perceptions are likely different from the excluded groups.

Limitations

There were several limitations of this study. The first limitation was related to sample size. I interviewed 10 instructional designers on their experiences, which was a fairly small sample of the instructional design community. Although the intent of my study was not to be generalizable to the entire population, there may be fewer opportunities for the results to be transferable due to this sample size. In Chapter 3, I describe the strategies I will employ to help establish transferability, like providing rich context to explain the significance of the data and diversifying the selection of participants where possible. The second major limitation of this study was the time-boundedness of the data. Generative AI tools have experienced rapid growth and expansion in recent years, and this trend is expected to continue. The data that will be collected will represent just one point in time when a certain collection of tools with certain functionality is available. Although still relevant and significant to the field of instructional design, the data from this study will not be representative of the collection of tools and their functionality at any other point in time. This limits the practical usability of the results from the perspective of application to any particular generative AI tool. There were no measures that could have been taken to address this limitation.

However, time does not limit the practical usability of the results in examining how the industry is changing, evolving, and moving forward. The final limitation of this study involved the perceptions that individuals have about generative AI tools and how that might influence their use and recollection of experiences. There are currently a wide variety of opinions on generative AI tools on topics like usefulness, ethicality, and appropriateness, amongst others. Personal opinions like these, which are both positive and negative, can dictate how the tools are used and how experiences are recollected. I purposefully tried and elicit a variety of recollections of experiences by asking about both positive and negative aspects and asking targeted prompts to encourage more details about experiences.

Significance

This study contributed to the instructional design field and the broader education field by extension. First, the results of this research served to expand knowledge in this relatively narrow topic area of generative AI use in instructional design. Modern generative AI tools are a relatively new innovation, so little is known about them, particularly in the context of instructional design work. Specifically, in studying successes and challenges that instructional designers have experienced in using generative AI tools, best practices and guidance for meaningful use could be better informed.

This study was also significant because of the potential contributions the study may make to advance instructional design practice. Generative AI tools have the potential to save time, improve quality, and create diverse ideas in course content, but due to the

novel nature of the technology, guidance and best practices have not yet been fully determined in all institutions. This study has informed these recommendations by building upon what instructional designers have tried, both successfully and unsuccessfully. With better guidance, instructional designers could create more engaging and innovative curricula, thereby positively affecting students and faculty.

Finally, this study had the potential to positively affect social change. Instructional designers have a complex job. They are charged with analyzing, designing, developing, implementing, evaluating, and maintaining curricula, along with all of the administrative tasks that go along with it. With so many responsibilities and considerations that need to be made in instructional design work, the process can be time-consuming and challenging to complete. Generative AI tools hold the potential to streamline the instructional design process in many ways, but in order to fully take advantage of this potential, additional information is needed to craft best practices. The information gleaned in this study contributed to that cause as well.

Summary

In Chapter 1, I provided introductory information to this study. To start, I described the background, problem statement, purpose statement, and research questions that ground and inform the project. This was followed by an introduction to the TPACK framework, which further guides the study. Next, I described the nature of the study, definitions that were critical to understanding the study, and the assumptions that need to be considered to accept this study. I ended this chapter with a discussion of the scope and delimitations, limitations, and significance of the study. In Chapter 2, I will further delve

into the conceptual framework that grounds this study as well as the literature to explain, support, and necessitate research on the integration of generative AI tools in online higher education instructional design.

Chapter 2: Literature Review

The integration of generative AI tools represents a paradigm shift in the educational domain that affects all stakeholders (Chen et al., 2023; Essien et al., 2024; Kadaruddin, 2023; Tlili et al., 2023; Yeh, 2024). The problem that was addressed in this study is that the rapid evolution of generative AI tools has created challenges for online higher education instructional design professionals who must evolve along with them pedagogically and continually evaluate and refine the balance of the use of generative AI tools with human development. The purpose of this qualitative study was to explore the perceptions of these instructional design professionals on the challenges and successes they are experiencing in integrating rapidly evolving tools into course design and development, and how these experiences have shaped their current perceptions about teaching and learning. In current literature, researchers have investigated the transformative potential of generative AI in education (Alammari, 2024; Yeh, 2024) as well as the limitations of the tools that could hinder progress. While generative AI offers innovative solutions for personalized learning (Essien et al., 2024; Schneider & Haried, 2024) and content creation (DaCosta & Kinsell, 2024), it also poses significant challenges for instructional designers who must adapt their practices to leverage these tools effectively (Karpouzis et al., 2024; McNeill, 2024). Studies have shown varying degrees of success in integrating and using generative AI, with factors such as prompt quality (Morales-Chan et al., 2023; Tupper et al., 2025), technical knowledge and skills (de Vincente-Yagüe-Jara et al., 2023; Stojanov, 2023), and professional development/training (Bao & Li, 2023; Kadaruddin, 2023) playing critical roles.

This chapter is divided into five major sections. In the first section, I will describe the strategies used to search the literature and select sources for the literature review. The second section includes a discussion of the TPACK framework, which undergirds this study. In the third section, I will provide a historical overview of AI, tracing its evolution and impact over the years. The fourth section includes an examination of the perceptions and effects of generative AI on educators, students, and institutions. In the final section, I will explore the impact of generative AI on instructional designers and content creators, detailing existing uses, perceptions, and suggested approaches.

Literature Search Strategy

To gather information for this literature review, I primarily used the Walden University Library and Google Scholar. The Walden University Library databases that I used included Education Source, ERIC, EBSCOhost, SAGE Journals, ProQuest Central, ScienceDirect, Taylor and Francis Online, and Library Search. To gather scholarly sources on the use of generative AI in education and, more specifically, instructional design, I used combinations and variations on keywords and phrases, including *TPACK, instructional design, content creation, learning materials design, teaching design, generative AI, ChatGPT, and higher education*. I also examined reference lists and searched for particular authors in the field to identify additional sources. For the literature review, I limited my search to sources published between 2022 and 2025, as generative AI tools did not increase in popularity in education until the release of ChatGPT in November 2022. The sections describing the conceptual framework and the history of AI, however, included seminal and historical resources as well. For the sections that explore

generative AI use and perceptions amongst students, educators, and institutions, I was able to use only empirical, peer-reviewed publications due to the volume of publications that meet the criteria. For the section on instructional design, there were fewer empirical, peer-reviewed articles available. I chose to include multiple papers from conference proceedings and several articles outside of higher education.

Conceptual Framework

The conceptual framework that was used to frame this study was the TPACK technology integration model developed by Mishra and Koehler (2006). This section will cover the history of the framework, an in-depth exploration of the different knowledge domains included in the framework, and an application of each knowledge domain to generative AI use in instructional design. This section will conclude with justification and rationale for the selection of TPACK.

History of the Framework

Researchers have worked to understand, define, and explain the knowledge required of educators to effectively teach for decades. One of the most notable contributions came from Shulman, who described educators' knowledge as specialized, complex, and set apart from other professions (Harris et al., 2017; Mishra & Koehler, 2006, 2009; Shulman, 1987). He proposed that PK and CK, which, to this point, were considered mutually exclusive domains of knowledge, are not enough for educators to be effective. They must also possess PCK, which blends PK and CK and describes how educators represent the subject matter in a way that is comprehensible by students (Mishra & Koehler, 2006). Since Shulman, many other researchers have worked to

further define requisite educator knowledge, including Clandinin and Connelly (1987), who articulated links between personal and professional knowledge in teaching, Tom and Valli (1990), who grounded educators' knowledge in philosophy, and Pierson (2001) who was the first to describe technology integration as a function of expertise in pedagogy. Technology integration in the classroom followed as a highly researched topic in education. One such 5-year study aimed to help educators successfully integrate technology in their teaching and to understand how to develop skills in technology (Mishra & Koehler, 2006). Although not the initial aim of the project, Mishra and Koehler (2006) developed a framework as a result of their body of work called the TPCK technology integration model. Building off Shulman's concept of PCK, the TPCK model added technology as a third foundational knowledge domain in addition to content and pedagogy (Koehler & Mishra, 2009). It was designed to describe the knowledge that educators need to integrate technology into the classroom, but was first fully applied to preservice educators and their education (Mishra & Koehler, 2006). In considering these three knowledge domains as both discrete and overlapping, the authors describe a new form of literacy that extends beyond disciplinary knowledge and pedagogical techniques (Mishra & Koehler, 2008).

Since its initial conception, TPCK has been edited, reimagined, and applied extensively. The first such edit was in response to its name. TPCK was difficult to pronounce and remember. The authors asked educational leaders at a national summit to brainstorm new and engaging titles, and they officially changed the framework's name to TPACK, which maintains alignment to the knowledge domains and describes the "Total

PACKage" of knowledge required of educators (Thompson & Mishra, 2007-2008). The second major change for TPACK centered around a fourth foundational knowledge domain, XK. Context was touched upon in the original publication, but it was not added to the diagram until later (Mishra & Koehler, 2008). Over the years, the authors further touted its importance in studying TPACK and eventually conducted a systematic review on the use of XK in other research. They found it was only included in 36% of TPACK applications and stressed that future research make the connection between context and successful teaching and learning (Rosenberg & Koehler, 2015). Applications of the TPACK framework have appeared in thousands of books, articles, and dissertations, and many of these are reimaginations of the original publication. Academics have added elements, combined TPACK with other models, and applied TPACK to their specific processes and skill sets to create offshoots like a lesson study TPACK, digitally-related pedagogical and content knowledge, a framework that combines TPACK with curriculum-based service learning, and a wealth of others (Mishra et al., 2024).

TPACK has also been studied and measured extensively over the years. Shortly after the initial publication, the original authors developed a validated survey instrument to measure TPACK in preservice educators (Schmidt et al., 2009). Since then, numerous other questionnaires, self-report measures, interview guides, observation tools, and assessments of performance were developed by other researchers to measure preservice and in-service educators' TPACK (Castéra et al., 2020; Tondeur et al., 2020; Valtonen et al., 2017). An additional measurement instrument is currently being developed and validated to apply it to generative AI (Islam & Mishra, 2024). The authors have also

applied TPACK to various specific case studies and schools of thought to deepen understanding. Examples include applications to design learning education, professional development and training design, interdisciplinary learning, and digital portfolios (Harris et al., 2009; Kereluik et al., 2011; Koehler et al., 2014; Koehler, Mishra, Akcaoglu, & Rosenberg, 2013; Kurt et al., 2014).

In addition to the application of the framework, the different facets of TPACK have been analyzed and criticized thoroughly in the literature. The original authors are responsible for much analysis including the idea of TPACK as responding to a "wicked problem" in education, repurposing non-educational technological tools for use in the classroom, educator knowledge and interdisciplinary learning, validation of existing TPACK measurement instruments, micro, meso, and macro contextual considerations, reconceiving what is meant by knowledge, and reimagining TK, TCK, TPK, and TPACK in the age of generative AI (Cavanagh & Koehler, 2013; Kereluik et al., 2011; Mishra & Koehler, 2008, 2009; Mishra et al., 2023; Phillips et al., 2017; Rosenberg & Koehler, 2015). As with any other conceptual framework, there are criticisms and limitations of TPACK that have been examined by the original authors and other researchers. One such criticism is around the unclear definitions and limited practical applications of the knowledge domains. (Brantley-Dias & Ertmer, 2013; Koehler et al., 2014). In addition to issues of clarity and application, some researchers find the process by which knowledge domains are developed to be lacking (Koehler et al., 2014). The knowledge domains themselves are static, which is misaligned with the dynamic nature of both education and technology (Brantley-Dias & Ertmer, 2013; Cox & Graham, 2009). The framework has

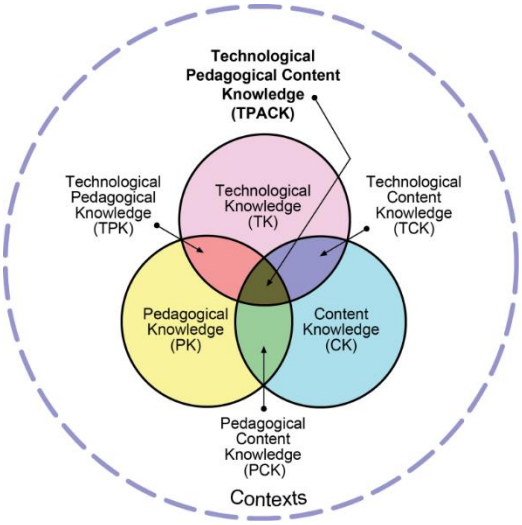
also been said to overly simplify the complex nature of teaching and learning (Cox & Graham, 2009; Voogt et al., 2013). Despite criticism, TPACK has been used extensively in the study of educational technology integration, having been cited in thousands of publications since its inception (Mishra, n.d.).

Domains of the Framework

In the TPACK framework, knowledge about content, pedagogy, and technology is all discrete, but the model is about more than just that. Each of the knowledge domains exists separately from one another, but, in education, they also interact, constrict, and afford one another (Koehler et al., 2014). Integral to the model is the complex interplay between the three knowledge domains, which result in PCK, TCK, TPK, and TPACK, which is a combination of all three knowledge domains (Mishra & Koehler, 2006). The interaction in the framework is depicted as overlapping circles in a Venn diagram where each circle represents one of the foundational knowledge domains (see Figure 1). These are all surrounded by a larger circle depicting XK (shown as "Contexts" in the diagram), which affects all aspects of technology integration in education (Mishra, 2019). Each of the elements of the framework is described in the context of the initial conception of TPACK and then as they relate to this study.

Figure 1

TPACK Framework



Note. From "Using the TPACK Image," by M. Koehler, 2011, TPACK.org (http://tpack.org). Copyright © 2012 by TPACK.org. Reprinted with permission.

Content Knowledge (CK)

CK, one of the foundational domains of TPACK, is described as the subject matter around which the lesson, course, or program is designed (Harris et al., 2009). CK has been described as the *what* of learning (Mejia & Sargent, 2023). This includes the central facts, concepts, theories, and procedures contained within the field of study (Mishra & Koehler, 2006). The concept of subject matter is straightforward when examining it in the context of a traditional classroom. In an Algebra class, the CK includes the Pythagorean theorem, principles of exponents, and the process of solving equations, and this varies greatly from the subject matter in a biology class. To effectively teach a course focusing on particular CK, an educator needs an understanding

of the subject matter otherwise they may present the material incorrectly or inadequately, which risks confusing students (Koehler & Mishra, 2009).

In the instructional design process, the instructional designer is generally not fully responsible for the CK. They work alongside subject matter experts (SMEs) and other academic leaders who are far more well-versed in the subject matter. Regardless, knowledge of the content is integral to the process of course design, and instructional designers do need to understand the CK to an extent to write effectively (Kanuka, 2006). In conversing with experts in the subject matter and engaging with resources on the topic, instructional designers can work to acquire CK and effectively develop course content.

Pedagogical Knowledge (PK)

The next foundational domain of TPACK is PK, which is defined as knowledge of instructional practices, strategies, methods, and techniques to deliver content to students and facilitate successful learning (Koehler et al., 2014). It is not enough to have deep knowledge of the subject matter being taught; educators should also be experts of learning management and how it encompasses educational purposes, values, and aims (Mishra & Koehler, 2006). PK also involves knowing how students learn, perceive, and retain knowledge, which is often described in educational and developmental theories (Mishra & Koehler, 2008). This foundational domain refers to anything done in the classroom and describes the *how* of learning, including the decisions educators make in how to best organize learning activities and resources so that students can learn the content (Mejia & Sargent, 2023).

This study focuses on the instructional designer position rather than on the educator, but the principles of PK are similar for both roles. When considering a team of professionals collaborating on course design, the instructional designer's expertise is in the PK. Their responsibility is in bringing skills and information on the overall teaching and learning process, instructional design theories and strategies, principles of assessment and evaluation, and all the tools needed to present the elements of a course and promote student success (Pollard & Kumar, 2022).

Technological Knowledge (TK)

In the initial conception of TPACK, the foundational knowledge domain TK included knowledge of a variety of tools that are useful in the classroom, the ability to select the most appropriate tools, and the ability to operate each technological tool (Mishra & Koehler, 2006). Classroom technological tools range from very basic like chalkboards, pencils, and books to more advanced like tablets, Smart Boards, and software. In addition to these skills and abilities, Koehler, Mishra, and Cain (2013) highlighted the instability of technology and the necessity that educators be adaptable and willing to learn new and evolving technological tools. They opined that "the definition of technology is in danger of becoming outdated by the time this text has published" (Koehler & Mishra, 2009, p. 64). Acquiring TK does not have an end state for this reason. It is constantly in flux, which is also a critical component of this study (Koehler, Mishra, & Cain, 2013).

Rather than considering knowledge of all different types of technology, the focus of this study is on one particular type of technology, which has drastically affected the

education field, generative AI tools. TK, in this instance, refers to the instructional designer's knowledge of and ability to effectively use generative AI tools in their daily work with conceiving, designing, developing, building, and maintaining online higher education course work. This is not a straightforward foundational knowledge domain because, like technology in general, generative AI is constantly evolving. Instructional designers need to, first, become familiar with generative AI tools and educate themselves on strengths, limitations, and responsible uses of the tools (Ch'ng, 2023; Hodges & Kirschner, 2024). They also need to understand how generative AI tools affect the student experience. All of this TK is relative because what is true about generative AI tools now may not be in the future, and this underscores the problem addressed in this study, which is that the rapid evolution of generative AI tools create challenges for online higher education instructional design professionals who must evolve along with them pedagogically and continually evaluate and refine the balance of the use of generative AI tools with human development.

Pedagogical Content Knowledge (PCK)

At the intersection of PK and CK is a blended knowledge domain, PCK, that explains the task of teaching specific content to students effectively. In this domain, the educator interprets the subject matter to be taught and selects the best methods and strategies for delivering it to students (Mishra & Koehler, 2008). It also includes an understanding of the connection between teaching, learning, content creation, assessing, and evaluation (Koehler & Mishra, 2009). In order to accomplish this complex task, the educator must have knowledge of student prerequisites and prior knowledge as well as an

understanding of the ways students may struggle with the concepts being taught (Mishra & Koehler, 2006). PCK requires that educators understand curricular scaffolding within the context of a particular subject area and build the content in a way that is comprehensible and accessible to students (Mejia & Sargent, 2023).

The instructional design professional needs to possess similar knowledge to the educator when designing and developing content for the online classroom (Richardson et al., 2019). Instructional designers' expertise is in the strategies, practices, methods, and techniques that are effective for student learning. PCK marries this with subject matter information gleaned from conversations and meetings with SMEs and reading on the topic throughout the instructional design process (Gottler, 2023). In the context of this study, the instructional designer needs to select and advocate for methods and techniques that, because of their knowledge and experience, work well alongside the subject matter and provide meaningful opportunities for learning. Understanding student capabilities, prior knowledge, and potential existing barriers to learning are also included in PCK (Koehler, Mishra, & Cain, 2013).

Technological Pedagogical Knowledge (TPK)

TPK, another of the blended knowledge domains, is an understanding of how technological tools can support and provide constraints and affordances to pedagogical practices (Mishra & Koehler, 2008; Mishra et al., 2023). Within this blended knowledge domain is also the understanding that integrating technology into the classroom can change learning and assessment (Hofer et al., 2015). For example, technological tools allow educators to mimic on-the-job experiences, present realistic examples, and provide

students with meaningful practice for their intended careers, which were not previously feasible with lesser technological tools, but the application of these innovations rest on the educator's TPK. The changes brought about by technological innovation are vast, and not all are comfortable shifts for educators. TPK includes the ability to adapt and evolve with technology as it improves and changes and apply it seamlessly into teaching practices (Mishra & Koehler, 2006). In addition, educators need to possess knowledge of the applications that technology affords, but, more than that, they also need to be able to understand technology that was not created for classroom use and be able to transform it into something teachable (Kereluik et al., 2011; Mishra & Koehler, 2009; Trif-Boia, 2023). Educators also need to have the ability to select and implement various technologies as part of the pedagogical choices they make to support student learning (Mishra & Koehler, 2006).

In the context of this study, the blended knowledge domain TPK involves knowing how generative AI can both enhance and hinder the instructional design process. While generative AI tools are able to enhance learning in many ways, there are certain traditional pedagogical principles that are rendered ineffective by generative AI tools and their capabilities (Sullivan et al., 2023). For example, generative AI tools can edit student writing and help students with grammar, spelling, and syntax. While students should still understand these skills, they are perhaps now not as important as critical thinking, problem solving, and communication. Instructional designers must have enough understanding of these capabilities to know where pedagogical adaptations are necessary and where generative AI can be integrated to facilitate processes. In addition, TPK

includes an understanding of how generative AI can enable new approaches to teaching and learning and facilitate creative expression in course content creation (Mishra et al., 2023).

Technological Content Knowledge (TCK)

Another blended knowledge domain in the TPACK framework is TCK. When integrating technology into the classroom, there is a need to understand which technology best suits the subject matter (Harris et al., 2009). It requires an understanding of not only how technology transforms the subject matter but how the subject matter reciprocally transforms the technology (Mishra & Koehler, 2006). For example, long ago, mathematical operations were calculated on paper with a pencil. With the invention and widespread availability of the calculator, the same concepts were transformed, and success in mathematics was redefined. In addition to understanding this relationship, educators also need to be able to discern the technologies that are best suited for integration into their subject matter area (Koehler, Mishra, & Cain, 2013).

In the context of this study, TCK describes an understanding of how instructional designers could use generative AI to improve their knowledge of the subject matter. TCK is also in understanding that the subject matter will be changed with the rapid evolution of generative AI tools (Mishra et al., 2023). As a result, curricular goals may change. For example, consider the field of computer programming. Generative AI has been proven to be able to write code in various languages with reasonable success and do so much faster than a human (Denny et al., 2024). This could change the knowledge and skills that are needed for success in the field when coding skills become automated, and as instructional

designers and academic leadership become aware of these types of changes, their goals and objectives for graduates should shift as well (Mishra et al., 2023).

Technological Pedagogical Content Knowledge (TPACK)

Perhaps the most complex blended knowledge domain, TPACK goes beyond just CK or PK or TK discretely. It is in interweaving of all three foundational knowledge domains and is the basis for effective teaching with technology (Mishra & Koehler, 2006). Educators proficient in this blended knowledge domain are able to understand and select pedagogical practices that integrate technology in constructive ways to deliver course content (Koehler & Mishra, 2009). They are able to represent concepts using technologies and determine how technology can be used to build upon prior knowledge (Mishra & Koehler, 2008). They have knowledge of what concepts are easy or difficult to learn within a subject area and which technologies can be applied to help address learning issues (Koehler, Mishra, & Cain, 2013). This blended knowledge domain also includes an understanding that there is no single technology that works for every educator in every situation or course (Mishra & Koehler, 2006).

Generative AI tools are able to perform powerful tasks unlike any tool educators have ever seen and hold the ability to change the way courses are developed altogether. TPACK, when applied to elements of this study, includes an understanding of the complex interplay between generative AI, pedagogical principles, and subject matter that allows instructional designers to develop course content. This includes the ways in which the three foundational knowledge domains interact, afford, and constrain one another (Koehler et al., 2014). This can be seen in many practical applications. For example,

instructional designers may continue to build on their CK by asking generative AI tools questions about the subject matter. Instructional designers could also use generative AI tools to assist with the selection of pedagogical strategies to align with the subject matter or with the selection of assessment deliverable that mimics on-the-job tasks. Along with knowledge of practical uses comes an understanding of when generative AI is not appropriate to use. Generative AI is not always the solution when designing courses and this can depend on the subject matter or the pedagogical strategies selected (Mishra & Koehler, 2006).

Contextual Knowledge (XK)

Surrounding all educational decisions is the foundational knowledge domain XK, which includes the external factors that affect the ways content can be written, educators can teach, and classrooms can be managed (Mishra, 2019). The researchers responsible for TPACK explained that the integration of technology in the classroom does not happen in a vacuum (Koehler et al., 2014; Mishra & Warr, 2021). Educators must always integrate technology within the parameters set by their institution, accreditors, or state/national policies, all of which they have little control over (Mishra et al., 2023). In addition to that, there exists a wealth of other external factors that can determine success or failure of technological integration like established procedures, culture, regulations, standards, and many more (Mishra & Warr, 2021; Rosenberg & Koehler, 2015). Educators need to always be aware of these contextual factors and adhere as needed.

XK as it applies to this study is similar to that of integrating any type of technology into the educational process in that it does not happen in a vacuum (Koehler

et al., 2014; Mishra & Warr, 2021). Like educators, instructional designers need to consider broader systemic factors when designing content (Smith & Staudt Willet, 2023). At the institution where instructional designers each work, there may be circumstances where generative AI tools are prohibited or limited by policy or regulation. They may also be missing or outdated policy around generative AI, all of which affect how instructional designers approach course design with generative AI tools. Instructional designers also work within an instructional design team, and the experiences, perceptions, opinions, and buy-in of other members of the team can influence whether or how generative AI tools are used. In addition, there are ongoing larger discussions about culture, bias, plagiarism, autonomy, and equity around generative AI within the research community (Currie, 2023; Karpouzis, 2024; Sullivan et al., 2023). As these discussions continue, contextual factors may change, which requires instructional designers to stay current and be adaptable with generative AI tool practices.

Rationale for Use of the Framework

Although this framework was initially developed to describe the knowledge that educators must possess to integrate technology in the classroom (Mishra & Koehler, 2006), this framework has also been applied to instructional designers, who play an integral part in online higher education (Abuhassna & Alnawajha, 2023; Bond & Dirkin, 2020). The traditional role of educator is considered multifaceted, involving tasks like designing lesson plans, identifying or creating resources, preparing for lectures or classes, delivering the content to students, and assessing student understanding of the subject matter (Quinn et al., 2017). Since 2006, the instructional design field has become more

commonplace, especially in online higher education, and the traditional roles associated with online higher education have been parsed out to members of an instructional design team (Halupa, 2019). Within the instructional design team, the role of educator is not necessarily responsible for all of the same tasks, so it follows that knowledge needed to engage in steps throughout the educational process has also been distributed amongst members of the instructional design team. Instructional designers are charged with holding expertise in PK, but they also need to have an understanding of technology to be integrated and subject matter to be delivered. The complex, multifaceted knowledge needed to create engaging, effective, technology-integrated online higher education course content mirrors that which is needed within the traditional educator's role to integrate technology into the classroom, and this is at the center of the TPACK framework.

In addition, the TPACK framework was a good fit for this proposed study because it aligns with the study's purpose and allowed me to apply the knowledge domains as a lens through which I can examine the perceptions of instructional designers. I have decided to focus this study around one particular type of technological tool, generative AI, and the knowledge needed for instructional designers to integrate it into the instructional design process. Similar to technology integration in the classroom, those charged with developing course content using generative AI tools not only need to have access to CK, PK, and TK; they also need to understand the complex interplay between the three types of knowledge. This study is aimed at exploring the perceptions of online higher education instructional design professionals on challenges and successes they have

experienced in making this integration. Because of this, I focused primarily on the TK, TPK, TCK, TPACK, and XK knowledge domains when drafting interview questions and analyzing data. When applying TPACK to the integration of generative AI in education, other researchers have similarly chosen to only focus on technology-related domains, which helps to justify my choice (Islam & Mishra, 2024; Mishra et al., 2023).

Although no study has used TPACK to study the use of AI in the context of instructional design for online higher education courses, the original authors did use online course design as an example of an activity to build TPACK in educators (Mishra & Koehler, 2006). There are also myriad studies that have used this framework to examine other disruptive classroom technologies and its influence on the classroom. For example, TPACK has been used to frame the integration of smart phones and smart phone applications in teaching and learning both in secondary and postsecondary classrooms (Hoffman, 2017; Hossain & Nurunnabi, 2021; Utami et al., 2019). TPACK has also been used in studies related to social media usage in the classroom (Glowatz & O'Brien, 2015; Muschaweck, 2023; Setiawan & Phillipson, 2020) Other disruptive technologies in education that have been studied through the lens of TPACK include virtual and augmented reality (Jang et al., 2021; Larsen, 2023), open educational resources (Feldman-Maggor et al., 2015), and gamification technologies (Mårell-Olsson, 2021). Generative AI is another disruptive technology that is making its mark on education. Researchers are already studying generative AI in the context of TPACK, but much of their findings are still forthcoming (Islam & Mishra, 2024). I will provide additional detail on how TPACK will inform methodology in Chapter 3.

Literature Review Related to Key Concepts and Variable

In the following section, I will go through the historical evolution of AI to machine learning to deep learning to generative AI. This is followed by an exploration of scholarly literature detailing the integration of generative AI tools in higher education. The final section is specific to the instructional design field and the integration of generative AI tools into the field.

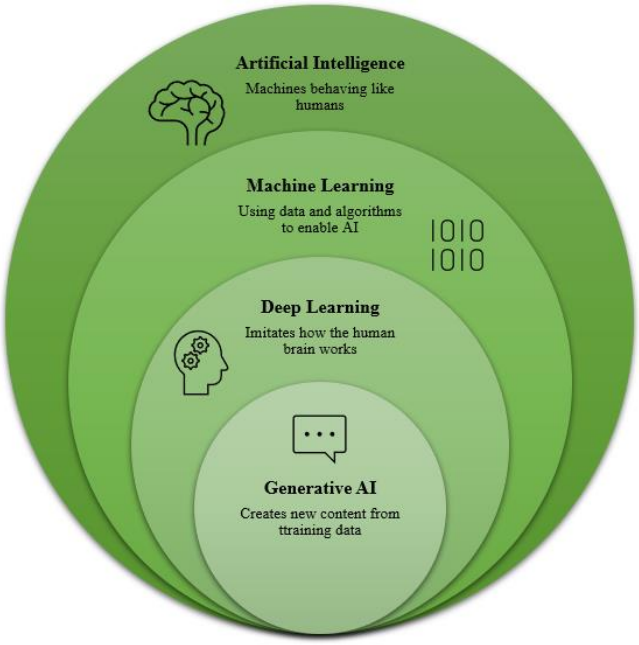
History of AI

The idea of intelligent machines has existed for millennia. As early as eighth century BCE, author and poet Homer described machines that could complete tasks automatically for the Greek god Hephaestus (McCorduck et al., 1977; Truitt, 2021). Numerous other authors and scholars have furthered this idea that machines will be able perform the same functions as a human brain, some through science fiction writing and some through legitimate scientific exploration (Grzybowski et al., 2024; Haenlein & Kaplan, 2019). While thousands of ideas, computations, proofs, and constructions were critical to the eventual development of AI, modern AI systems really began taking shape in the mid-20th century with Alan Turing and his groundbreaking publication on whether machines can think (Copeland & Proudfoot, 2007; Grzybowski et al., 2024), then with the 1956 Dartmouth conference, which is considered the formal establishment of the AI field (Mijwel, 2015). This section on the history of AI contains four broad headings: the evolution of AI, machine learning, deep learning, and generative AI. This is because, under the larger umbrella of AI, evolutions in technique and intelligence have led scientists to innovative approaches ultimately leading to the current state of AI. Machine

learning is a subset of AI, deep learning is a subset of machine learning, and generative AI is a subset of deep learning (see Figure 2). To understand the progression of technology and how the field of AI has evolved into what it is today, I will describe each of these concepts from a historical perspective along with milestone events and tools that have been instrumental in pushing innovation forward.

Figure 2

The Evolution of AI



The Evolution of AI

AI, which is the broadest category depicted in Figure 2, encompasses a wide range of computational techniques and systems. At its most simple, the AI field deals with the creation and development of machines that think and act like humans (Lake et al., 2017). This can come in the form of machines that can perceive, reason, learn, problem-solve, make decisions, and self-correct, amongst other tasks. Since even before

the field of AI was established, there have been significant milestones that have shaped AI research and application and pushed it to evolve over the years. Grasping the history of AI and examining the individual technological advancements and milestones are essential for understanding the trajectory that has led to our current era of generative AI.

Although not a new idea, one of the most passionate champions for intelligent machines was mathematician, computer scientist, and military officer Alan Turing (1912-1954) whose contributions were so significant that he is referred to as the father of computer science and AI (Grzybowski et al., 2024). Some of Turing's most notable contributions include the development of "The Bombe," which effectively broke the German encryption machine, Enigma, the designing of the universal Turing machine, which could perform any complex mathematical operation, and conceiving the idea of artificial life, or A-life, which attempts to amalgamate human-like behaviors with computers (Grzybowski et al., 2024; Guo, 2015; Haenlein & Kaplan, 2019; Hughes-Warrington, 2022; McCorduck et al., 1977; Mijwel, 2015; Muggleton, 2014). Turing believed that a machine is capable of solving any problem as long as the problem can be presented and solved using an algorithm (Mijwel, 2015). He was responsible for developing the Turing Test, which posits that if a human cannot distinguish between a machine and another human, the machine is said to be intelligent (Haenlein & Kaplan, 2019). The Turing Test is still the most famous threshold test for AI and is cited often in current definitions (Hughes-Warrington, 2022). Finally, Turing published a landmark paper in 1950, which described many of the current trends and developments in AI that were seen 50 years after its publication including the question "can machines think?"

(Delipetrev et al., 2020; Muggleton, 2014). Although the term AI was not coined until 1956, Turing's work laid the foundation for many of the advances in the field.

Several other milestones occurred simultaneously to Turing's work. In 1950, Claude Shannon developed a robotic mouse, Theseus, that could successfully pass through mazes and remember its movements (Roser, 2022). The year 1951 brought innovations in the form of both checkers and chess-playing machines developed by Christopher Strachey and Deitrich Prinz respectively (Grzybowski et al., 2024; Mijwel, 2015). Then in 1955, Allen Newell, J. C. Shaw, and Herbert A. Simon unveiled the first computer program capable of performing automated reasoning called Logic Theorist (Copeland & Proudfoot, 2007; Grzybowski et al., 2024; Mijwel, 2015). This program was able to prove more than half of the mathematical theorems found in Russell and Whitehead's *Principia Mathematica*, and its introduction is widely considered the first usage of AI computer technology (Grzybowski et al., 2024).

In 1956, the term "artificial intelligence" was coined, and the field was officially established as an academic discipline (Alzubi et al., 2018; Haenlein & Kaplan, 2019). One of just ten scientists working on AI, John McCarthy, planned an 8-week conference at Dartmouth with an aggressive agenda aimed at building machines capable of simulating human intelligence by mapping every significant feature of learning and intelligence (Delipetrev et al., 2020; Haenlein & Kaplan, 2019). All ten "fathers of AI" worked on the premise that every aspect of learning or intelligence can be described in such detail that a machine can be programmed to mimic it (Sloat, 2023). McCarthy determined the conference a failure, but the Dartmouth College Summer Artificial

Intelligence Conference, which was funded by the Rockefeller Foundation is cited as the official origination of the AI field (McCorduck et al., 1977).

Immediately following the Dartmouth conference, John McCarthy wrote the computer language “Lisp,” which was central to the computer development of AI (Grzybowski et al., 2024; Mijwel, 2015). In the same year, 1957, Herbert Simon, Cliff Shaw, and Allen Newell unveiled the General Problem Solver program, which was able to automatically solve certain kinds of simple problems like the Towers of Hanoi and missionaries and cannibals (Copeland & Proudfoot, 2007; Ernst, 1969). The acceptance of this program contributed to increased interest in AI as well as increased funding for additional research (Haenlein & Kaplan, 2019). In 1959, John McCarthy and Marvin Minsky founded the first AI laboratory at MIT, and in 1965, Joseph Weizenbaum wrote the ELIZA AI program (Mijwel, 2015). ELIZA was a language processing tool that was able to simulate human conversations, and it was one of the first programs capable of taking the Turing Test (Haenlein & Kaplan, 2019). Also in 1965, Edward Feigenbaum initiated the DENDRAL effort, which aimed to develop software to map the molecular structure of organic compounds over a 10-year span (Grzybowski et al., 2024). This was the first expert system, which is a type of AI that uses a knowledge base containing if-then rules to derive conclusions and solve problems (Anjaneyulu, 1998).

In 1973, the U. S. Congress began to criticize the amount of time and money that was being spent on AI research (Haenlein & Kaplan, 2019). This was coupled with mathematician James Lighthill publishing his opinion that AI systems would only ever be able to achieve the intelligence of an experienced amateur at best (Delipetrev et al.,

2020). These events ushered in the winter of AI (1973-1980) where hype turned into disappointment and advancements were few (Haenlein & Kaplan, 2019). Eventually, in the 1980s, AI made a resurgence for several reasons. The advancement of computers and microprocessors and the introduction of the first personal computers by IBM contributed to the shift back toward AI research (Mijwel, 2015). The Japanese Fifth Generation Computer Systems project launched in 1982, which amplified interest and, in turn, funding in AI research (Treleaven & Lima, 1982). There was also a renewal of interest in machine learning and neural networks due to the development of backpropagation, a method for training neural networks by applying calculus to labeled data sets (Delipetrev et al., 2020; Muthukrishnan et al., 2020; Wang, 2017). Although there were additional events that contributed to the advancement of the field of AI, machine learning surged in the 1990s contributing to a significant transformation of the landscape of intelligent systems.

Machine Learning

Machine learning, a subset of AI, uses data and algorithms to enable computer programs to replicate human learning (IBM, 2023). Through a recursive process of refinement against large data sets, machine learning systems gradually improve their ability to make decisions, predictions, and recommendations (Hughes-Warrington, 2022). This iterative approach allows machines to discern patterns and insights that may not be immediately apparent to human analysts, significantly enhancing their decision-making capabilities (Nieto et al., 2018). There are different types of machine learning that are categorized by the way they learn. Supervised machine learning uses labeled data sets to

train algorithms and is best described as learning by examples (Alzubi et al., 2018). The most common applications for supervised machine learning algorithms are classification and regression of data to make predictions (Sarker, 2021). Unsupervised machine learning analyzes unlabeled data sets using pattern recognition and clustering. It is most often used when the classifications of the data are as yet unknown (Alzubi et al., 2018). Training for unsupervised machine learning involves inputting large quantities of unlabeled data, which the algorithm clusters and learns from independently (Delipetrev et al., 2020). Semi-supervised machine learning uses some labeled and some unlabeled data to train the algorithm. This method is an attempt to gain benefits of both supervised and unsupervised machine learning to provide better outcomes for predication (Sarker, 2021). Reinforcement machine learning does not rely on sample data but learns by trial and error. This approach is generally used when the problem is not basic or straightforward (Sarker, 2021). Training for reinforcement machine learning is done through exploration of possibilities and ruling out options where the algorithm learns how to get the correct output most efficiently (Alzubi et al., 2018). Understanding the evolution of machine learning is critical within this study because it supports many of the recent advances in AI including generative AI, which is the focus of this study. The position of machine learning as a subset of AI and the parent set of deep learning and generative AI also make it historically important.

Although the origins of machine learning can be traced back to the 1950s, modern machine learning only became popular in the late 1980s and early 1990s when the backpropagation learning algorithm, which was a fundamental method used in training

artificial neural networks, was popularized. The use of this algorithm type propelled the focus of machine learning to being data-driven rather than knowledge-driven (Alzubi et al., 2018; Fradkov, 2020). The amount of data that was being collected at this time necessitated innovations for analyzing and applying, and machine learning approaches were spurred by this need more so than by scientific curiosity (Fradkov, 2020). During this time period, researchers also began to study neural networks in machine learning, which were AI models that mimic the human brain. There were several notable advancements and applications as a result of the study of neural networks. In 1990, Robert Schapire introduced the concept of boosting, which mitigated bias within the supervised machine learning process by weighting strong learning classifiers (Foote, 2021, 2024; Lavallin & Downs, 2021). In 1995, Corinna Cortez and Vladimir Vapnik published their prominent paper on support-vector networks, which are a type of supervised learning algorithm used for classification and regression. This paper fueled much machine learning research and application (Fradkov, 2020). The bagging method was introduced in 1996 by Leo Breiman, which improved the accuracy and stability of models by training multiple versions of a model on different subsets of data then combining their outputs (Lavallin & Downs, 2021). In 1997, Jürgen Schmidhuber and Sepp Hochreiter described a strategy called long short-term memory, which is a key component of speech recognition programs (Foote, 2021, 2024; Van Houdt et al., 2020). Long short-term memory is another type of neural network designed to manage some of the limitations of traditional recurrent neural networks. In 2000, Cynthia Breazeal and the MIT team developed the Kismet robot, which could imitate human movements and make

gestures mimicking emotion (Copeland & Proudfoot, 2007; Mijwel, 2015). Also in the early 2000s, Honda developed the ASIMO robot with machine learning technology, which was regarded as the closest robot to human ability and skill (Mijwel, 2015). Facial recognition made a large stride in 2006 as well when the Face Recognition Grand Challenge program graded the current systems as ten times more accurate than those used in 2002, and this is due to the innovations associated with machine learning (Foote, 2021). Finally, IBM's Watson, which began to be developed in 2005, successfully defeated Ken Jennings, noted Jeopardy quiz show winner, in 2011 (Alzubi et al., 2018). Each of these applications used machine learning in conjunction with other technology like neural networks, natural language processing, robotics, and cognitive computing, but Watson used deep learning, which was seen as the "next big thing" in AI innovation (IBM, 2023).

Deep Learning

Within the larger set of machine learning programs is a subset called deep learning. The two terms machine learning and deep learning are often used synonymously, but they are, in fact, distinct from one another. Both use algorithms but in different ways; deep learning uses much more data to learn than machine learning and is composed of at least three layers of unlabeled data (IBM, 2023; Marr, 2016; Minar & Naher, 2018; Pouyanfar et al., 2018). Deep learning can be thought of as a scalable version of machine learning because it is able to manage larger data sets, handle more complex tasks, and operate without human intervention (IBM, 2023; Wang, 2017). The concept of deep learning, like machine learning, existed long before it was popularized. It

was only described in its current form in the early 2000s when proposed as an artificial neural network, or a computer program that is loosely based on the structure of the human brain (Alzubi et al., 2018; Deng, 2014; Schmidhuber, 2015; Wang, 2017). This was also around the time that computer processors had enough speed to accommodate this type of technology and the amount of data that was available for training algorithms outpaced what a human could input manually (Deng, 2014; Pouyanfar et al., 2018; Wang, 2017). Because of the ability of deep learning programs to automate training, they are somewhat of a black box with regard to understanding how they work (Haenlein & Kaplan, 2019; Pouyanfar et al., 2018). Nevertheless, understanding the concept of deep learning overall is important to this study as the most dramatic shifts in computing have been a result of deep learning (see Plebe & Grasso, 2019). In addition, deep learning is the set within which generative AI exists, which is the ultimate focus of this study.

Like machine learning, deep learning has origins that date back decades prior to it becoming useful and popular in the scientific community. The first mathematical model of a neural network was introduced in 1943 by Walter Pitts and Warren McColloch, and the first working deep learning network was created in 1965 by Alexey Ivakhnenko and V. G. Lapa (Ganatra & Patel, 2018). While these were considered significant advancements in science, the term was not popularized until the early 2000s by Igor Aizenberg and his team while discussing artificial neural networks (Ganatra & Patel, 2018). Then, in the mid-2000s, Geoffery Hinton and Ruslan Salakhutdinov published a demonstration of training multi-layered neural networks one layer at a time, and this contributed to the popularization of deep learning (Marr, 2016). In 2006, Geoffery Hinton

claimed to fully understand how the brain works and introduced the ideas of unsupervised pretraining and deep belief nets (Ganatra & Patel, 2018). This was followed by Fei-Fei Li beginning work on the ImageNet database in 2009, which spurred the advancement of the deep learning field and became the basis for an annual competition for image recognition algorithms (Ganatra & Patel, 2018; Karjian, 2023). Also in 2009, at the Neural Information Processing Systems workshop titled Deep Learning for Speech Recognition, it was discovered that with a large enough data set, pretraining is not necessary for neural networks (Marr, 2016). This finding led to another significant decrease in error rates for deep learning programs. In 2011, Apple introduced the world to Siri (Foote, 2024; Wang, 2017), Alex Krizhevsky unveiled AlexNet (Ganatra & Patel, 2018), and Jurgen Schmidhuber, Dan Claudiu Ciresan, Ueli Meier, and Jonathon Masci designed the first convolutional neural network that achieved superhuman performance (Karjian, 2023). Then, in 2012, Geoffery Hinton, Ilya Sutskever, and Alex Krizhevsky introduced a convolutional neural network that won the ImageNet competition and prompted an upsurge in research on deep learning implementation of deep learning applications (Karjian, 2023; Serre, 2019). This was also the year that the Google Brain algorithm trains itself to recognize cats by watching YouTube videos (Gent, 2024; Marr, 2016; Wang, 2017). In 2013, Google introduced DeepMind AlphaGo, which was capable of deep reinforcement learning and achieving superhuman levels of game play (Karjian, 2023; Pouyanfar et al., 2018). DeepMind AlphaGo went on to defeat multiple Go champions and eventually began learning by observing human moves, mastering chess in 4 hours (Grzybowski et al., 2024; Haenlein & Kaplan, 2019; Wang, 2017). The year 2014

brought more innovation including IBM's TrueNorth processor, which was structured similarly to a human brain, GoogLeNet, which was considered a foundational algorithm to modern deep learning, and the application of deep learning to speech recognition (Aurora University Phillips Library, n.d.; Ganatra & Patel, 2018). In 2015, Facebook inserted DeepFace in their platform, which could automatically recognize and tag photos (Alzubi et al., 2018; Karjian, 2023; Wang, 2017). Uber started a self-driving car pilot program in Pittsburgh in 2016, which was a new application of deep learning (Karjian, 2023). In 2019, GoogleAI and Langone Medical Center piloted an algorithm that outperformed human radiologists in detecting potential lung cancers (Karjian, 2023; Wang, 2017).

These innovations and tools are a mere handful of the numerous deep learning applications that have occurred since the early 2000s. Deep learning surpassed human learning in the mid-2010s, and it is at the heart of many of the shifts in current computing trends (Plebe & Grasso, 2019; Wang, 2017). Recent years have seen deep learning take another turn into generative AI. Although deep learning has continued to grow and evolve, many of the advances in AI in the late 2010s and beyond fall under the generative AI category as well as deep learning.

Generative AI

As was detailed at the beginning of this "History of AI" section, deep learning is a subset of machine learning, and machine learning is a subset of AI. The final subset and the focus of this study is generative AI, which encompasses a multitude of tools and models. Generative AI tools use both machine learning and deep learning algorithms to

create meaningful synthetic content that is yet unseen in the form of text, images, audio, and other multimedia (Feuerriegel et al., 2024; García-Peñalvo & Vázquez-Ingelmo, 2023; Kalota, 2024). This technology is best used when creativity or innovation are needed or when the problem to be solved is open-ended (Kılınç & Keçecioğlu, 2024). This varies from traditional AI systems, which are better suited for well-defined, specific problems in areas like data analysis and production (Kılınç & Keçecioğlu, 2024). In addition to deep learning and machine learning algorithms, generative AI uses a variety of underlying techniques and algorithm types including, but not limited to, natural language processing, large language models, and transformers. Natural language processing enables computers to understand, analyze, and interpret human language using tokens and classification (Kalota, 2024). Large language models are trained on vast amounts of data, which allow them to understand the complexities of language and predict human-like responses to questions (Dasgupta et al., 2023; Kalota, 2024). Transformers are a type of machine learning that can analyze the connections between words and sentences to make inferences (Kılınç & Keçecioğlu, 2024). When someone uses a generative AI tool, it begins with input text. The user crafts a prompt and natural language processing techniques are employed to tokenize the text, which separates it into fundamental units to process (Maulud et al., 2021). The tokenized text is, then, run through a large language model, which is built on transformer architecture (Cao et al., 2018). The transformer processes the information through multiple encoder and decoder layers that work to understand the relationship between the words (Doshi, 2020). Based on this analysis, the tool uses its learned knowledge to generate an output. The output can

be refined further using techniques like grammar checkers, sentiment analysis, or feedback loops (Maulud et al., 2021). While this process seems straightforward, the underlying mechanics behind how generative AI tools work is considered unexplainable, even for experts in the field (Dasgupta et al., 2023; Kalota, 2024). Nevertheless, interest in generative AI tools spiked significantly in recent years and use of generative AI tools in multiple industries has become standard (García-Peñalvo & Vázquez-Ingelmo, 2023). Although short, it is important to understand the history of generative AI as the final element in the sequence of AI tool types. In addition, generative AI tools are the overall focus of this study, and their history helps the reader fully understand their progression, capability, and popularity.

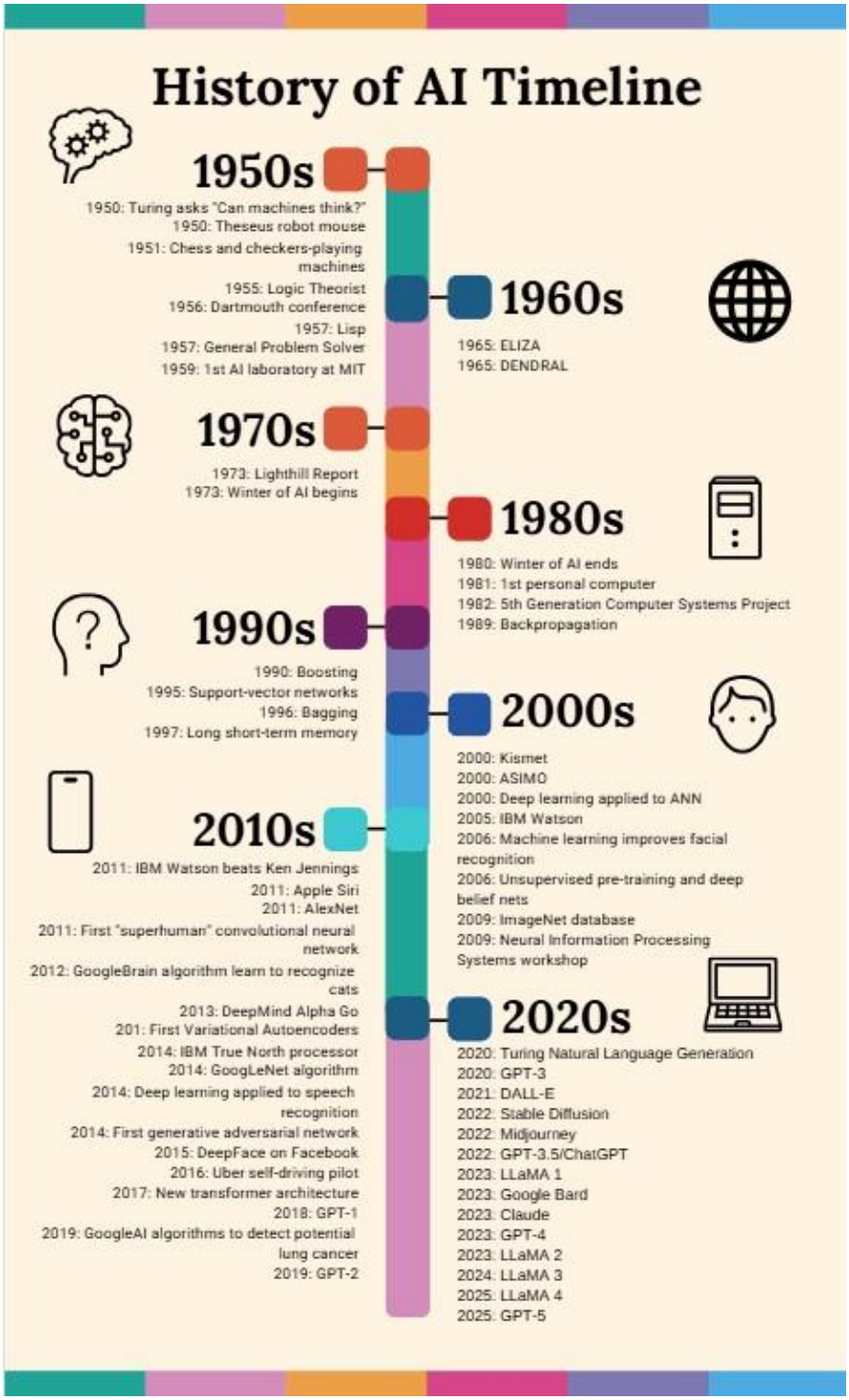
Similar to deep learning and machine learning, the origins of generative AI tools can be traced back to the 1940s and 1950s with Hidden Markov Models and Gaussian Mixture Models (Kilinç & Keçecioğlu, 2024). Early models were primitive and used techniques that differ from modern systems. The same factors that propelled the development of deep learning also changed generative AI models as well, namely the availability of big data and exponential growth in computing power (Dasgupta et al., 2023). In 2013, Diederik Kingma and Max Welling introduced variational autoencoders, one of the first types of generative AI systems (Bengesi et al., 2024; Karjian, 2023). While effective, variational autoencoders were complex, so another model, generative adversarial networks, which were introduced in 2014 by Ian Goodfellow and his team was preferred by scientists in the AI field (Kilinç & Keçecioğlu, 2024). Generative adversarial networks, which pit two neural networks into competition, were a critical

milestone because they were the first to produce high quality images, and Goodfellow and his team are credited with bringing the term “generative artificial intelligence” into popularity (Bengesi et al., 2024; Kilinç & Keçecioğlu, 2024). In 2017, transformer architectures were proposed by Vaswani and team, and this paved the way for the first version of generative pre-trained transformer (GPT; Kilinç & Keçecioğlu, 2024). In 2018, OpenAI introduced GPT-1, a neural network that uses deep learning architecture to create text outputs and converse with users (Bengesi et al., 2024; Foote, 2024). The next iteration, GPT-2 was released in 2019, which was a 10 times improvement on the original (Al-Amin et al., 2024; Bengesi et al., 2024). The year 2020 brought the introduction of Turing Natural Language Generation, which was the largest language model to date (Grzybowski et al., 2024; Karjian, 2023). That same year, OpenAI released GPT-3, which was a 100 times improvement on GPT-2 (Al-Amin et al., 2024; Bengesi et al., 2024; Grzybowski et al., 2024). Photorealistic image creator DALL-E was created by OpenAI in 2021, and Stable Diffusion, an open-access text to image generator was released by Stability.ai in 2022 (Karjian, 2023; Stability.ai, 2022). Also in 2022, David Holz created Midjourney, a text-to-image generator aimed at facilitating users’ imaginations through simple functionality (Vartiainen & Tedre, 2024). OpenAI’s GPT model was further improved with the introduction of GPT-3.5 in 2022 (Al-Amin et al., 2024; Bengesi et al., 2024). ChatGPT, which was built using GPT-3.5, was released in November 2022 and almost immediately exploded in popularity (Al-Amin et al., 2024). Because it was freely accessible and seemingly impossible to distinguish from human written words, its release created massive demand for more tools and more functions

across various fields. After only two months, ChatGPT had more than 100 million users earning it the title of the fastest growing computer application to date (Grzybowski et al., 2024). This prompted numerous companies to release their own chatbots and large language models including Meta and their LLaMA large language model in February 2023, Google and Google Bard chatbot (later renamed Gemini) in March 2023, and Anthropic and Claude in March 2023, amongst others (Anthropic, 2023; Grzybowski et al., 2024; Malik & Paul, 2023; Rayhan, 2024). Each of these tools and models has gone through rapid revisions and updates that have yielded increased efficiency and performance. For example, in March 2023, GPT-4 was released and was, again, a massive improvement on its predecessor with the ability to process both text and images and generate up to 25,000 words (Wang et al., 2023). GPT-5 was also released in August 2025 with OpenAI touting as being smarter, faster, and more accurate than previous models (OpenAI, 2025). LLaMA has also released versions 2, 3, and 4, which were trained on more diverse data sets and are capable of processing larger prompts (Mok, 2024; Reuters, 2025). Figure 3 illustrates the significant milestones for AI, machine learning, deep learning, and generative AI cumulatively. The current landscape of generative AI chatbots, large language models, and image generators is quite competitive with new releases being announced daily. Even as I write this paragraph, generative AI offerings are likely changing more, and it is nearly impossible for one person to keep up to date. However, generative AI is a major disrupter in many fields including education and a critical component to this study, so it is imperative that the reader understands the various types of generative AI, the progression of tools, and the implications of their use.

Figure 3

History of AI Timeline



The Influence of Generative AI in Higher Education

In reviewing the literature on the integration of generative AI tools in online higher education instructional design, two major themes and six subthemes emerged as pertinent to this study. The first major theme involves the influence that these tools have had under the wider umbrella of higher education. Within this larger theme, there are three main facets of higher education that have been affected by generative AI tool integration, and they are students, educators, and institutions. In the section about student learning, I will synthesize scholarly literature that discusses student experiences, motivation, behaviors, and uses for the tools, potential benefits and concerns students have identified, and recommendations for integration and assessment. The section on educators and pedagogy is structured much the same with a discussion of experience, benefits, and concerns followed by the role of the educator and the skills needed to use generative AI tools. The final subtheme on institutional policies and practices includes information on the role of the institution in integrating generative AI tools, policies and guidelines, and training and support.

Generative AI in Student Learning

Throughout the literature, authors and student research participants have used phrases like transformative technology (Yeh, 2024), paradigm shift (Essien et al., 2024; Yeh, 2024), and impactful to student outcomes (Tlili et al., 2023) to describe the potential effects of generative AI integration in higher education and beyond. There is little doubt that generative AI technology has spurred a significant change in higher education whose full consequences are yet to be determined. Since late 2022 when generative AI tools

became popular, numerous students have been surveyed, interviewed, and experimented with and their perceptions documented. In general, regarding the future of higher education, students collectively called for a curricular change that includes instruction on generative AI competencies critical to their future careers and way of life (Chan, 2023; Chiu, 2024; Essien et al., 2024). In a survey from Cengage Group (2024) the results showed that 70% of graduates believe that basic skills in generative AI should be integrated into their course work, and 55% of participants felt they were not adequately taught how to use AI at this time. They also concluded based on a large-scale quantitative online survey that the way writing is taught and managed, in particular, needs to change (Helm & Hesse, 2024). Overall, students suggested that the response to generative AI in higher education should involve a strategic integration approach rather than banning technology (Denecke et al., 2023), and that institutions should surround students with guidance and policy to facilitate responsible use and better meet evolving student needs (Yeh, 2024; Yusuf et al., 2024). The following sections will include an analysis of students' reported experience and motivations related to generative AI tools, potential advantages and concerns that they perceive, and their recommendations for moving forward in this dynamic educational environment.

Student Experience and Motivations. Since the release of ChatGPT in November 2022, awareness and experience with generative AI tools have both increased drastically. It is difficult to pinpoint exactly how many students have heard about different generative AI tools and when they were made aware due to the quickly evolving nature of the tools and the nature of research. For example, a mixed methods study of

students and educators conducted in July of 2023 reported that both sets of participants had relatively low experience with generative AI tools (Chan, 2023). Another mixed methods study published in early 2024 reported that 60% of students who participated in their pretest, intervention, and post-test had past experience using generative AI tools (Essien et al., 2024). A third study published in March 2024 reported that 82% of participants in their mixed methods online survey were familiar with generative AI tools (Yusuf et al., 2024). This conflicting message could be due to the varying populations that were sampled or could show the progressive influx in popularity over time. Overall, Helm and Hesse (2024) reported that only a year after the release of ChatGPT, more than half of students in their study were familiar with using the application, and they are finding out about generative AI tools through social media rather than through their higher education institution (Bonsu & Baffour-Koduah, 2023; Kelly et al., 2023). While this was not necessarily considered negative, the preference was to use instruction to engage students to facilitate responsible use rather than have students guess at proper use strategies. In addition to awareness of generative AI tools, students have also gradually gained knowledge around the potential benefits and limitations of using these tools (Chan & Hu, 2023; Foung et al., 2024). They do not, however, have knowledge about the inner workings of these tools as they are described by some in this qualitative study as a sort of black box (Chiu, 2024). As students continue to learn, and institutions begin threading generative AI use within their curriculum, awareness and experience will likely continue to grow.

Motivation for students choosing to try using generative AI tools as well as reasons for continuing to use them have been examined by multiple researchers. In several studies, student participants expressed excitement and motivation to use generative AI tools and found them fun and entertaining (Alammari, 2024; Yeh, 2024). Student motivation reported in one set of mixed methods experimental case studies stems from the user-friendliness, speed, and quality of generative AI tools (Elkhodr et al., 2023) as well as the fluidity of conversation as found in a multi-staged qualitative study (Tlili et al., 2023). Students in a Poland-based quantitative survey were motivated to begin and continue using generative AI tools by performance expectancy and habit (Strzelecki, 2023). Helm and Hesse (2024) conducted an online survey of students on generative AI use, and, although the findings were relatively vague, they reported that students who feel that they are able to evaluate the potential risks of generative AI tools and work around those risks are more likely to use the tools. The general consensus among higher education students who participated in these studies are that these tools are interesting and fun to use and that they want to continue using generative AI tools to perform better in their coursework, especially when they consider themselves digitally literate.

Student Tool Usage and Behaviors. The ways in which students use generative AI tools and the behaviors that they engage in were also studied in several articles. Regarding student behavior and engagement with generative AI tools, some students said that they were open to adopting generative AI in their academic and personal behaviors (Chan, 2023). Other student participants believed that ChatGPT would be useful in completing non-exam assessments and that they were confident in using the tool (Chiu,

2024). Although familiar with generative AI, students were not yet integrating them into their daily workflows (Helm & Hesse, 2024), and this could be for several reasons. Some students chose not to engage due to a lack of institutional guidance on best practices or regulations (Schneider & Haried, 2024; Yusuf et al., 2024). Some were leery of getting caught using generative AI in a way that is not sanctioned so chose avoidance instead (Schneider & Haried, 2024).

When they do engage with the tools, students prefer to use generative AI for the more mundane tasks to save time and effort for complex or creative tasks (Essien et al., 2024). Although the perception is that many students use generative AI tools to draft entire texts or cheat, the reality may be much less (Helm & Hesse, 2024). The findings of Yusuf et al. (2024) indicate that only 39% of the 1217 participants have cheated using generative AI tools, and many report that they would not do it again. Students in one intervention-based research study reported that their use of generative AI tools was only for tasks that did not include creating new work (Essien et al., 2024), and only 26.7% of participants in a mixed methods survey with 305 responses claimed to use generative AI on exams (Denecke et al., 2023). These results are in contrast to Schneider and Haried (2024) who asked students about homework preparation and found that 80% of participants used ChatGPT in this way.

Behaviors when using generative AI tools may be dependent on other factors like degree level, tech savviness, or writing proficiency. According to one study, undergraduates relied more heavily on generative AI tools than graduate students (Elkhodr et al., 2023). The authors postulated that this may be due to graduate students'

desire to actually learn rather than just finish assignments quickly. Students were also more likely to use generative AI tools when they had less confidence in their own writing skills as was reported by their professors in a smaller qualitative study in South Africa (Singh, 2023). Experience is one of the best predictors of continued generative AI use. As students used the tools more, they gained confidence in them, thereby leading to increased use (Schneider & Haried, 2024). This sentiment is echoed in the Helm and Hesse (2024) study, which reported that students who were better able to judge benefits and limitations of the tools are more likely to use them, and this ability came through experience. This claim was also substantiated by the 19 student interviewees who participated in an action research study in late 2023. They reported that improved conversation with generative AI tools yielded higher quality and frequency of use (Michalon & Camacho-Zuñiga, 2023). The results of these studies showed varying reasons that students use and continue to use generative AI tools, and these factors likely fluctuate depending on the task at hand.

Throughout the literature, students have indicated that they used generative AI tools in completing a wealth of academic and personal tasks. Several studies focused specifically on ways that the tools are being used to support different phases of the writing process. Some of the tasks students found most helpful occurred in the beginning phases of writing like brainstorming, text planning, and idea generation (Helm & Hesse, 2024; Nguyen et al., 2024; Wang et al., 2024). Students reported that using generative AI tools for foundational tasks and baseline knowledge were the most effective ways as they capitalized on the strengths of the tools (Stojanov, 2023; Tlili et al., 2023). Students also

reported using generative AI tools toward the end of the writing process in tasks like proofreading, editing, and formalizing language and tone (Li et al., 2024; Nguyen et al., 2024; Wang et al., 2024). Writing tasks, in general, were cited as some of the most common uses for generative AI tools amongst students, however, several studies also asked students about other uses for generative AI tools outside of writing. One mixed methods survey of students and lecturers found that students use the tools for fun, translation, data analysis, and art creation amongst other applications (Denecke et al., 2023). Understanding complex problems, creating practice opportunities, tutoring, self-learning, and creating a debate partner were other cited uses (Li et al., 2024; Rahman & Watanobe, 2023; Yusuf et al., 2024). The potential uses for generative AI tools are vast and will likely evolve as the tools and students' reactions to them also evolve.

The effective use of generative AI tools, despite some claiming to be inherent to digital natives (Kelly et al., 2023), requires certain skills and competencies that have been mentioned in the findings and conclusions of multiple studies. At the basic level, most tools are operated using conversational language, which is not necessarily advanced, but basic conversations yield very basic outputs. To produce meaningful content that meets students' needs, specific skills and competencies are needed, and, according to the 20 graduate students who were interviewed in one particular study, many students are needing to re-skill or upskill themselves to adapt to integrating generative AI tools in their personal workflows (Kolade et al., 2024). Digital literacy, which is a broader set of skills needed to operate technology effectively, contains a subset, AI literacy, that refers to the knowledge of limitations associated with, and best practices surrounding AI tools

(Foung et al., 2024). Digital and AI literacy skills were both emphasized throughout the literature as critical skills needed to navigate generative AI tool integration in higher education (Chan, 2023; Chiu, 2024; Denecke et al., 2023; Elkhodr et al., 2023; Essien et al., 2024; Foung et al., 2024; Mogavi et al., 2024; Tzirides et al., 2024). Perhaps just as critical as digital and AI literacy is the need for a newer skill called prompt engineering (Michalon & Camacho-Zuñiga, 2023; Sáez-Velasco et al., 2024; Tlili et al., 2023). While generative AI tools are often conversational in nature, there is skill involved in providing context and detail in adequate amounts to yield the desired outputs, and this is likely a skill that will need to be cultivated in students to be successful in school and in their future careers. On top of those skill sets, several studies mentioned critical thinking skills and their importance in evaluating tools and outputs (Chan, 2023; Denecke et al., 2023; Habib et al., 2024; Michalon & Camacho-Zuñiga, 2023; Tlili et al., 2023). Choosing the correct tool is not always inherent without thinking critically, and all outputs from generative AI tools should be evaluated carefully to ensure that they are accurate, unbiased, and maintain the human author's tone and voice. Finally, content or subject matter knowledge pertinent to generative AI queries is also needed to self-assess and evaluate the outputs (Chiu, 2024; Li et al., 2024). These are some of most critical skills needed to use generative AI tools in a meaningful way that improves student outcomes.

Luckily, many of the skills that are necessary for effectively and responsibly using generative AI tools are cultivated through practice and experience. In several studies, students showed personal growth in skills and competencies like critical thinking (Essien et al., 2024), prompt engineering (Li et al., 2024; Wang et al., 2024), and AI

literacy (Tzirides et al., 2024). Students in the Michalon and Camacho-Zuñiga (2023) study also demonstrated that their proficiency in communicating with generative AI tools improved drastically with use from 20% effectiveness to almost 90% effectiveness over the course of the study. All of the students who participated in that study also self-reported improvement in generative AI tool use with practice. As tools continue to develop and improve, additional skills will undoubtedly be needed, so students should continue to learn and grow and be adaptable to change.

Benefits of Generative AI Tools. Generative AI tools have been touted by many as transformational assets in higher education, and they do possess the potential to revolutionize teaching and learning although their full potential is still uncertain. In fact, the literature described several specific benefits of using generative AI tools as reported by student participants. In this section, those that pertain to student users are highlighted beginning with benefits associated with functionality. Personalized support was recognized by student participants in several studies as a key advantage of using generative AI tools (Chan & Hu, 2023). Personalization came in many forms including offering individual feedback (Li et al., 2024), revising the learning environment to meet individual needs (Essien et al., 2024), and providing practice problems unique to student needs (Rahman & Watanobe, 2023), among other functions. Students also found that writing development and support were among the most useful benefits of using generative AI tools (Chan & Hu, 2023; Nguyen et al., 2024; Rahman & Watanobe, 2023; Rejeb et al., 2024; Singh, 2023). There was also agreement in several studies on the benefits of automating administrative tasks to save valuable time (Chan & Hu, 2023;

Denecke et al., 2023; Essien et al., 2024). In addition to these benefits, undergraduate and graduate students who participated in one qualitative study suggested that students are now able to complete tasks that they previously could not like coding or creating computer applications (Chiu, 2024) without training or education on these tasks. Other student participants explained that generative AI provides opportunities to simulate real-life scenarios, facilitate collaboration, and improve communication (Elkhodr et al., 2023; Kolade et al., 2024; Mogavi et al., 2024). Supporting learning through tutoring, generating extra practice problems, and explaining concepts were also mentioned as benefits (Chan & Hu, 2023; Kolade et al., 2024; Rahman & Watanobe, 2023). A final function that was mentioned in several studies was the ability to ask questions anonymously without fear of judgement (Chan, 2023; Denecke et al., 2023; Stojanov, 2023; Wang et al., 2024) which, according to the results of a quantitative investigation of students, could lead to a more equitable learning environment (Chen et al., 2023). These functional benefits are just a handful of the possible beneficial uses of generative AI tools for students. As students become more comfortable with the tools and the tools continue to evolve, additional functional benefits will undoubtedly be seen.

In addition to functional benefits, researchers have queried students on the personal benefits that they gained through using the tools. Experience with the tools has been correlated with increased enthusiasm, empowerment, engagement, and interest in learning according to a quantitative study of 350 students and instructors (Muñoz et al., 2023). Several other benefits that have been linked with generative AI use are listed in Table 1. These benefits associated with improving workflows and academic products can

better meet the diverse needs of all students as reported in a qualitative study of 13 student teachers (Yeh, 2024), and this includes those for whom English is not their first language (Singh, 2023).

Table 1

Benefits Associated With Generative AI Use

Benefit	Empirical study
Increased student autonomy and responsibility	Elkhodr et al. (2023); Habeb Al-Obaydi et al. (2023)
Increased enthusiasm, empowerment, engagement, and interest in learning	Muñoz et al. (2023)
Being forced to check facts more frequently	Michalon & Camacho-Zuñiga (2023)
Better timesaving and efficiency	Denecke et al. (2023); Elkhodr et al. (2023); Essien et al. (2024); Nguyen et al. (2024)
Higher quality and accuracy in student work	de Vincente-Yagüe-Jara et al. (2023); Elkhodr et al. (2023); Essien et al. (2024); Singh (2023); Li et al. (2024)
Enhanced critical thinking	Elkhodr et al. (2023); Essien et al. (2024)
Increased creativity	Habib et al. (2024); Schneider & Haried (2024)
Improved problem-solving skills	Elkhodr et al. (2023); Wang et al. (2024)
Improved ability to apply concepts to real-life scenarios	Elkhodr et al. (2023); Essien et al. (2024)

Concerns Associated With Generative AI Use. With any new technology associated with large-scale change generally comes apprehension and fear for some. While generative AI tools are still new, and individuals and institutions are still learning

how to adapt to them, the concerns raised tend to be more numerous than the benefits. In this section, several of those concerns that are pertinent to student users are described. The first several concerns that are mentioned repeatedly in the literature involve issues with the outputs of generative AI tools.

Many generative AI tools are trained by skimming the internet and ingesting any and all open access content. Unfortunately, the tools do not differentiate between good information and information that is biased or inaccurate, and this can lead to outputs with prejudices, mistakes, or other problems that are confidently presented as fact. Denecke et al. (2023) reported that student participants view biases as a major weakness in generative AI tools. This concern is echoed in multiple studies (Essien et al., 2024; Foung et al., 2024; Rahman & Watanobe, 2023; Schneider & Haried, 2024) as is a warning that bias could potentially harm users (Tlili et al., 2023). In addition to bias issues, accuracy in generative AI outputs was also mentioned frequently in the literature and was viewed as one of the biggest concerns associated with generative AI tool use. In Denecke et al. (2023), 66.7% of surveyed students reported inaccurate outputs when using generative AI tools. Students in another mixed methods quasi-experimental study of 61 Chinese undergraduate students listed false information as their main concern in using generative AI tools (Li et al., 2024). The presence of this concern in numerous studies solidifies it as a pervasive and pertinent concern amongst students (Chan & Hu, 2023; Denecke et al., 2023; Elkhodr et al., 2023; Essien et al., 2024; Schneider & Haried, 2024; Tlili et al., 2023; Tzirides et al., 2024; Yusuf et al., 2024). To combat this issue, students have expressed the need to fact-check all generative AI outputs (Dergaa et al., 2023; Essien et

al., 2024; Michalon & Camacho-Zuñiga, 2023) regardless of how difficult fact and falsities can be to distinguish as it was described in one case study analysis (Stojanov, 2023). In addition to bias and accuracy concerns, students also reported that generative AI tools are limited in their ability to understand context, empathy, interpersonal connection, complexity, and logical organization, all of which lead to less than desirable outputs (Denecke et al., 2023; Essien et al., 2024; Li et al., 2024; Sáez-Velasco et al., 2024). The issues plaguing generative AI tool outputs require vigilance on the part of the user to verify all facts and mitigate biases and other issues, and as was discussed, not all users possess the knowledge and skills to do this effectively. This was particularly concerning when students are completing assessments without verifying the outputs (Sáez-Velasco et al., 2024).

Concerns over the outputs of generative AI are not the only ones discussed in the literature. Students have also reported their concerns about how using generative AI tools might affect theirs and their peers' behaviors or emotions. Most pervasive in the literature are the topics of cheating and plagiarism. While many authors are faculty who are perhaps the most concerned about this issue, students are also expressing wariness over the implications of dishonesty. Chan (2023) reported that many of the 457 participants felt a sense of unfairness regarding their peers getting ahead on assignments, while others recognized the relative ease of cheating on online exams with generative AI tools and worry about the validity of assessments (Rahman & Watanobe, 2023). There was also general concern amongst students about potential increases in cheating and plagiarism and the implications on student outcomes (Denecke et al., 2023; Habib et al., 2024; Tlili

et al., 2023). In addition to trepidation surrounding plagiarism, students were also concerned about potential overreliance on generative AI tools (Chan, 2023; Chan & Hu, 2023; Wang et al., 2024; Yeh, 2024). They warned, through their responses in two different studies, that overreliance could yield impaired problem-solving and critical thinking skills (Elkhodr et al., 2023; Rahman & Watanobe, 2023). This is seen as almost a "use it or lose it" situation where students who are not forced to use higher order thinking skills lose the ability over time. Yusuf et al. (2024) also projected that overreliance on generative AI tools may impede personal and professional growth, and the mixed methods study results of Habib et al. (2024) warned of fixation of thought as a byproduct of overreliance. These concerns, which are prevalent throughout the literature, are shared with educators and institutional leaders.

Effects of AI on creativity was another concern-related theme that occurred throughout the literature. Students in one mixed methods study expressed concerns in their reflection entries about generative AI taking over the thinking process and stifling creativity and confidence (Habib et al., 2024). Tlili et al. (2023) similarly reported student concern over generative AI tools diminishing innovative capacities. This is in contrast to another study where focus groups were conducted with students and faculty who reported that using generative AI tools may actually increase creative thinking (Sáez-Velasco et al., 2024). Additional concerns related to student emotions include reported frustration stemming from generative AI tools not conversing like a human (Sáez-Velasco et al., 2024), anxiety surrounding the potential of getting caught using generative AI in an unsanctioned way (Schneider & Haried, 2024), and issues with focus

and digital distraction (Wang et al., 2024). Finally, while only mentioned in a handful of studies, students did express concerns about equity amongst peers as many generative AI tools have both a free version and a premium version. Not all students are able to access premium tools, and this could widen the already present technology gap according to written reflections and focus groups in one qualitative study (Foung et al., 2024). Many of the concerns described in this section were gathered through qualitative methods based on perceptions of students. While these are valid findings, many of the concerns are based on fears around new technology and change rather than observed phenomena.

Student Learning and Perceptions. Student learning is another major theme that is discussed in multiple studies. Despite the many concerns and limitations of generative AI tools that students have reported, the overall perception was that these tools were useful to support their learning (Stojanov, 2023). Habeb Al-Obaydi et al. (2023) conducted a qualitative study to examine how the use of generative AI tools aligns with various definitions of learning and found that, overall, several types of learning were facilitated through using these tools when paired with other learning methods. This sentiment was echoed in an intervention-based study's findings that stated that the integration of generative AI tools in higher education should support rather than replace traditional learning methods (Essien et al., 2024). Foung et al. (2024) found that students were forced to cultivate critical thinking skills by evaluating tools and outputs, and Li et al. (2024) reported that using generative AI tools helped students grasp a deeper understanding of complex concepts. Largely, the sentiment around whether generative AI

tools facilitate learning was positive, which could help further ideas around generative AI tools being a positive addition to higher education rather than a negative one.

Throughout the literature, student participants also provided their overall perceptions of the tools. One mixed methods study, which was conducted by surveying 384 students then interviewing 10 from within that sample, stated that using generative AI tools excited students and made them want to learn (Wang et al., 2024). Students' overall perceptions about generative AI were mixed, but there tended to be more positive than negative sentiments in the literature (Tlili et al., 2023). Overall, students reported that they were comfortable using generative AI tools like ChatGPT based on a mixed methods study involving an online survey and semi-structured interviews (Bonsu & Baffour-Koduah, 2023) and that they find the tools enjoyable and entertaining (Strzelecki, 2023). Wang et al. (2024) reported that more than 90% of participants in the quantitative part of their mixed methods study rated the impact of generative AI tools on higher education as either somewhat or very positive. This positive perception was seen in other studies that reported student enthusiasm for the integration of generative AI tools in EFL teaching (Yeh, 2024) as well as the quantitative portion of a study where 100% of respondents believed in the positive impact of generative AI technologies in higher education (Chan, 2023). Overall, the literature indicated that students were very interested in using generative AI tools more if their institution allowed it (Chiu, 2024). The negative perceptions student participants reported were markedly less than the positive. Students worried that the use of generative AI tools would make them lazy or

unmotivated to learn (Bonsu & Baffour-Koduah, 2023) and that the tools were not good enough yet to fully integrate into their workflows (Helm & Hesse, 2024).

Assessment. The final major theme discussed in the literature was around the effects of generative AI tools on student assessments. Students enjoyed and desired to use generative AI tools in their assessments (Elkhodr et al., 2023; Strzelecki, 2023; Wang et al., 2024), but many who participated in these studies recognized that this presented a problem for our traditional assessment methods (Chiu, 2024). For example, more than 50% of the 305 participants in the quantitative section of the Denecke et al. (2023) study foresaw severe impacts to assessments involving creating text, answering questions, programming, and creating code. The same study also recognized the challenges around fair assessment and grading. This was reaffirmed in a qualitative survey that highlighted how simply students were able to cheat on online exams using generative AI tools (Rahman & Watanobe, 2023).

Rather than the traditional methods like lecture, drill and practice, memorization, and writing papers, students suggested focusing on critical thinking, increasing student understanding, formative assessment, student-centeredness, and deep analysis to prevent AI-generated content from compromising student outcomes in the assessment process (Chan, 2023; Chiu, 2024). They offered some ideas for assessment like collections of deliverables (e.g., a paper plus video) or the integration of certain competencies within assessment like oral communication, prompt engineering, and fact checking to circumvent generative AI tool use (Chiu, 2024; Denecke et al., 2023; Dergaa et al., 2023; Essien et al., 2024; Tzirides et al., 2024; Wang et al., 2024). Findings from several

studies also included recommendations that assessments be built around generative AI limitations by evaluating originality (Chiu, 2024; Habib et al., 2024), accuracy (Essien et al., 2024; Michalon & Camacho-Zuñiga, 2023; Stojanov, 2023), creativity (Habib et al., 2024; Yusuf et al., 2024), and complexity (Denecke et al., 2023). Assessment will undoubtedly need to change in some ways in response to the popularization of generative AI tools. How they will change is yet to be determined fully.

Overall, students were supportive of institutions adopting generative AI, but they highlighted the need for regulations, policies, and limitations due to the "addictive" nature of the tools (Bonsu & Baffour-Koduah, 2023; Yusuf et al., 2024), concerns around being caught cheating (Schneider & Haried, 2024), and the potential for generative AI use to cause laziness (Bonsu & Baffour-Koduah, 2023). The findings of Chan (2023) emphasized that when integrating generative AI into institutions, student participants suggested that a balanced approach be used that recognizes both potential benefits and limitations of the technology. They also recommend that generative AI tools go through continuous evaluation, revision, customization, and optimization for them to be most helpful (Chen et al., 2023).

Rethinking Pedagogical Approaches

"With the integration of AI, the educational landscape is on the brink of a significant transformation" (Alammari, 2024, p. 10). In several studies, educators have called generative AI revolutionizing and unstoppable both in positive and negative ways (Alshraah et al., 2024; Sáez-Velasco et al., 2024). The literature is clear that stakeholders in education recognized the significant changes that are forthcoming in higher education.

Educators need to be prepared for a new future and become proficient with generative AI to continue being successful in the classroom (Muñoz et al., 2023). They also need to work to integrate generative AI into their teaching practices in a meaningful and responsible way to enrich learners' experiences and enhance student outcomes (Kolade et al., 2024). The future of higher education is still somewhat undecided, but with technology that is this disruptive, it is likely to change several aspects of teaching and learning as well as the role of the educator.

Experience and Uses Amongst Educators. Although it is sometimes assumed that students are the only group already using generative AI tools in higher education, educators also have experience using the tools in their personal lives and in their work. Ironically, many of the 12 educators who were interviewed in one qualitative study reported that they had used AI tools in the past without knowing it referencing applications like Alexa, Siri, and Fitbit (Kohnke et al., 2023). In a mixed methods study aimed at exploring the ramifications of integrating generative AI in higher education, 62% of the participants fall into one of the two middle categories of the technology integration framework: understanding and familiarity (Alammari, 2024). The more recent studies reported an even higher number of participants (82%) with familiarity and experience with generative AI tools (Yusuf et al., 2024). With the assumption that generative AI will be a ubiquitous part of life in the future (Essien et al., 2024), the recommendation is that educators experiment with and look for new pedagogical techniques to respond to technological advancements and change (Mishra et al., 2023). In addition, students continue to call for changes to curriculum that integrates generative AI

tools to better prepare them for the future, so educators need to gain experience with the tools.

Educators have already started using generative AI tools in their preparatory activities, writing, and teaching according to several studies. Lesson planning and creating teaching materials were some of the more common kinds of preparatory activities that educators have referenced in the literature (Bao & Li, 2023; Denecke et al., 2023; Rahman & Watanobe, 2023). Alshraah et al. (2024) conducted a quantitative survey of linguistics instructors and found that the vast majority of participants (92%) used generative AI primarily as a digital assistant to help them with assessments, quizzes, and grading. The same study showed that 86% of instructors also liked to use generative AI tools to tailor academic activities to their students' needs. Educators used generative AI tools in their writing similarly to how students use them for tasks like translation, grammar, creating tables, and streamlining tasks (Alshraah et al., 2024; Bao & Li, 2023; Kohnke et al., 2023). They also were integrating the tools in their teaching. A large-scale survey of 293 lecturers from forty institutions reported that 80% of educators found generative AI tools useful in general pedagogy (Alshraah et al., 2024). There were also applications in personalizing the learner experience (Kohnke et al., 2023), facilitating student-focused learning (Denecke et al., 2023), and answering student questions (Rahman & Watanobe, 2023). Most of the uses described in the literature were teacher-centered rather than student-centered, so there is room to expand and enhance educator uses with time and experience (Bao & Li, 2023).

Overall, the results of several studies suggest that educators were open to further integrating generative AI in their classrooms and recognized both the benefits and issues associated with that decision (Chan, 2023). They did, however, provide several recommendations to help ensure effective integration both institutionally and personally. First, several studies included suggestions for a balanced, strategic approach to integration (Alammari, 2024; Denecke et al., 2023). This involved educators not avoiding the tools but, rather, providing guidance and instruction to students to facilitate proper use (Habib et al., 2024). One study found that banning generative AI tools in higher education is not a reasonable or effective strategy (Kohnke et al., 2023), but using the tools required a knowledge of the benefits and limitations (Chan, 2023; Tlili et al., 2023). Authors also suggested that there should be collaboration between all stakeholders using the tools to ensure that they are used safely and effectively (Habeb Al-Obaydi et al., 2023). Educators desired guidance in using and integrating the tools including information about the limitations and risks associated and steps to manage those risks (Tzirides et al., 2024). Institutional policies around generative AI should be flexible rather than one-size-fits-all to allow for adaptation and growth along with the evolving tools, and educators should be taught strategies for using generative AI tools in the classroom (Bao & Li, 2023; Habib et al., 2024). In fact, several studies included conclusions that educators are not receiving enough training on use and strategy (Kohnke et al., 2023; Lee et al., 2024). Adequate support and training were considered critical to successful integration of generative AI tools, and this includes hands-on workshops,

professional development opportunities, and both technical training and guidance on ethical ramifications (Kadaruddin, 2023; Kohnke et al., 2023; Yeh, 2024).

One of the key facets of higher education that educators in literature anticipated will transform as a result of generative AI is assessment. According to one mixed methods study aimed at exploring the impact of AI on higher education, educators were concerned about traditional methods in assessment thinking that they will no longer be effective (Lee et al., 2024). The relative ease with which users can find answers and generate writing with a mere click of a button necessitated the rethinking and reworking of traditional assessment models to minimize the possibility of plagiarism (Chiu, 2024; Singh, 2023) and maintain an equitable learning environment (Rejeb et al., 2024). No longer can educators fully confirm student learning and performance and ensure they truly understand the content, and higher education institutions do not yet know how to fix that issue fully (Chaudhry et al., 2023; Lee et al., 2024).

Traditional assessments often focus on the product, output, and outcome (Chan, 2023), but with generative AI changing the effectiveness of the current methods, educators suggested that the focus should shift to process and assessing student learning throughout the term rather than just at the end (Mogavi et al., 2024; Singh, 2023). It is also recommended, through an analysis of social media content, that rather than focusing on the artifact produced, the focus should be on the learning outcomes and the process of meeting them (Mogavi et al., 2024). In several studies, there have been suggestions for how to approach assessment that account for the presence of generative AI. In the brick-and-mortar classroom, educators have the ability to administer closed book, in-person,

and oral exams as well as pen-and-paper essays, but these strategies are not appropriate in all settings or situations (Denecke et al., 2023). Other studies suggested assessments that were informal, project-based, scenario-based, and hands-on to increase the validity of assessments (Chiu, 2024; Habeb Al-Obaydi et al., 2023; Mogavi et al., 2024). Educators who participated in the mixed methods study conducted by Kadaruddin (2023) suggested that assessments should be more adaptive. Assessments, particularly exams, should also be more complex and should balance AI tools and human intelligence (Denecke et al., 2023; Singh, 2023; Tzirides et al., 2024). This will likely require educators to re-skill and upskill themselves (Singh, 2023). Buy-in amongst faculty and educators is critical to applying these new strategies as is budget and time. Although educators recognize the need to cultivate their own experiences and uses of generative AI tools, additional training and learning new skills are needed within that population.

Benefits and Concerns Amongst Educators. Within the literature, there was a common theme of duality between the benefits and concerns correlated with generative AI tools (Alammari, 2024). Educators understandably were wary of the obstacles associated with generative AI tools as they have had to adjust their practices in between the release of the open access ChatGPT and the release of policies and guidelines in their institutions. During this time when policy may have been unclear or missing altogether, educators were left to manage student use of these revolutionary tools without the guidance of their institution, and the experience has understandably caused negative attitudes (Alshraah et al., 2024; United Nations Educational, Scientific and Cultural Organization, 2023).

With regard to the potential benefits of generative AI tools in higher education, educators recognized many of the same benefits that were discussed by student participants including personalized support and feedback (Alammari, 2024; Chaudhry et al., 2023; Yusuf et al., 2024), automation of tasks (Denecke et al., 2023), the ability to ask questions anonymously (Chan, 2023), and faster access to baseline information (Tlili et al., 2023). In addition, in a large-scale online survey of linguistics lecturers, 93% of participants agreed that using generative AI tools in the classroom helped them improve student engagement (Alshraah et al., 2024). A large majority (92%) of participants in the same study said that generative AI tools assisted them with lesson planning and teaching proficiency, and more than 80% of participants said that generative AI tools have helped them improve pedagogical practices. This is echoed in the Chiu (2024) study, which offered the conclusion that generative AI has the potential to improve teaching. Generative AI tools also have the potential to help teach specific skills and plan activities for various topics (Bao & Li, 2023). Many of the studies that surveyed and interviewed teachers occurred early in the generative AI era, and there are undoubtedly additional benefits that educators have identified since that has yet to be included in the literature.

Similarly to students, concerns were reported throughout the literature alongside the benefits of using generative AI tools. One study analyzed tweets related to ChatGPT and reported that there were more positive than negative tweets, but that the negative tweets represented deeper, more serious concerns, and more of the positive tweets were about the novelty of the tool (Tlili et al., 2023). Many of the concerns educators had about generative AI tools mirrored those described by student participants. Examples

included concerns about accuracy (Alexander et al., 2023; Bao & Li, 2023; Habeb Al-Obaydi et al., 2023), biases (Denecke et al., 2023; Tlili et al., 2023), overreliance (Alammari, 2024; Lee et al., 2024), academic integrity (Alshraah et al., 2024; Rejeb et al., 2024), inequity (Tlili et al., 2023; Yusuf et al., 2024), and the potential for deterioration of basic skills (Chan, 2023). Educators, however, tended to have slightly different concerns around these larger topics. Plagiarism or cheating is mentioned as possibly the largest concern of educators, with educators being unsure how to grade papers that they are certain are written wholly by generative AI with no policy, guidance, or way to prove it. Detection of AI generated text was also a major concern of educators. Currently, there does not exist a consistent and accurate generative AI text detection tool (Rahman & Watanobe, 2023). The detection tools that do exist are not effective for text that is partially human written and partially AI written (Alexander et al., 2023). In a quantitative experimental study, Perkins et al. (2024) found that detection tools had a 39.5% accuracy rate for AI-generated text, and a 67% accuracy rate for detecting human written samples. When adversarial techniques were implemented in the same study, the accuracy rate dropped further to 22.14%. Detection tools were also easy to fool and tend to disproportionately flag text written by students for whom English is not their first language, according to several publications, both empirical and non-scholarly (Myers, 2023; Perkins et al., 2024). Educators are left to try and distinguish the text themselves, which has also been shown to be an unreliable technique (Alexander et al., 2023; Chaudhry et al., 2023).

In addition to detection issues, educators have reported anxiety around generative AI tools lessening the number of available jobs in their field (Alammari, 2024; Sáez-Velasco et al., 2024). They also feared that they will be replaced altogether by machines in the future (Kohnke et al., 2023). Fear of being replaced has led many educators to try and upskill themselves with generative AI, and this has caused additional types of stress. Kohnke et al. (2024) conducted a study of technostress amongst educators in the generative AI era and found that many were feeling anxiety around techno-complexity and techno-insecurity, which have paralyzed them in their classrooms. Educators also expressed concerns about the lack of human connection and social interaction when using generative AI tools. Skills like reading body language and inferring based on tone, they worry, will negatively affect communication in teaching and learning (Denecke et al., 2023; Sáez-Velasco et al., 2024). Many of these concerns would be mitigated with meaningful guidance from their institution, and this is unfortunately lacking for many (Denecke et al., 2023; Schneider & Haried, 2024).

Perceptions of Educators. The overall perceptions of educators who were surveyed and interviewed in studies were varied. Many recognized the transformative power of generative AI tools and their ability to motivate and engage students, but there were also worries and general pessimism reported in many studies (Lee et al., 2024; Muñoz et al., 2023; Tlili et al., 2023). Overall, the subject of generative AI in higher education was complex because educators had varying experiences with the tools both personally and professionally (Alammari, 2024). On the positive perceptions side, one study involving 350 students and educators suggested that the longer an educator had

been in the classroom, the more positive their outlook was about generative AI tools and their effects on student motivation and participation (Muñoz et al., 2023). Participants in the Alammari (2024) study reported mostly positive attitudes, and the authors surmised that this could be due to the ease of ChatGPT use, the perceived value of tools, and the rapid rise of ChatGPT spurring educators to familiarize themselves with the tools. Educators in other studies remarked on the potential of generative AI tools like ChatGPT to improve quality, efficiency, and personalization in their classrooms (Schneider & Haried, 2024). They also commented on the potential reduction of their workload but qualified their optimism with the suggestion that AI be used to support them in their work rather than displacing or replacing them (de Vincente-Yagüe-Jara et al., 2023).

Not all educator perceptions in the literature were positive, however. Some were disappointed that outputs were flawed while others found the outputs to be robotic with low complexity (Alexander et al., 2023). Around student use, educators tended to make assumptions that many students are using generative AI quite a bit in their work and that they are cheating on their work with the tools, but a handful of studies said that is an overreaction or overestimate (Lee et al., 2024; Singh, 2023). Participants in Lee et al. (2024) were open to students using generative AI tools in their work, but they required transparency about how the tools were used. They also required that their students edit outputs to maintain their human voice (Sáez-Velasco et al., 2024). Educator perceptions about generative AI, which were both positive and negative, are likely also evolving as more educators gain experience with the tools and how to best integrate them into the classroom.

Educator Roles and Skills Needed. Another key conversation in the literature was around the evolving role of the educator in response to the popularization of generative AI tools (Essien et al., 2024). Instructors hold an important responsibility toward students in this progressive time. First, instructors' communication with students is paramount to successful integration (Lee et al., 2024) as are communication rules (Mogavi et al., 2024). Not unlike other disruptive technologies, educators need to be committed to teaching students how to prompt generative AI tools (Wang et al., 2024) as well as teach the limitations, rules, and expectations associated with them (Mogavi et al., 2024; Singh, 2023; Tzirides et al., 2024). To be successful, this involves becoming familiar with the tools, re-imagining and re-designing assessments and being agile with their pedagogy (Foung et al., 2024; Mishra et al., 2023; Tzirides et al., 2024). It is also important that educators teach not only how to use generative AI tools but also why ethical use matters (Essien et al., 2024). Finally, because generative AI tools are novel, educators should encourage sharing and applying knowledge (Ngo et al., 2024), self-reflection (Tzirides et al., 2024), and the improvement of digital and AI literacy amongst students (Singh, 2023). The role of the educator in the generative AI era is dynamic, so the overall takeaway is that educators need to stay agile and open to flexing their pedagogical techniques as needed to meet student needs (Alammari, 2024).

Educators also need to be dedicated to updating their knowledge and skills (Bao & Li, 2023). They arguably have a more challenging job than students because they not only have to learn new skills and techniques; they also are responsible for teaching the skills to students. Some key skill sets are shared between educators and students

including AI literacy (Chan, 2023; Chiu, 2024), critical thinking (Denecke et al., 2023; Sáez-Velasco et al., 2024), and prompt engineering (Bao & Li, 2023). Generative AI tools have also been studied in relation to educators' TPACK knowledge domains. Alshraah et al. (2024) reported that most lecturers have TK of generative AI tools to enhance teaching and become a more proficient teacher. Conversely, other studies included reports that TK of generative AI could be improved in educators (Bao & Li, 2023). The same study found that educators were able to acquire TCK much easier than TPK and that training was needed to assist in the cultivation of these domains as they relate to generative AI. Participants in Kohnke et al. (2024) anticipated that they will need to move beyond regular TPACK and adopt pedagogical models that are specific to generative AI. The same study's conclusions postulated that improving TPACK in this way could lead to a reduction in technostress. Refining skills and adapting are not simple, and institutions need to commit to providing professional development opportunities and training faculty appropriately (Bao & Li, 2023; Chan, 2023).

Institutional Policies and Practices

"AI is necessitating systemic changes within higher education" (Kolade et al., 2024, p. 15). The changes that are needed require policymakers and decision makers to maintain openness and be willing to experiment to find the best way to integrate the tools. "In addition to students and educators, institutional responsibilities are discussed throughout literature as critical to the successful integration of generative AI tools in higher education. Overall, there were recommendations that institutions develop and

implement policies and guidelines for safe and responsible use of generative AI tools and that they develop training programs to educate faculty and students about responsible use.

The Role of the Institution in Integration. As was previously described, students and educators are both already using generative AI tools in the classroom, so institutions cannot ignore that they exist (Schneider & Haried, 2024). Several studies examined how institutions should approach generative AI tools through policy, guidance, and integration efforts, but they were not always in agreement on the best path forward. In multiple studies, there were recommendations for institutional policy to include the same balanced approach that students and educators suggested where potential benefits and concerns are both highlighted (Habib et al., 2024; Kelly et al., 2023; Yusuf et al., 2024). Singh (2023) suggested that institutions reevaluate the definition and notion of plagiarism to align with this new era. Another study concluded that institutions need to continuously monitor potential consequences of using generative AI tools to ensure students are benefiting from the tools within a controlled environment (Li et al., 2024). Although not a peer-reviewed article, McDonald et al. (2024) conducted an analysis of over 100 policy documents from various institutions and made several suggestions on a general approach to generative AI integration. In their analysis, they noticed that several institutions provided a mixed message in their policy and guidance statements. The authors reported that 27% of institutions both provide guidance for integration and recommendations to discourage use. Many policies analyzed in the same study also included a statement about embracing generative AI but also provide strategies to

mitigate student use. Faculty struggled with this dual message and found it challenging to both embrace generative AI and monitor its use.

Although some institutions are providing mixed messages through their policies, integration of generative AI tools is a necessity due to the popularity and pervasiveness of the tools in higher education. Studies have shown that attempting to ban generative AI tools does not work, and, besides, AI is expected to play an increasingly large role in many fields in the future, so bans are not in the best interest of students (de Vincente-Yagüe-Jara et al., 2023; Muñoz et al., 2023). Showing students how to use the tools and using them in a meaningful way is the better approach. When integrating generative AI tools into the classroom, there were several suggestions in the literature on considerations and strategies. First, privacy, security, equity, and accessibility for all students must always be considered when planning integration (Muñoz et al., 2023). Ethical frameworks for generative AI use should also be developed and provided to help guide users (Nguyen et al., 2024). Committees and boards should be formed with diverse groups of stakeholders to make decisions and monitor the integration and continued use (Bonsu & Baffour-Koduah, 2023; Chan, 2023). Through all these recommendations, the overall goal is for institutions to integrate generative AI tools in a responsible and ethical way and teach students likewise to prepare them for their futures (Tzirides et al., 2024).

Institutional Policies and Guidelines. Because generative AI tools are so widespread in higher education, many studies recommended that institutions create and continuously update policies to ensure responsible use (Kohnke et al., 2024). According to McDonald et al. (2024), many institutions already have policies in place, but the

content within them varies significantly. Ethics were discussed in over half of the 109 policies that were analyzed in that study, and 60% of institutional policies contained warnings about privacy and sensitive information when using generative AI tools. These critical policy inclusions were also mentioned in a mixed methods study of over 600 students and educators (Chan, 2023) and a qualitative study where Internet data were mined and analyzed (Rejeb et al., 2024). Other topics that are mentioned in the literature that ought to be included in institutional policies included the ethics of AI use (Chan, 2023), acceptable use (Chaudhry et al., 2023), equitable access and use (Essien et al., 2024; Foung et al., 2024), and AI literacy (Tzirides et al., 2024). In addition, it is recommended that policies be adaptable rather than static and that there be a focus on teamwork, leadership, empathy, and creativity with generative AI use (Chan, 2023; Kohnke et al., 2023). In addition to policies governing the integration and use of generative AI tools, it is also recommended that institutions provide students and educators guidelines for acceptable use (Ngo et al., 2024; Tlili et al., 2023). The development of policies and guidelines for faculty and students can help ensure that users know what they are doing and are using the tools to improve efficiency and quality in their workflows.

Training and Support. Another institutional theme that was mentioned throughout literature is the necessity for meaningful and comprehensive training to prepare educators and students to use generative AI tools responsibly, effectively, and ethically (Chan, 2023; Elkhodr et al., 2023). Throughout literature, authors made specific recommendations about what ought to be included in training and how the training

should be delivered. Several studies mentioned digital and AI literacy as necessary topics to be included in a training (Alshraah et al., 2024; Chiu, 2024). Teaching pedagogical skills relative to generative AI to faculty was also recommended (Kadaruddin, 2023). Kohnke et al. (2024) saw a need for training sessions that teach a range of generative AI skills from fundamental to advanced and called for customizable AI toolkits for faculty. All these skills and resources can be provided through workshops, professional development, and support options to facilitate a tech-savvy workforce and student population (Chiu, 2024; Foung et al., 2024; Kadaruddin, 2023). The combination of policy, guidelines for use, and training for educators and students are critical to any institutional integration plan, especially in this case where the technology can be so disruptive.

The perspectives, insights, and recommendations that were described throughout literature regarding students, educators, and institutions paint a picture of constant change, pressing needs, and groups that are unsure how to proceed with generative AI tools. Each of these groups plays an important part in integrating generative AI tools in higher education, and, although they are the most mentioned groups in the literature, they are not the only stakeholders involved. Administrators, operations executives, advisors, and finance professionals are also impacted by the popularization of these tools, amongst others. As this research will be focused on instructional design professionals, the next section will examine literature specific to that group and to the act of creating content for classrooms.

The Use of Generative AI in Course Content Creation

The literature that described generative AI use in instructional design, content creation, and lesson planning was noticeably less than that pertaining to education in general. Of the 34 articles on the topic that were identified, 15 only described case studies or described the authors' reflections on using generative AI tools, three were focused on K-12 settings, and nine were conference papers describing preliminary results of studies. Of the seven peer-reviewed, empirical articles published in scholarly journals that dealt with larger sample sizes, several were only tangentially related to true instructional design. Of those articles, one involved a comparison of AI-generated versus human written lesson plans, one involved rating prompts, one was specific to assessment writing, and one was an analysis of AI-generated lesson plans. One article most similar to the topic of this study examined the roles instructional designers play in generative AI integration. Another study that was similar to my own asked six corporate and educational instructional designers to participate in a reflective interview on their integration of generative AI tools in their work, but they did not focus solely on higher education. No peer-reviewed, empirical publication is specific to perceptions of higher education instructional designers on using generative AI tools in their daily work. Although there is a clear gap in the literature dealing with integrating evolving generative AI tools in online higher education instructional design, the articles that have been published contain some key themes that are useful to understanding the topic: strengths of generative AI tools in content creation, challenges associated with generative AI in content creation, and the roles humans and generative AI tools have in creating content.

Strengths of Generative AI in Content Creation

In nearly all of the scholarly literature, regardless of the specific application of generative AI, authors were quick to point out the potential strengths associated with using the tools in instructional design tasks (DaCosta & Kinsell, 2024). McNeill (2024) conducted a large-scale mixed methods survey, and in the preliminary findings presented at a conference found that a large majority of instructional designers see value in integrating AI into their processes with 66% of participants expecting moderate to high increases in future adoption and usage. Much of the anticipation around the integration of generative AI tools in instructional design are due to its overall usefulness, improvements in quality of content, diversity in idea generation and application, and the possibility of being more time efficient throughout the instructional design process.

The first main strength that was highlighted in literature was the overall usefulness of generative AI tools to instructional designers' processes. Generative AI tools had a way of broadening the thinking of instructional designers by acting as a "creative instigator" (Meron & Araci, 2023, p. 12) and suggesting new and innovative strategies they may not have used before (DaCosta & Kinsell, 2024). In a mixed methods study involving pre-service teachers, researchers found an enhancement in innovation and richness of content when generative AI tools were integrated into course design (Chen et al., 2025). Researchers who conducted studies where they used generative AI tools to create course content commented on the tools' ability to increase the capabilities of the human users (Dogan, 2025; Nagy et al., 2024) and promote critical thinking (Choi et al., 2024). Rister and Velez (2025) added to these findings by stating that some of the

key benefits of using generative AI tools in course creation were enhanced creativity and innovation. The ability of generative AI tools to break creative lulls and fatigue was also mentioned as being of great use to instructional designers (McNeill, 2024). These overarching strengths of using generative AI tools are seen across applications.

The quality of the generated content was another strength highlighted in the literature. In various studies where generative AI tools were used to create courses and materials, the resulting content was described as well-written (Davis & Lee, 2024), practical (Hu et al., 2024), structured (Mangaroska et al., 2024), and accurate (Mikroyannidis et al., 2024). In one study, generative AI tools were used to draft learning outcomes for a course, and the results were generally sensible, properly written, and aligned with appropriate Bloom's taxonomy verbs (Sridhar et al., 2023). Another study that involved the creation of a customized chatbot to write lesson plans, and the perceptions of its outputs were generally positive (Krushinskaia et al., 2023). Both of these studies were preliminary reports that were presented at conferences rather than published in a peer reviewed journal. In a peer reviewed publication that involved the use of generative AI tools to design a massive open online course, the authors and participants in the course also provided much positive feedback commenting on quality and effectiveness of the resulting content specifically (Morales-Chan et al., 2023). These positive attributes and experiences were not, however, consistent in all studies, and the quality of generated content often depended on whether the outputs were accepted as-is or iterated upon with additional prompting (Davis & Lee, 2024).

Another significant strength of generative AI tools was around diversity of ideas and content generation. Whether generative AI was used as a brainstorming partner or to draft content, the tools were capable of providing perspectives that vary from that of the instructional designer, and this combination of perspectives often yielded more creative and engaging content (DaCosta & Kinsell, 2024; Mikeladze, 2023; Morales-Chan et al., 2023). Generative AI tools were also able to personalize, customize, and adapt content to make it more accessible and beneficial for students (Karpouzis et al., 2024; Kumar et al., 2024; Mikroyannidis et al., 2024; Ryall & Abblitt, 2023; van den Berg & du Plessis, 2023). In addition, some studies highlighted the need for contextualization in delivering course content, which can be enhanced with generative AI tools (Mikeladze, 2023; van den Berg & du Plessis, 2023). Overall, the diversity of content and the ability to generate ideas that instructional designers may not have considered produced positive insights in the literature (Choi et al., 2024; DaCosta & Kinsell, 2024).

The theme of diversity in ideas goes hand in hand with the ability of generative AI tools to perform a wide variety of tasks critical to the instructional design process. For example, in several studies, generative AI tools were used to draft learning outcomes and objectives for lessons and courses. The resulting content garnered positive feedback with authors calling the outcomes and objectives sensible, sufficient, concise, clear, advantageous, and, in one case, exceptional (Choi et al., 2024; Houssaini et al., 2024; Hu et al., 2024; Morales-Chan et al., 2023; Sridhar et al., 2023). Researchers conducting other studies used generative AI tools to draft full courses then reflected on the process. In one such study, Tupper et al. (2025) found that ChatGPT was competent to plan and

design all the components of a course. This was echoed in the findings of Kozan et al. (2025) who listed multiple course elements like scenarios, images, and rubrics being amenable to generative AI tool use and Rister and Velez (2025) who expressed excitement that generative AI tools were able to provide on-the-spot support for all instructional design tasks. Another study found that generative AI outputs were better suited toward being a course plan or outline than a finished product, but the authors still found value in that (Okulu & Muslu, 2024). In other studies, generative AI tools were used to draft assessments and instructional prompts, templates, and other teaching materials, and the various authors touted the strength of generative AI tools in performing these tasks well (Choi et al., 2024; Küchemann et al., 2023; Meron & Araci, 2023). These studies just scratch the surface of what is possible when using generative AI within the instructional design process. As additional research is published, more innovative and novel applications will likely be evaluated.

Efficiency and time savings are also amongst the most mentioned strengths associated with using generative AI tools in the instructional design process (Kozan et al., 2025; McNeill, 2024; Ryall & Abblitt, 2023; Tupper et al., 2025). This includes time saving in developing individual materials (Davis & Lee, 2024; Kostikova et al., 2024; Kumar et al., 2024; van den Berg & du Plessis, 2023), planning and creating full lessons and courses (Amando-Salvatierra et al., 2023; Karpouzis et al., 2024; Krushinskaia et al., 2023; Meron & Araci, 2023; Morales-Chan et al., 2023), automating time-consuming tasks (Mikroyannidis et al., 2024), and finding information to support learning (Houssaini et al., 2024; Nagy et al., 2024). The potential savings in time discussed throughout the

literature have myriad benefits for instructional designers. With more efficient processes, tasks that are more intellectual, creative, and complex can be allocated more time (Ryall & Abblitt, 2023). Amando-Salvatierra et al. (2023) mentioned tasks like improving functionality, designing assessment, and facilitating student engagement as requiring more complex thinking and thereby more time. Bolick and da Silva (2023) added to this list with decision-making, higher order thinking, and other human judgment related tasks as being unable to be rushed. Other researchers posited that additional time could facilitate improved scaffolding of learning (Choi et al., 2024), more strategic lesson planning (Madunić & Sovulj, 2024), and deeper curricular and pedagogical efforts (Kumar et al., 2024). In being able to focus more time on these types of tasks, instructional designers could potentially produce higher quality content (Bolick & da Silva, 2023) and mitigate workload issues they often face (Choi et al., 2024; Nagy et al., 2024; Sridhar et al., 2023).

The strengths of generative AI tools within the instructional design process are widely acknowledged in the literature, but many of these studies had small sample sizes, which make generalizability of the results questionable. In addition, all of the studies cited paired any strengths with challenges and drawbacks that were experienced. Generative AI tools are not perfect and have well-documented limitations that restrain their integration in the instructional design process, many of which are described in the next section.

Challenges Associated With Generative AI in Content Creation

Nearly all the scholarly literature on the use of generative AI tools in content creation included a discussion of the challenges of the practice, some of which are similar to that of all educators and students. For example, the topic of accuracy in generative AI outputs was mentioned throughout. Several authors warned that instructional designers and educators need to be aware of the commonality of inaccuracies (Davis & Lee, 2024; Karpouzis et al., 2024; Kostikova et al., 2024; Kozan et al., 2025; McNeill, 2024; Tupper et al., 2025; van den Berg & du Plessis, 2023). They expanded their warning to specific types of inaccuracies that affect instructional designers in their work. The most common and perhaps most disturbing in academia is the falsification of resources and evidence to support responses (DaCosta & Kinsell, 2024; Davis & Lee, 2024; Kumar et al., 2024; Okulu & Muslu, 2024). Instructional designers found trusting these tools difficult due to this propensity (Madunić & Sovulj, 2024). In a different qualitative study that used one set of prompts to generate multiple courses, the authors highlighted generative AI tools' tendency to assign unreasonable tasks to be completed in a short timeframe (e.g., summarize a full textbook in one week) and produce inconsistencies in the outputs (Choi et al., 2024). This type of inaccuracy was also seen in the Okulu and Muslu (2024) study as the generative AI tool created timetables for task completion did not add up to the total amount given, and it added sections back into the course after they had been manually removed. The authors of this study noted that without real-life experience, generative AI tools made unrealistic estimations despite their theoretical knowledge. Inaccuracies are

just one type of challenge associated with generative AI tools that necessitate a human user to prompt and verify.

Also like the challenges associated with generative AI use by educators and students were concerns related to quality and ethics (Kostikova et al., 2024; Kumar et al., 2024; McNeill, 2024). Authors of studies on content creation and instructional design highlighted bias and discrimination in outputs as some of their major concerns, and this could be due to generative AI tools being trained primarily on Western data (Amando-Salvatierra et al., 2023; DaCosta & Kinsell, 2024; Kozan et al., 2025; Rister & Velez, 2025). Alongside biased outputs were those that are of poor or questionable quality (Choi et al., 2024; Kumar et al., 2024). In one study that asked prospective physics teachers to either use textbooks or generative AI tools to create assessments, the quality of the AI-generated assessments was rated below neutral by the participants (Küchemann et al., 2023). Another study involved an author-drafted prompt script that was used to generate course content that was, then, evaluated, and in this case, the authors found that much of the content required editing to get it to match the quality of human-written content (Madunić & Sovulj, 2024). Mikroyannidis et al. (2024) explored generative AI tools specific to distance education content creation and found the overall writing of the tools to be poor. This was echoed in another study that used generative AI to draft course learning outcomes finding them sensible but unfocused and often in violation of best practices (Sridhar et al., 2023). The overarching consensus of these studies was that the quality of generative AI responses was lower than human-drafted content and at such a level that they were not usable as-is in student-facing content (Lammert et al., 2024).

In addition to topics that were mentioned by educators, students, and institutions, the literature included several other challenges with using generative AI to create educational content like issues with securing data, the basic, non-creative nature of outputs, and issues of connections and appropriateness. The use of institutional data was a major concern when using generative AI tools to create course content (Nagy et al., 2024). Not only were there proprietary and copyright issues with using institutional data in generative AI prompts, but there were also concerns about student data and transparency (Amando-Salvatierra et al., 2023). Researchers recommended that instructional designers exercise caution when inputting content altogether as well as thoughtfulness with how outputs and results are used (Kumar et al., 2024). Regarding responses and outputs, studies involving instructional designers and creators of course content have criticized generative AI outputs as low tech, basic, and generic (Baytak, 2024; Meron & Araci, 2023). Choi et al. (2024) identified several of these weaknesses in the outputs calling them inconsistent, redundant, vague, and low level. Other studies described generative AI tool outputs as being repetitive (Davis & Lee, 2024), lacking in specific explanations (Lammert et al., 2024), and having low task specificity (Küchemann et al., 2023). Rutecka et al. (2025) also found that generative AI tools were not capable of creating a curriculum at the same quality level as a human because the task is too complex. In addition, the assessments generated in the Baytak (2024) study were mostly multiple-choice quizzes rather than something creative or technology infused. According to these studies, generative AI tools have a limitation when it comes to

creating detailed, specific, or creative course content, which fuels the argument that full automation of course design is not likely to be valuable (Mangaroska et al., 2024).

Finally, several researchers commented on the inability of generative AI tools to comprehend complex concepts, make connections, and use these connections to generate appropriate outputs. Davis and Lee (2024) conducted a case study where they used a series of prompts to create a course, then enrolled three education graduate students who evaluated the content. The findings highlighted several issues with repetition of information as the AI-generated course got deeper into the semester. The authors questioned the depth of information that was generated and how it connected both with other topics pertinent to the students' studies and with the topics presented earlier in the course. Another study yielded similar results as the course content they generated failed to connect with the subject matter and failed to incorporate context or history (Hu et al., 2024). Results highlighted issues with generative AI tools producing outputs that were far too advanced for the desired level as well as failing to cover the requisite topics for which it was prompted (Hu et al., 2024). Rutecka et al. (2025) confirmed this issue and found that more detailed prompts yielded less accurate or useful outputs. Contextual considerations were also a challenge in the Meron and Araci (2023) self-exploration and the Choi et al. (2024) study, which both stressed the importance of understanding the student and setting in instructional design. In another study, which analyzed AI-generated course content documents, the authors found that generative AI tools faced additional limitations regarding complex concepts (Okulu & Muslu, 2024), and it was postulated

that this could be a semantic and pragmatic issue with language as most machine learning algorithms are challenged by this aspect of language (Khademi, 2023).

Overall, the findings of instructional designers and other educational content creators are that generative AI tools could be useful in their work, but that humans are still needed to provide adequate prompting and evaluate and refine the outputs. Several studies on this topic stressed the concept of balance between automation and human touch to ensure that course content is understandable and is infused with critical elements like nuance and cultural sensitivity (Amando-Salvatierra et al., 2023; DaCosta & Kinsell, 2024; Kostikova et al., 2024). Balance can also be beneficial when considering potential negative perceptions of generative AI tools. Not all instructional designers and course content creators have the same mindset regarding these tools and their use in education, but with a balanced integration, negativity may be lessened and the perception that these tools are a kind of cheat could be mitigated (Nagy et al., 2024; Tokita, 2024). To be truly helpful in instructional design, generative AI tools need additional training and iteration to mitigate some of these challenges and capitalize on strengths (Khademi, 2023).

Roles of Humans and Generative AI Tools in Content Creation

A third key theme found in the literature centered around the assumption that in this new era, generative AI tools and humans could be seen as partners in the instructional design process. If this is the case, there is a need to rethink methods used and the players involved. There is consensus within the instructional design and research communities that generative AI tools are not capable of replacing humans currently (Amando-Salvatierra et al., 2023; Dogan, 2025; Kostikova et al., 2024; Meron & Araci,

2023; Okulu & Muslu, 2024). They should be considered auxiliary and supportive tools rather than autonomous (DaCosta & Kinsell, 2024; Mikroyannidis et al., 2024; Morales-Chan et al., 2023; Sridhar et al., 2023). Both humans and generative AI tools have strengths and weaknesses, and to best incorporate the tools into the process, the strengths of each partner should be leveraged including the distribution of knowledge, ensuring quality and ethicality, and verifying outputs for accuracy and appropriateness (Ch'ng, 2023).

Knowledge is one area where the balance between human and machine is critical. Generative AI tools have access to a vast amount of information based on their training data, but the tools do not possess wisdom, understanding, or experience that are common to humans. To be most efficient with generative AI tools in content creation, the human user must, first, understand the best way to use the tools. This includes knowledge of how generative AI tools work as well as knowledge of how to prompt the tools to produce the best results (Chen et al., 2025; Mikeladze, 2023). In their case study analysis, Madunić and Suvulj (2024) recommended that instructional designers experiment with the functionalities of generative AI tools to better understand their capabilities and limitations. Other researchers concurred and suggested that expertise in prompting was required to use the tools most effectively in instructional design (Davis & Lee, 2024; Meron & Araci, 2023; Tupper et al., 2025). Deep knowledge of the subject matter on which the content is based was also recommended when using generative AI tools to develop course content (Choi et al., 2024; DaCosta & Kinsell, 2024; Mikeladze, 2023; Okulu & Muslu, 2024). While the vast amounts of information generative AI tools

possess are useful to instructional designers, the human touch is still required to ensure that course content is accurate and appropriate.

Human expertise is also needed to get the most out of generative AI tools regarding quality (Dogan, 2025; Madunić & Sovulj, 2024; Meron & Araci, 2023). As was evident in the sections about strengths and challenges in using generative AI tools in instructional design, there is disagreement among researchers as to the quality of AI-generated materials. In a study that involved creating a generative AI media selection tool, the authors found that the tools tended toward variability and unpredictability (DaCosta & Kinsell, 2024). Instructional designers who participated in the study needed to ensure alignment with the needs of the project. Another study that used one set of prompts to create multiple courses suggested that human interventions and modifications were necessary for the content to be reliable and trustworthy (Choi et al., 2024). Human intervention was also associated with improved creativity, integrity, rigor, and writing style (Mikroyannidis et al., 2024; Nagy et al., 2024). Ultimately, the instructional designer is responsible for the quality of the content that is placed in a classroom regardless of whether generative AI tools were used, so care must be taken (McNeill, 2024).

Finally, and perhaps most importantly, human users are responsible for evaluating and verifying all generative AI outputs prior to placing it in any classroom (Kozan et al., 2025; Madunić & Sovulj, 2024; van den Berg & du Plessis, 2023). Kostikova et al. (2024) reinforced the fact that the results generative AI tools produce were not perfect; checking, reviewing, analyzing, adjusting, correcting, and optimizing both written

content and sources remain critical parts of the role of instructional designers (Choi et al., 2024; Kumar et al., 2024; Madunić & Sovulj, 2024). In several studies, the importance of fact-checking and editing were highlighted as essential to ensuring alignment, quality, and accuracy (Madunić & Sovulj, 2024; McNeill, 2024; Mikeladze, 2023). In their case study, Rister and Velez (2025) also found issues with outputs and emphasized the need for human oversight and discretion throughout the course development process. These actions were also recommended to infuse the human voice in course content (Lammert et al., 2024) and to ensure that the course content meets learners' needs (van den Berg & du Plessis, 2023).

Generative AI tools are competent at the tasks they are overtly designed to accomplish (Meron & Araci, 2023). They are good at producing words. They are not as competent with other tasks that are simple for instructional designers and educators like understanding the needs of learners, analyzing challenges in content design and delivery, and designing scaffolded activities (Hu et al., 2024). In the small amount of scholarly literature that exists on integrating generative AI tools into the instructional design process, it is clear that successful integration requires balance. Generative AI tools can and should be used to enhance and support the work of instructional designers, but they are not capable of replacing human insight, experience, or intuition. They should, therefore, be approached with caution keeping in mind their limitations and challenges (Amando-Salvatierra et al., 2023).

Summary and Conclusions

This chapter contained a thorough examination of the literature describing perceptions and use of generative AI tools by various groups of stakeholders. Chapter 2 began with an overview of the TPACK framework and an explanation of how each of the knowledge domains applies to instructional designers' use of generative AI tools. The following section, which begins the literature review, followed AI from its inception to current applications detailing milestones and critical innovations that have propelled AI to its current state. Although this section does not pertain directly to the topic of this study, understanding the evolution of AI over time helps to illustrate the speed with which current versions of the tools are changing. In the third major section, the influence of generative AI in higher education was analyzed. The literature on this topic included perspectives and recommendations for students, educators, and institutions. In the final section, the research that examined the use of generative AI tools in instructional design, content creation, and lesson planning was synthesized. These two final sections, together, serve as the basis for exploring the perceptions of online higher education instructional designers on the challenges and successes that they are experiencing in integrating rapidly evolving generative AI tools in course design and development.

The first main theme found in the literature, the influence of generative AI in higher education, contained three main subthemes: generative AI in student learning, rethinking pedagogical approaches, and institutional policies and practices. Literature pertaining to higher education students contained an overall positive attitude about the integration of generative AI tools in education (Chan, 2023; Tlili et al., 2023; Tzirides et

al., 2024), but each study balanced positivity and potential benefits with various concerns (Chan & Hu, 2023; Elkhodr et al., 2023; Schneider & Haried, 2024) and caution about limitations of the tools (Denecke et al., 2023; Essien et al., 2024; Li et al., 2024; Stojanov, 2023). Students were motivated to adopt and use generative AI tools in their course work (Alammari, 2024; Yeh, 2024), but there were significant concerns about doing so due to accuracy (Michalon & Camacho-Zuñiga, 2023; Yusuf et al., 2024), bias (Denecke et al., 2023; Essien et al., 2024; Rahman & Watanobe, 2023), and academic integrity issues (Chaudhry et al., 2023; Habib et al., 2024) amongst others. To counter some of these issues, authors stressed the importance of training students on responsible and ethical use of generative AI tools (Foung et al., 2024; Kolade et al., 2024; Sáez-Velasco et al., 2024) as well as the need for developing digital and AI literacy in students (Chan, 2023; Chiu, 2024; Elkhodr et al., 2023).

Literature that focused on educators contained similar anticipated benefits and concerns, although results of educator-focused studies contained a more hesitant attitude than that of students. Anticipated benefits reported by educators include the capacity to personalize learning (Kadaruddin, 2023; Schneider & Haried, 2024; Yusuf et al., 2024), improve pedagogy (Alshraah et al., 2024; Chiu, 2024), automate tasks (Alammari, 2024; Denecke et al., 2023), generate feedback (Chan, 2023; Chaudhry et al., 2023) and produce ideas with relative ease (Sáez-Velasco et al., 2024; Tlili et al., 2023). Concerns raised by educators outweighed the benefits identified. Many mirrored those mentioned by students like accuracy (Alexander et al., 2023; Bao & Li, 2023; Habeb Al-Obaydi et al., 2023) and bias (Denecke et al., 2023; Mogavi et al., 2024; Tlili et al., 2023), but there

were several concerns specific to educators highlighted throughout the literature. These include the fear of being replaced (Alammari, 2024; Kohnke et al., 2023), issues with students cheating using generative AI (Alshraah et al., 2024; Rejeb et al., 2024; Yusuf et al., 2024), concerns over detection of AI use (Alexander et al., 2023; Chan, 2023; Chaudhry et al., 2023), and the loss of the human touch and voice (Denecke et al., 2023; Sáez-Velasco et al., 2024). Overall, educators saw the potential for generative AI tools to be useful both for themselves and for students (Alshraah et al., 2024; Sáez-Velasco et al., 2024; Tlili et al., 2023), but they highlighted the importance of a strategic integration plan that focuses on balancing positives and limitations of the tools (Alammari, 2024; Chan, 2023; Denecke et al., 2023). They also stressed that additional research and development is needed on generative AI tools (Kohnke et al., 2024; Ngo et al., 2024) as well as comprehensive guidance and policy (Elkhodr et al., 2023; Tlili et al., 2023).

Institutional involvement was also discussed in several research articles as regulation and policy often influence how and when generative AI tools can be used in higher education. Like both students and educators, the overall recommendation was for a balanced approach to generative AI integration for institutions (Nguyen et al., 2024; Yusuf et al., 2024). The potential benefits that generative AI tools possess cannot be ignored by institutions (Schneider & Haried, 2024), but strong policy and guidance are needed to encourage responsible and appropriate use (Chaudhry et al., 2023; Yusuf et al., 2024). Recommendations for what ought to be included in institutional policy varied across studies, but most suggested that training (Alshraah et al., 2024; Chiu, 2024; Elkhodr et al., 2023), ethics (Chan, 2023; Nguyen et al., 2024), equity (Essien et al.,

2024; Foung et al., 2024), and security be included (McDonald et al., 2024; Ngo et al., 2024). It was also suggested that additional research be conducted on the use of generative AI tools and how use affects student progress to ensure that integration is beneficial to students rather than detrimental (Li et al., 2024; Ngo et al., 2024).

In analyzing the literature related to higher education as a whole and examining generative AI tool use through the lenses of students, educators, and institutions, the field is in a state of flux. The overall attitude toward the tools was more positive than negative, but there still exists some debate in several areas of education. For example, there is no consensus on how best to use the tools or encourage responsible use within the learning process. This is likely due to the various limitations and challenges associated with current generative AI tools and stakeholders' reluctance to encourage use when the tools are evolving so quickly. This same feeling was present in research studies that were specific to instructional design and content creation. Three major themes were identified related to this aspect of higher education: strengths of using generative AI tools, challenges associated with using generative AI tools, and the roles of humans and generative AI tools within content creation.

It is discussed throughout the literature related to educational content creation that generative AI tools have the potential to improve upon the well-established instructional design process (DaCosta & Kinsell, 2024; Madunić & Sovulj, 2024). Although just how instructional designers can capitalize on the tools' strengths was debated, there are several potential benefits that were carried throughout the literature. Generative AI tools, when used to supplement instructional designers, can create time savings and efficiencies

(Bolick & da Silva, 2023; Davis & Lee, 2024; Kostikova et al., 2024; Kumar et al., 2024; McNeill, 2024; Tupper et al., 2025), strengthen the creativity of course content (Choi et al., 2024; DaCosta & Kinsell, 2024; Mikeladze, 2023), increase the quality of content (Hu et al., 2024; Mangaroska et al., 2024; Morales-Chan et al., 2023), and allow for more personalization and customization (Karpouzis et al., 2024; Mikroyannidis et al., 2024; Ryall & Abblitt, 2023). With each of these potential benefits, however, researchers were quick to point out that generative AI tools are not capable of replacing humans in the instructional design process (Amando-Salvatierra et al., 2023; Kostikova et al., 2024; Meron & Araci, 2023). They recommended that the tools only be used to support and strengthen human work (Morales-Chan et al., 2023; Sridhar et al., 2023).

Challenges associated with using generative AI tools in content creation were another key theme found in the literature. Although securing data (Amando-Salvatierra et al., 2023; Kumar et al., 2024) and integrating into the process were key challenges (Nagy et al., 2024; Tokita, 2024), those relating to generating usable outputs were the most mentioned. Like other educational stakeholders, there were major concerns about the accuracy of generative AI outputs amongst instructional designers (Choi et al., 2024; DaCosta & Kinsell, 2024; Davis & Lee, 2024; van den Berg & du Plessis, 2023). Researchers highlighted the crucial need for instructional designers to verify the truthfulness of outputs and make edits as needed (Kostikova et al., 2024; Lammert et al., 2024; McNeill, 2024). Outputs that are too basic (Choi et al., 2024; Küchemann et al., 2023; Meron & Araci, 2023), overly complex (Choi et al., 2024; Hu et al., 2024), or uncreative (Baytak, 2024; Kumar et al., 2024; Meron & Araci, 2023) were other

challenges experienced by instructional designers. Overall, there was a hesitancy amongst instructional designers to automate parts of the instructional design process or potentially lose some of the human touch (Choi et al., 2024; Nagy et al., 2024; Sridhar et al., 2023; van den Berg & du Plessis, 2023).

The final subtheme identified relating to generative AI tools in content creation is around the distribution of roles between humans and the tools in the instructional design process. Both instructional designers and generative AI tools have strengths and weaknesses, and researchers have concluded that the most successful integrations leverage the strengths of both (Kumar et al., 2024; Mangaroska et al., 2024; Nagy et al., 2024). While generative AI tools can recall mass amounts of information and draft text quickly (Krushinskaia et al., 2023; Meron & Araci, 2023; Nagy et al., 2024), they lack human experience and creativity (Baytak, 2024; Okulu & Muslu, 2024; Tokita, 2024). Humans may not have the vast memory of generative AI tools, but their ability to make connections (Davis & Lee, 2024; Hu et al., 2024; Tupper et al., 2025), scaffold (Choi et al., 2024), synthesize (Nagy et al., 2024), and infuse human qualities like creativity and nuance exceeded that of the tools (Kumar et al., 2024; Meron & Araci, 2023; Ryall & Abblitt, 2023). To be most effective, researchers recommended that instructional designers use caution when integrating generative AI tools into their work and capitalize on the strengths of the tools.

Although there were several studies identified that discussed instructional design and the creation of content using generative AI, there were still several gaps that the literature does not yet examine. Of the articles and conference papers related to content

creation, only four used instructional or learning designers as participants in the research. The first study was a qualitative exploration of the role instructional designers play in the integration of generative AI tools in higher education institutions and how they use the tools in practice (Kumar et al., 2024). The second study used a mixed methods approach to explore the current usage of generative AI tools amongst instructional designers (McNeill, 2024). The third study was a multi-case study examining corporate and educational instructional designers' integration of generative AI into their work (Kozan et al., 2025). The fourth study used a mixed methods approach to investigate how learning designers are adapting to the changes brought about by advances in generative AI technology (Ryall & Abblitt, 2023). This study was designed to explore the perspectives of instructional designers on the challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development, an area not yet thoroughly examined. Additionally, while one article related to generative AI and instructional design was grounded in the PCK domain of the TPACK framework (Hu et al., 2024), no studies have used the technological domains to investigate instructional designers' perspectives. In this study I addressed this gap by employing qualitative methodology and using the TK, TPK, TCK, TPACK, and XK domains of the TPACK framework as a lens to explore instructional designers' perspectives.

Chapter 3: Research Method

The purpose of this qualitative study was to explore the perceptions of online higher education instructional design professionals on what challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development, and how these experiences have shaped their current perceptions about teaching and learning. To fulfill this purpose, I used the TK, TPK, TCK, TPACK, and XK domains of the TPACK framework to structure interview questions, which were used to gather information from instructional design professionals. In this section, I will describe the research design and my role as a researcher in this study. The methodology section will follow, where I detail the participant selection strategy, selection criteria, and procedures for selecting participants. I will also describe instrumentation, recruitment, data collection, and data analysis. This chapter concludes with a discussion of trustworthiness and ethical considerations that I considered within this study.

Research Design and Rationale

The research questions I developed to guide this study were as follows:

RQ1: What are online higher education instructional design professionals' perceptions of the challenges they are experiencing in integrating rapidly evolving generative AI tools in course design and development?

RQ2: What are online higher education instructional design professionals' perceptions of the successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development?

RQ3: How have online higher education instructional designers' experiences with generative AI tools formed their current perceptions about teaching and learning?

With the popularization of generative AI tools and their heavier integration into higher education, instructional designers are often integrating them into their daily work. In doing so, they are experiencing successes and challenges in using the tools. This is the central phenomenon I examined in this study. I chose to study this phenomenon using a basic qualitative design. This type of generic qualitative inquiry was an appropriate design when the researcher is interested in subjective opinions and reflections on experience and already has an understanding of the topic that they want to explore more deeply from participants' perspectives (Percy et al., 2015). I considered conducting this study using other common qualitative approaches, but none were suitable for the topic and intent. Ethnography involves finding cultural meanings, usually through immersion, which was not appropriate for this study (Ravitch & Carl, 2021). Case studies are in-depth investigations into a single instance or event (Percy et al., 2015), but the intent of this study was not to focus on one single case or experience. Phenomenology involves investigating lived experience, but the focus of my study is on cognitive processes or the essence of the phenomenon more so than the actual content of individual reports, so this design was also not suitable (see Merriam & Tisdell, 2015). With a basic qualitative design, I was able to investigate instructional designers' reports of their experiences, attitudes, opinions, and recommendations around generative AI use, which aligns well with the purpose of this research (see Percy et al., 2015).

Role of the Researcher

In this study, I was not an observer or a participant in the research but, rather, the research designer, recruiter, interviewer, coder, and analyzer. As the recruiter, I was solely responsible for identifying participants and scheduling interviews. In my role as interviewer, I developed and applied the interview protocol, including informed consent, semistructured interview questions, and spontaneous probing questions. From there, I was responsible for transcribing data from the interviews, familiarizing myself with the data, and engaging in coding and labeling. The final part of my role was to analyze the codes, draft and re-draft clusters and themes, and write up a full analysis to address the review questions.

While I am employed by an educational institution where my previous role was primarily in course content creation, participants for this study were recruited more broadly. Participants with whom I have a previous professional relationship were not under my direct supervision, and I ensured that any existing relationship was not cause for conflict or bias. My former role within the instructional design field did not conflict with the collection of information from instructional designers. It did, however, serve to provide a deeper understanding of the methods included within the instructional design process and the skills and knowledge required to create high-quality course content.

Methodology

In the following section, I will explain the methodology choices I have made in this study. To begin, I will describe the selection of participants, including the inclusion criteria, the number of participants, and the procedures for recruitment. This will be

followed by an instrumentation section where I detail the interview protocol information and rationale for the interview questions.

Participant Selection

For this basic qualitative study, the population was individuals who engage in instructional design activities as the main focus of their job at either an online higher education institution or in support of such institutions. There were three criteria that I used to select participants for this study. Participants needed to self-select based on meeting the following inclusion criteria: (a) their main job function was in course content creation, (b) they worked for an institution of higher learning that was either fully online or partially online or a company that supported online higher education institutions, and (c) they had meaningful experience in using generative AI tools in course design and development activities in multiple ways or for different types of course elements. Participants were identified through the Walden participant pool and my professional network and were contacted via email and direct message, where I sent informed consent information with the initial communication.

Purposive sampling, a strategy that involves the intentional pursuit of individuals who will help the researcher understand the problem and research question, was employed to recruit participants (Cresswell & Cresswell, 2018). This strategy was chosen not for representativeness, but rather to gather the richest and most detailed information possible (see Thomas, 2017). Ravitch and Carl (2021) discussed common sampling strategies used in qualitative research and explained that because qualitative researchers are interested in participants who have particular knowledge of the subject matter, they

should be deliberate in their selection rather than random. Patton (2015) also discussed the importance of selecting participants who can provide rich and in-depth information. Because I chose to question instructional design professionals about their generative AI use, it was critical that the participants I selected have this type of experience, making purposive sampling appropriate.

I conducted semistructured interviews with 10 participants to work toward an analysis that is in-depth, rich, and complex. Although this study explored an emerging technology that is still evolving, I found that a sample of 10 participants was adequate for fully exploring the topic and that the information gleaned from these 10 interviews was rich and complex. Data saturation is often touted as the benchmark for determining sample size in qualitative research; however, this study focused on information power, as described by Braun and Clarke (2022). First proposed by Malterud et al. (2016), the concept of information power was built upon the premise that when a sample contains more strong information, fewer participants are needed. Information power is dependent on several factors, including the aim of the study, the sample specificity, theoretical underpinnings, interview quality, analysis strategy, and the connections between these factors. As I conducted interviews and analyzed the data, I continuously kept these factors in mind to determine the ultimate sample size.

Instrumentation

For this study, I created an interview protocol to systematically gather data and to ensure consistency throughout the semistructured interviews (see Burkholder et al., 2020). The interview protocol included logistical information like name, date, start, and

end times, and details about the recording. It also included an introductory statement that explained the purpose of the study to participants and explained informed consent procedures. Screening questions followed the introduction. With these questions, I hoped to further ensure that participants are knowledgeable enough in generative AI use in instructional design tasks and that they are not imposter participants, or individuals who exaggerate their experiences or fake their identity as an instructional designer (see Roehl & Harland, 2022). Screening questions were followed by interview questions and probes, which are detailed in Table 2, and a conclusion statement thanking the participant and explaining the next steps. The full interview protocol is included in Appendix B. I conducted each semistructured interview using Microsoft Teams and recorded each through the platform. As a backup, I also used an external digital recorder in case of platform malfunction. I only had to use the backup device to clarify content in one of the interviews. In this circumstance, the participant had a poor Internet signal, which led to issues in recording and transcribing within Microsoft Teams.

Table 2

Interview Questions Aligned to Conceptual Framework

IQ	Question	TK	TCK	TPK	TPACK	XK
IQ1	I'd like to start out with you just telling me some stories about times you used generative AI tools to create course content. Let's start with a positive story.	X	X	X	X	X
IQ2	Now, let's think about the other side of the coin. Can you share a story of a time that using generative AI for creating course content went wrong.	X	X	X	X	X
IQ3	In your experience, how have personal or institutional perceptions affected your generative AI use? This could be perceptions of the tools themselves or of AI-generated content.					X
IQ4	What is your opinion on the impact of the integration of generative AI tools on the ID process as a whole?			X		
IQ5	What is your experience with determining when to not use generative AI tools within the course design process? Like are there certain tasks you definitely would not use generative AI tools?				X	
IQ6	In your experience, how have external factors like policies or accreditation affected your use of generative AI in course content creation?					X
IQ7	What are your thoughts on the impact of generative AI tools on traditional pedagogical approaches or teaching strategies?			X		
IQ8	What is your experience with using generative AI tools as a way to deepen subject area knowledge?		X			
IQ9	Explain whether you think the integration of generative AI tools led to any changes in the subject area content that is included in course work? For example, if AI can generate code with better accuracy than a human, do we still need to teach coding?		X			
IQ10	Do you think that access to or expertise in subject area knowledge has changed with generative AI tools becoming more widely used? For example, do you think that generative AI tools are contributing to more people being knowledgeable about more topics or is it having the opposite effect?		X			
IQ11	Some educational experts think that to effectively integrate technology into the classroom, one needs to understand the technology, the subject area, and effective ways to teach the content and how all these things work together. With the integration of generative AI in the instructional design process, how do you see the three elements interrelating?				X	

Note. IQ = interview question

As the researcher, I drafted all interview questions and probes independently. Each question was related in some way to my interpretation of the TK, TPK, TCK, TPACK, and XK domains of the TPACK framework as it related specifically to generative AI technologies in the instructional design process. The TPACK framework was initially developed to describe the various domains of knowledge that educators need to effectively integrate technology into the classroom (Mishra & Koehler, 2006). In this study, I extrapolated the domains to instructional designers who are a part of an educational team in some institutions and applied it to one particular technology, generative AI. When analyzing the existing TPACK framework, I synthesized framework-related applications as they were described in scholarly literature and also described the framework domains through the lens of this study, instructional design, and generative AI as the technology to be studied. These interpretations were used to draft the interview questions.

The concept of validity is related to the concept of truth (Burkholder et al., 2020). When applied to research, the validity of content means that the tools used to collect data accurately assess what the researcher intends to assess. To ensure that the interview questions measure what I intended them to measure, I structured them to align directly with the TK, TPK, TCK, TPACK, and XK domains of the TPACK framework. Each question drew language directly from my interpretation of their application to this study. In addition, I intentionally drafted the questions to touch upon a variety of topics within each domain. This was in an effort to spur participants to think across varying experiences, thereby gathering information that is more comprehensive. In using the

interview protocol and the probes designed to redirect and refocus participants on the intended content, and conducting a pilot interview, content validity was established. All interview questions and probes went through review cycles with my dissertation chair to ensure alignment with my study and the research questions.

Procedures

In this section, I will explain the procedural details of this study. To begin, I will explain recruitment procedures, including the various ways I will identify potential participants, how identified participants were contacted initially, and how informed consent was acquired. This will be followed by the procedures for participation, focusing on the interview details. Finally, I will explain the data collection procedures, including information about the proposed timeline for interviews and recording procedures.

Procedures for Recruitment

The data for this study were gathered from instructional design professionals who work in online higher education. Following Institutional Review Board (IRB) approval (#06-05-25-1120213), my first phase of recruitment involved advertising the need for participants in the Walden University participant pool. The second recruitment phase, which took place simultaneously with the first phase, was conducted through the LinkedIn network. At present, I am connected with several instructional design professionals within this network. I sent messages directly to those individuals asking both for their participation and for the names of additional instructional designers who may be a good fit for the study. The final recruitment phase was connected to the previous phase, as I contacted potential participants who were identified through direct

messages, as well as instructional designers recommended by LinkedIn. After reading the recruitment information, if they were interested in volunteering to be a participant in the study, instructions directed them to complete a questionnaire asking for a work email, requesting interview preferences, and screening for inclusion criteria. I contacted each potential participant via their work email to set up a time for the interview and send informed consent materials. Using a work email was necessary to reduce the likelihood of imposter participants being interviewed. Participants' completion of the questionnaire and email confirmation indicated consent to participate, which I also confirmed within the interviews themselves.

I transcribed the interviews and coded continuously as I moved through the interviews rather than starting only when I had completed all the interviews. This allowed me to make some initial notes about topics and interesting thoughts from participant to participant to potentially touch upon in probing questions. It also assisted me in determining when sufficient information power was achieved.

Procedures for Participation

Once participants consented to participate, I contacted them via email to schedule an interview time and ensure they do not have any concerns or questions. Each interview lasted between 30-60 minutes and was comprised of semistructured interview questions and probes related to their experiences and opinions on using generative AI tools in course content creation. Interviews were conducted using Microsoft Teams and were recorded both through the platform and with a second external recording device. During the interview, I posed each drafted open-ended question and used probing questions to

ensure that rich and complex data were acquired and that participants fully answered the questions. I conducted my interviews in a conversational and casual manner to gain trust with my participants and help them feel more comfortable sharing their experiences. In engaging with participants in this way, I intended to motivate them to provide more thoughtful and accurate information about their experiences in using generative AI tools.

At the conclusion of each interview, participants were thanked and asked whether they had questions or any other thoughts to add per the interview protocol script. I did not anticipate that any follow-up interviews would be needed, but I still asked permission to contact the participant if I had questions or needed to clarify any language or information with them. I did not need to follow up with any participants in this way.

Procedures for Data Collection

During the data collection process, I planned to conduct one or two interviews of online higher education instructional designers per week depending on recruitment and scheduling. Some weeks, I was able to follow this plan, but during others, I had either more than two or none at all. After the first interview, I met with my chair to discuss how the interview went and how I could improve. I also began the familiarization phase of data analysis immediately, which included listening to the audio multiple times while reading and correcting the transcripts. I also began initial coding of the transcripts immediately following each interview.

Preparing, editing, and redacting within the interview transcripts are an important detail that indicates a good qualitative study (Cibilis, 2019). As I conducted each interview, I extracted transcripts using the Teams platform and uploaded the text to

Microsoft Word. I took the software-prepared transcript and, while listening to the audio, corrected inaccuracies and added punctuation as needed. I also improved the clarity of the transcript by removing filler words and adding brackets to indicate voice changes, emotion, unintelligible words, pauses, and random phenomena that occurred. I redacted all confidential information in the transcripts like participant names, organization names, and geographical areas and formatted the document for readability using breaks and spacing. During this process of listening to the audio and cleaning the transcript, I also made memos and interpretive notes in my reflexive journal spreadsheet to review later on during data analysis.

Alongside the interview recordings and transcripts, I kept a reflexive journal as an additional audit trail and analysis tool. Included in the journal was a record of all research activities as well as notes and ideas that occurred to me throughout the process (see Braun & Clarke, 2022). The reflexive journal allowed me to continuously reflect on the process, refine my thinking, and evaluate my own role within the process. Data collection was completed in less than 2 months.

Data Analysis Plan

For this basic qualitative study, I followed Braun and Clarke's method of reflexive thematic analysis (2022). This method involved a series of nonlinear phases through which the researcher moves to make sense of the data collected. In the first phase, I familiarized myself with the data by immersing myself in it. This meant reading the transcripts multiple times and listening to recordings while making notes. The second phase involved assigning codes and code labels to the data. In reflexive thematic analysis,

codes can apply to any interesting or potentially meaningful text as it applies to the research questions. Although Braun and Clarke (2022) discouraged keeping a formal codebook, I still kept a log of all code labels as they were developed as well as their full definition and scope. The process of defining or labeling codes has been found to be a clarifying activity for many researchers (Ravitch & Carl, 2021) and the act of keeping a running list or paper trail of codes can be useful in organizing and reorganizing data as needed (Saldaña, 2021). Phase 3 was the generation of candidate themes based on the codes and code labels. These are described by Braun and Clarke (2022) as clusters of data that the researcher perceives as connected and related to the research questions. Although the candidate themes may not all be used in the final analysis, they were for this study. In the next phase, I worked to assess the candidate themes and their fit within the full data set as well as within the larger story of the analysis. During this phase, the central ideas within each theme were analyzed against the codes as were the relationships between the candidate themes. Within this phase, I used claim tables and show and tell tables similar to those described in Rockmann and Vough (2024). Phase 5 involved further iteration and connecting of themes. It is during this phase where I finalized the wording of the theme, wrote a theme description, and created a short title for each theme (see Braun & Clarke, 2022; p. 108). This phase was a fine-tuning of the analysis as well as a place to label the themes in preparation for the final write up, which was Phase 6. In the final phase, I told the story of the data along with my own interpretation as an answer to the research questions. While each phase of this method is demarcated, Braun and Clarke heavily emphasized that these phases are not linear and that moving backward and forward

between phases is normal and encouraged. During my data analysis, I did move both forward and backward often through phases to ensure alignment and think through interpretations. Another key component of this approach was the researcher and their interpretations. For this reason, I kept a reflexive journal throughout all phases noting initial reactions, thoughts, ideas, emerging patterns, and any other notes that could potentially hold significance within the reflexive thematic analysis process. In doing so, I gained a better understanding of my own role in generating data (see Harland, 2025) as well as the "why" behind my thoughts and meaning-making (see Braun & Clarke, 2022).

I planned to check and recheck themes and interpretations often throughout the data analysis process for data that does not fit cleanly within any cluster or theme or even contradict the themes that I developed. These types of data are called discrepant data, outliers, negative cases, divergent data, or disconfirming evidence. Ravitch and Carl (2021) suggested that researchers view discrepant data as a way to challenge interpretations, preconceived notions, and candidate themes in an effort to deepen and complicate analysis. Because this study was focused both on challenges and successes that instructional designers experienced, all codes fit within the clusters and themes, so I did not need to manage discrepant data.

I used multiple methods to familiarize, code, and develop candidate themes. Paper copies, highlighters, and pens allowed me to familiarize myself in an immersive way with the data. As I noticed interesting quotes and patterns, I jotted notes in the margins and began making connections in that way. I did not, however, only use paper copies and notes. I also used Microsoft Excel to separate out data, organize it, and make it movable

and searchable, particularly when drafting candidate themes and organizing themes into a full write up of findings. I also used Dedoose software to further organize and analyze my data.

Trustworthiness

Although qualitative research does not align well with the quantitative notions of validity, reliability, and replicability, the trustworthiness of study must still be ensured. Considering and planning strategies for ensuring trustworthiness were critical to the overall rigor of this study as well as assuring that the study is conducted in an ethical manner. Measures of trustworthiness that I accounted for include credibility, transferability, dependability, and confirmability.

Credibility

For qualitative research, Burkholder et al. (2020) defined credibility as a parallel concept to interval validity in quantitative research. The authors explained that for a study to be credible, the findings must be believable based on the data that was presented. Ravitch and Carl (2021) expand upon that definition by adding that credibility is the researcher's ability to "take into account all of the complexities that present themselves in the study" (p. 168) as well as to explore and make sense of complicated patterns in the data. Burkholder et al. (2020) recommended that qualitative researchers use the following strategies to improve the credibility of qualitative research: "prolonged engagement, persistent observation, peer debriefing, negative case analysis, progressive subjectivity, member checking, triangulation, and reflexivity" (p. 91) For this study, I attempted to use the triangulation strategy by analyzing claims from multiple participants and from

multiple times of data collection. This subset of triangulation is considered data triangulation according to Morgan (2024). For example, for each theme identified, I analyzed whether that theme was seen across multiple participants. Because generative AI tools are evolving rapidly, I also considered triangulating based on the time of interview. While triangulation across participants was helpful to my analysis, triangulation based on time of interview did not yield any significant patterns. The second strategy I used to establish credibility was peer debriefing. To accomplish this, I engaged with another qualitative researcher to discuss the progress of the study as well as tentative findings, as recommended by Burkholder et al. (2020). Finally, I used the strategy of reflexivity by documenting notes and memos that discuss my own experiences, subjectivity, biases, affiliations, and perceptions as they related to the study (see Braun & Clarke, 2022). In implementing these three strategies, I ensured that my study was legitimized from a credibility standpoint.

Transferability

Transferability involves providing such detailed context in a study that readers can independently assess whether and to what extent the findings can be applied to other settings or situations (Braun & Clarke, 2022). Related to the quantitative concept of external validity, transferability is the way that qualitative research can be applicable in other contexts (Ravitch & Carl, 2021). Burkholder et al. (2020) recommended the strategies of thick description and maximum variation to establish transferability. For this study, I used Braun and Clarke's (2022) approach to qualitative reflexive thematic analysis, and while these authors advised against the use of the term "thick description,"

they did recommend that researchers focus on contextualizing data extracts or providing rich context to explain the significance of the data and the interpretation of it. In addition to implementing this strategy, I also applied the maximum variation strategy to the selection of my participants. This means that I intentionally selected participants with diverse viewpoints (see Burkholder et al., 2020). As all participants were online higher education instructional designers, I could only diversify by place of employment, job function, experience with generative AI tools, and personal differences, but this strategy still strengthened the transferability of my study that others can then apply to their own setting or population.

Dependability

Houghton et al. (2013) defined dependability as the stability of the data. Similar to the concept of reliability in quantitative research, dependability necessitates that researchers have a valid argument for how data are collected and that the research question is being answered through the completion of the study (Ravitch & Carl, 2021). Burkholder et al. (2020) recommended that the strategies of triangulation and inquiry audits be used to establish dependability. In this study, I employed triangulation as described in the credibility section. I also employed an audit trail strategy where I kept detailed record of how data were collected, how clusters and themes were formed, and how decisions were made with regard to analysis. This strategy helps to inform the reader of the rationale behind decisions (Houghton et al., 2013).

Confirmability

Finally, confirmability is the concept that, although the qualitative researcher admits subjectivity, the study is as neutral and bias-free as possible. Confirmability means that if another researcher was provided with the same data, they would arrive at the same conclusion (Burkholder et al., 2020). This measure of trustworthiness contradicted many of the tenets described by Braun and Clarke (2022). From their constructivist/interpretive epistemological position, subjectivity is seen as a primary tool in the process, and the concept of bias is not seen as a disadvantage. However, reflexive thematic analysis involves heavy reflexivity, which is described as a way to establish confirmability. In this study, I used a reflexive journal throughout the process to improve my own self-awareness and analyze the data through the lens of my preconceived notions and personal beliefs (see Houghton et al., 2013). Burkholder et al. (2020) also recommended that I maintain an audit trail as described in the dependability section, which I also employed.

Ethical Procedures

Ethical thinking, according to Braun and Clarke (2022), is integral to all elements of research practice. Following ethical procedures is also a part of establishing the trustworthiness of a research study. For this study, I adhered to all procedures necessitated by the Walden University IRB aimed at protecting research participants. Prior to identifying participants or collecting any data, I submitted the proper application to the IRB including all of the details of my study, and, following approval, used the IRB

standards to ensure beneficence or that participants' welfare was focused on as well as avoiding harm (see Ravitch & Carl, 2021).

As this study was relatively low risk to participants, many of the ethical procedures I addressed were related to treatment of participants and treatment of data. Participants were recruited exclusively through the Walden University participant pool and through social media channels using the preapproved IRB invitation. I ensured that participation was low-pressure and completely voluntary and that employing organizations of participants were not aware of who did and did not participate. I shared a study-specific consent form with all participants before the interview allowing them time to read and understand the study and took time prior to the interview to discuss any questions or concerns regarding consent with participants. Burkholder et al. (2020) explained that all informed consent forms should reflect respect for persons, beneficence, and justice, all of which I ensured were present. I made it clear that participation was voluntary and that participants were able to withdraw themselves at any time. All interviews were conducted through Microsoft Teams from a private and secure environment. I used the Microsoft Teams platform to record each interaction with cameras turned off during recording. After the first interview, I prepared a transcript and checked its accuracy using the recording. I shared the recording and transcript for the first interview with my committee chair for review and feedback at this time.

Throughout data collection, transcript creation, and analysis, I ensured that all files were kept in password protected files that were only accessible by my committee chair and me. Ravitch and Carl (2021) explained that confidentiality can be complicated

due to the nature of technology and social media, so additional care must be taken. I maintained confidentiality by removing the identities of all participants immediately and replacing them with pseudonyms both for the participants and for their workplaces as needed. Files were stored with pseudonyms as the file names to further mask the identities of participants for 5 years, at which time, the files will be permanently deleted.

Summary

In this chapter, I described the design of my research study and the rationale behind my choices related to research design. After that, I explained my role within the study as a research designer, recruiter, interviewer, coder, and analyzer. In this section, I also explained my place within the instructional design community and how that influenced my research. In the next section, methodology, I explained the procedures for selecting participants including inclusion criteria, number of participants, and rationale for these choices. I also included a section on instrumentation that detailed interview questions and the interview protocol for this study. Procedures for recruitment, participation, and data collection was the next section, and in it I described details about informed consent, data collection events, and debriefing. A data analysis plan was also presented in this section. Following that, I explained the importance of trustworthiness and, specifically, ensured that credibility, transferability, dependability, and confirmability were defined and accounted for. The final section was on ethical procedures. To end this chapter, I explained the various safeguards for human participants that I made allowance for as well as various ethical concerns I anticipated and addressed.

Chapter 4: Results

The purpose of this qualitative study was to explore the perceptions of online higher education instructional design professionals on what challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development, and how these experiences have shaped their current perceptions about teaching and learning. To fulfil this purpose, I conducted semistructured interviews with instructional design professionals who have experience with using generative AI tools in creating course content. To frame this study, I used a subset of the domains of the TPACK framework developed by Mishra and Koehler (2006) to answer the three RQs aligned to the study. The three RQs were an exploration of the challenges and successes that instructional designers have experienced when using generative AI tools, as well as the way those experiences have shaped their current perceptions of teaching and learning.

RQ1: What are online higher education instructional design professionals' perceptions of the challenges they are experiencing in integrating rapidly evolving generative AI tools in course design and development?

RQ2: What are online higher education instructional design professionals' perceptions of the successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development?

RQ3: How have online higher education instructional designers' experiences with generative AI tools formed their current perceptions about teaching and learning?

In this chapter, I will describe the study setting and how data were collected. I will explain my process of analyzing the data, then report the results of the interviews. I will also explain evidence of trustworthiness for the study.

Setting

The setting for this study was completely online. Participants were recruited using direct messaging on LinkedIn and the Walden participant portal. All of the participants who were recruited for this study resided within the United States, but they were spread out geographically. Because of the locations of the participants, all interviews were conducted through Microsoft Teams; therefore, there is no true setting for this study. Several conditions may have affected the interpretation of the study results. First, each participant had varying levels of training and experience with generative AI tools. Participants also have different employers who either encourage or discourage the tools to a degree. Each of these conditions could alter participants' experiences and perceptions and thereby my interpretations of their responses.

The participants for this study included six male and four female professionals with varying titles and geographic locations in the United States. Although all participants engaged in instructional design work for online course content, their roles and approaches differed, and their varying institutional standards led each to approach generative AI tools in slightly different ways. Specific job titles and other participant information are included in Table 3. These and many more factors also contributed to each participant's overall perceptions of generative AI tools.

Table 3

Participant Demographics

Participant Number	Job Title	Institution	Level of Adoption
P1	Instructional Designer	Small private STEM/business university	Early Majority
P2	Instructional Designer	Community college system with 23 campuses	Innovator
P3	Sr. Manager, Learning Experience Design	Large online university	Early Adopter
P4	Instructional Designer	Large public university with online options	Early Adopter
P5	Instructional Designer	Large public university with online options	Early Majority
P6	Learning Experience Designer	Large online university	Late Majority
P7	Senior Learning Experience Designer	Small hybrid university	Late Majority
P8	Instructional Designer	Community college with hybrid options	Early majority
P9	Learning Experience Designer	Large public university	Early Majority
P10	Sr. Manager, Learning Experience Design	Medium healthcare—focused online university	Late Majority

P1 worked as an instructional designer for a small private institution that focuses primarily on science, technology, engineering, and mathematics (STEM) and business programs. This person had a background in English and held a doctoral degree. In analyzing their responses, I have characterized this person as an early majority adopter based on the diffusion of innovations theory. Throughout the interview, this person touted the capabilities of generative AI tools within the instructional design process. They, however, expressed worry and concern about several consequences of the tools becoming more integrated. They worried about the capabilities of future generations, who will

likely use generative AI tools, as well as the future of higher education. Overall, P1 projected a somewhat cynical attitude toward the tools and their place in the classroom, with multiple quotes about replacing humans with machines and issues with academic integrity.

P2 worked as the sole instructional designer for a community college system with 23 campuses and has a doctoral degree in instructional design. This individual was an innovator with generative AI tools and shared that they enjoyed experimentation with any and all generative AI tools. Unlike P1, this person was optimistic and excited about generative AI tools and how the tools may supplement their lack of a team. The community college system for which this person works does not prescribe a particular tool or use that is most appropriate but rather allows their staff to decide on applications. This has been motivational for P2, who said they "went in with eyes wide open, feet fully in the deep end" with generative AI tools. This participant held high ethical and moral standards with generative AI, more so than some other participants who had not experienced nearly as many tools.

The next participant, P3, had a background as a high school teacher who transitioned into higher education and now works as a Senior Manager of Learning Experience Design. This person, who held an Ed.S. degree, managed a team of learning experience designers and did course development work as well. As an early adopter in an institution that limited employee use of generative AI tools, P3 was a "closet user" of generative AI tools at first, who has since become an outspoken advocate within their institution. This participant recognized the paradigm-shifting effects of generative AI

tools in higher education and used their position to educate others and find efficiencies that can be shared across their team.

Another doctoral degree holder, P4, was an instructional designer for a large, well-known university focusing on developing engineering programs. With a background in English and a doctoral degree in curriculum design, this person was an early adopter of generative AI tools. P4 spoke openly about the challenges of developing course content in fields that are not one's specialty, and this has propelled their adoption of generative AI tools. This participant differs from the others in that they are a proponent of creating AI agents to complete discrete tasks, and this was rewarded in their institution when agents are shared across teams. P4 was an experimenter and someone who sees value in using generative AI tools to save budget and time, which is deeply encouraged in their institution.

P5 was also an instructional designer who worked for a large, well-known university, but had a background in writing and a master's degree. Possibly the most colorful participant in this study, P5 held deep moral and ethical convictions that slanted their opinion of generative AI tools as well as certain uses of the tools. They spoke openly about the many ways they use generative AI tools but also provided several cautions about ethical issues like consumerism, environmental impact, social problems, and theft of original work. P5 seemed somewhat torn about generative AI tools, between wanting to find efficiencies within their work and maintaining their deep social consciousness.

Senior learning experience designer, P6, was the next interview subject. They hold a master's degree as well and have a background in writing. A late majority adopter, P6 was initially very affected by their employer's limitations and cautions around using generative AI tools in student-facing course content. This institution, a large online university, eventually licensed a secure generative AI tool, then encouraged employees, including P6, who have since integrated generative AI into their processes. P6 was still somewhat wary of certain generative AI tool uses and had some trepidation about the potential for flattening creativity. Because they were a late adopter, they also seem somewhat behind other participants in terms of AI literacy and social consciousness.

P7 was a senior learning experience designer with a Ph.D. who worked for a small university with hybrid options. This small institution was still in the early stages of generative AI adoption, which contributed to the late majority adoption status of P7. Of the 10 participants, P7 seems to be the most cautious and minimal generative AI tool user, and they were the only participant who expressed the need for more research on the consequences of generative AI tool adoption. Throughout the interview, P7 focused more on warnings and negative outcomes than on potential benefits, displaying their hesitancy and uncertainty with the tools.

Another instructional designer, P8, held a doctoral degree and had been in educational technology and instructional design for their entire career. They were an early majority adopter despite working for a community college that is only moderately AI-integrated. Like P3, P8 was also a secretive generative AI user at first who only became open once their institution endorsed the tools. P8 seemed very concerned with

ethical considerations like accessibility and equity for students. They did still see a need for a new approach to assessment but recognized that these considerations need to be reflected in how higher education moves forward.

P9 was a learning experience designer for a large, well-known university who held a master's degree. Unlike other participants, P9 worked collaboratively on a large team of learning experience designers for this moderately integrated institution and adopted generative AI tools in the early majority. P9 was very pragmatic about generative AI tools, their influence in higher education, and how instructional designers need to approach teaching skills, but they also spoke openly about the value of the human touch and of expertise. Overall, P9 seemed sensible about generative AI tools and focused on finding effective ways to integrate them.

Finally, P10 was a senior manager of learning experience design for a mid-sized healthcare-focused university. Holding a doctoral degree and having a background in information science, this person made some interesting comments about their own AI adoption level. While normally an innovator or early majority adopter, with generative AI, they fell into the late majority category. This was due, in part, to mixed messages from their institution, and feeling threatened and fearful of the tools at first. P10 spoke about having to catch up with colleagues who adopted earlier and the regret they feel at falling behind. They, overall, recognized the need to adapt across all aspects of higher education and felt a mix of both excitement and fear of the future.

Data Collection

In preparation for data collection, I submitted an application to the IRB and was granted approval on May 5, 2025. I began recruiting immediately. Recruitment was done through multiple channels. I advertised on the Walden participant pool and used the LinkedIn social media platform to send direct messages first to connections who may meet the criteria for the study. Once I exhausted potential participants from my personal connections, I sent direct messages to potential participants who were recommended by LinkedIn and to those who declined to participate due to not meeting the criteria. I was also contacted by several participants as a result of my advertisement on the Walden participant pool website. I conducted a total of 10 semistructured interviews using Microsoft Teams. I used the embedded recording and transcription tools within Microsoft Teams and used a small external device as a backup recorder. The interviews lasted between 28 and 56 minutes, and I used a reflexive journal to record post-interview thoughts after each interview. The 10 interviews were conducted per the specifications described in Chapter 3. The only aberration in the interviews was a brief pause during P10, where the participant had to answer the door. All other interviews were uneventful.

Virtual interviews were conducted using Microsoft Teams between June 10, 2025, and August 5, 2025. For each interview, I followed the interview protocol's open-ended questions and added additional prompts and probes to build upon participant responses and gather more information. Table 4 shows the dates when interviews were confirmed, the dates of interviews, and the length of each interview.

Table 4

Interview Dates and Duration

Participant number	Date interview confirmed	Interview date	Length of interview
P1	6.9.25	6.10.25	34 minutes
P2	6.10.25	6.16.25	38 minutes
P3	7.7.25	7.8.25	28 minutes
P4	7.4.25	7.10.25	48 minutes
P5	7.8.25	7.11.25	56 minutes
P6	7.3.25	7.15.25	41 minutes
P7	7.9.25	7.18.25	36 minutes
P8	7.17.25	7.21.25	26 minutes
P9	7.24.25	7.31.25	32 minutes
P10	8.4.25	8.5.25	32 minutes

To prepare each interview for data analysis, I exported the transcript that was automatically prepared by Microsoft Teams and immediately de-identified each to protect confidentiality. I went through each transcript and made obvious edits without the audio first, then I listened to each interview while reading through the transcript a second time to further refine and correct any inaccuracies.

Data Analysis

Data analysis for this study was conducted using the reflexive thematic analysis techniques described by Braun and Clarke (2022). This method is made up of six nonlinear phases, which I followed using a mix of low and high technology mediums. In this section, I will describe how I managed each phase and the technology I used to support my analysis.

Phase 1: Familiarizing Self With the Data Set

In this phase, Braun and Clarke (2022) recommended that the researcher becomes "deeply and intimately familiar with the content of the dataset" (p. 35) I internalize information best through reading text, so I chose to, first, use the transcripts to read through the interviews. After reading through several times, I also listened to the audio and followed along with the transcripts to further ruminate on the content. While doing this, I described my thoughts and reactions to the interview content in my reflexive journal. I used Microsoft Word exclusively for this part of my analysis.

Phase 2: Coding

The second phase of reflexive thematic analysis involves coding of individual data excerpts. After each interview, I conducted a first round of coding by splitting the text into individual thoughts and copying each thought into a Microsoft Excel spreadsheet. Once the entirety of each interview was copied over, I did a round of open coding on each just to further orient myself to the data. I followed this protocol of immediate coding for each interview. Once all interviews were conducted, I went through each interview again with the codebook to recode and combine codes where necessary. I recognized at this stage that I had a tendency to overcode my data and that I would need to work to refine my codes to a more manageable number. I decided to also use the Dedoose software during this phase to further organize and analyze my data. As I input each individual transcript into Dedoose, I conducted another round of recoding and combining and lessened the number of codes significantly in this way.

Phase 3: Generating Initial Themes

In Phase 3, I began to organize my codes into clusters based on similarities and how they might answer the research questions. During this phase, I was still recoding and combining codes in Dedoose, but I found the clustering difficult in the software. For this reason, I exported all of the codes to a Microsoft Excel spreadsheet and then to a printout to reorganize and think through. Also at this point, I determined that there was a significant amount of data that did not answer either of my two original RQs. I decided that I needed to add a third RQ to adequately finish my study, so I submitted a change request to the IRB on July 28, 2025 and received approval for the change on July 31, 2025. I came up with 10 different clusters during Phase 3. Three clusters aligned to RQ1; Four clusters aligned to RQ2; Three clusters aligned to the new RQ3 that was added.

Phase 4: Developing and Reviewing Themes

Phase 4 of the reflexive thematic analysis process involves continuing to develop and review the themes. When I first drafted the 10 clusters in phase 3, I identified them as themes, but in discussing with my chair, I realized that these were clusters that I should use to formulate themes. During this phase, I was still reorganizing and combining codes. Braun and Clarke (2022) encourage this and remind their readers often that the phases of reflexive thematic analysis are meant to be nonlinear. Alongside this coding work, I was looking for additional patterns and ideas that thread across clusters and was able to construct five themes from the clusters. Microsoft Copilot assisted me in wordsmithing the themes to ensure that my ideas were clear, comprehensive, and thoughtful. During

this phase, I also used Dedoose and Microsoft Excel in addition to paper printouts and post-it notes for analysis.

Phase 5: Refining, Defining, and Naming Themes

In preparation for writing up my themes, I needed to structure the data in a way that was easily manipulable and useful, so I decided to use a storyboard approach in Microsoft Excel. I also integrated some of the recommendations that Rockmann and Vough (2024) presented to help organize my quotes into tables and determine which ones to use in the narrative. I color-coded the sets of codes to keep them organized and added narrative around the ideas to help inform my write up in the next phase. At this time, I was ensuring that the codes were presented in an order that fit well within the story I was creating to drive the themes. I also drafted theme descriptions and titles during this phase to further illustrate the storyline from the participants. To keep my titles interesting and engaging, I decided to use Microsoft Copilot to brainstorm. I confirmed that the five themes and 10 clusters I had drafted still aligned well to the storyline.

Phase 6: Writing Up

For the final stage of the processes, Phase 6, I used my storyboards to draft narrative. While much of the preprepared narrative from the storyboards ended up being used in the final draft, some of the storyboard material served more as a starting point to generate better, more clear thoughts and weave together the codes and quotes. The narrative that I drafted in Phase 6 is included in the Results section.

Results

In this section, I have organized my results by theme, which are aligned to this study's RQs. Themes 1 and 2 align to RQ1; Theme 3 aligns to RQ2; and Themes 4 and 5 align to RQ3. The theme information is presented in Table 5. For each of the themes identified, I will provide a definition of the theme, explain participant quotes to support the theme, and share my interpretations.

Table 5

Theme Information

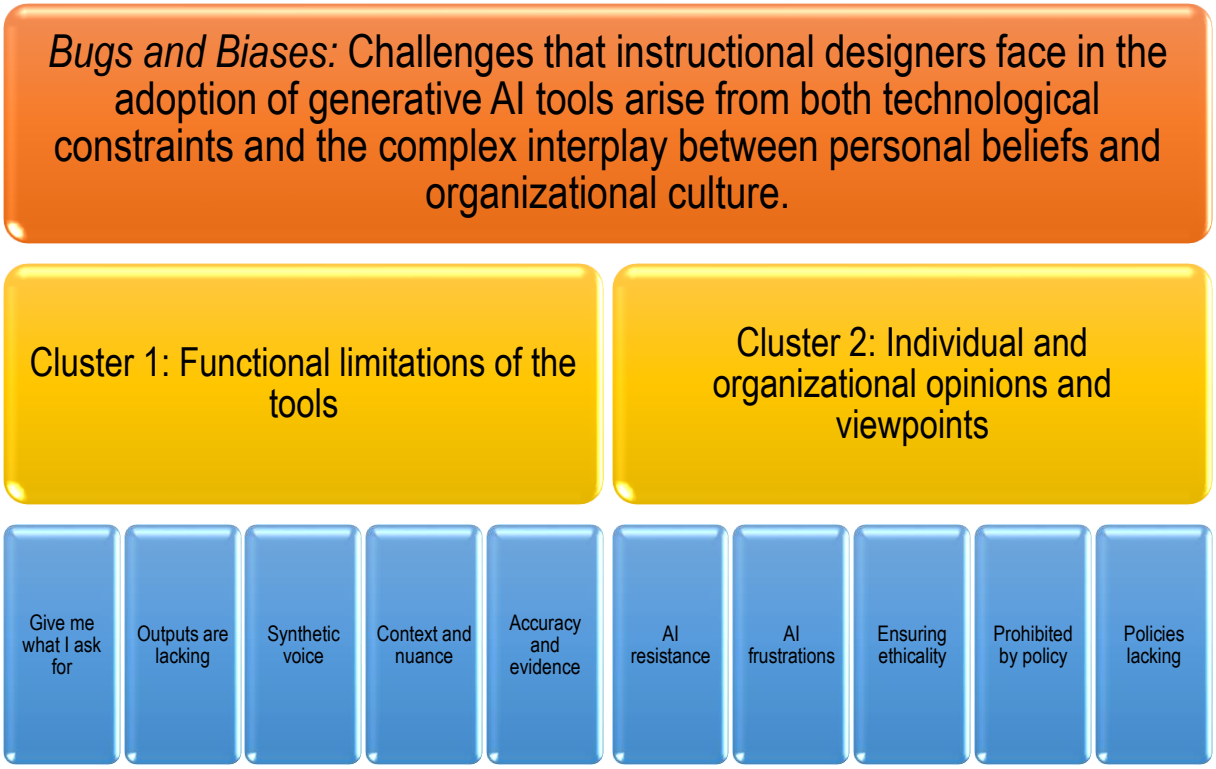
RQ	Theme number	Short theme title	Full theme
RQ1: Challenges	1	Bugs and Biases	Challenges that instructional designers face in the adoption of generative AI tools arise from both technological constraints and the complex interplay between personal beliefs and organizational culture.
	2	Existential AI Crises	The integration of generative AI tools into education has sparked complex philosophical debates about the nature of learning, authorship, and the value of human intelligence.
RQ2: Successes	3	Sparking Success	While process streamlining sparks initial success with generative AI tools, instructional designers feel most empowered when given time, space, and motivation to explore based on their personal needs.
RQ3: Perceptions of teaching and learning	4	Rewiring the Brain	Effective integration of generative AI by instructional designers requires the continuous development of best practices informed by diverse experiences, cautions, and evolving perspectives.
	5	The Undefined Future	Higher education is at a crossroads, with instructional designers grappling with generative AI's potential to transform roles and redefine well-established educational practices, owing to the critical need for continued education and research.

Theme 1: Bugs and Biases

The first theme, Bugs and Biases, is aligned to RQ1. This theme is all about the challenges that instructional designers face in the adoption of generative AI tools and how they arise both from technological constraints and the complex interplay between personal beliefs and organizational culture. Two clusters make up Theme 1: functional limitations of the tools and individual and organizational opinions and viewpoints, and 10 codes between these two clusters contributed to the development of the theme. These codes and clusters are detailed in Figure 4.

Figure 4

Theme 1 Code Tree: Bugs and Biases



Theme 1 Definition

Throughout each of the interviews that I conducted, the participants talked openly about the many challenges that they experienced in using and adopting generative AI tools in their daily work. As I assigned codes to the various excerpts, it was clear that, first, functional limitations were a huge hindrance to the participants. When the tools do not work, they are not helpful. There were also challenges stemming from how individuals and institutions view both generative AI tools and their outputs. These two sets of challenges, when combined, illustrate how instructional designers struggle to know when and how generative AI tools are acceptable to use.

There are two clusters of codes within this theme, which are functional limitations of the tools and individual and organizational opinions and viewpoints. Functional challenges mentioned by participants include, first, struggles to get the outputs that are desired. This is a result of generative AI tools producing nonsensical content or content that was not asked for or the tools failing to comprehend what is being asked for in the prompt. Another challenge several participants described was that outputs lacked quality and/or detail. Despite being prompted specifically and properly, participants described several outputs as skeletal, insufficient, and not smart. The next challenge that contributed toward this cluster was what I call "synthetic voice." Generative AI tools have a particular way of drafting text that is conspicuous, and not in a good way. This robotic and uninspired tone, when noticed by students, is problematic. Similarly, when educational professionals notice synthetic voice in student work, it can raise issues of academic integrity. The next set of challenges stem from the inability of generative AI tools to understand nuance or fill in contextual gaps. Tool users must explicitly define nuance and context for the tools, which can be time consuming. Finally, and arguably most distressing, is the tendency for generative AI tools to produce inaccurate or unsubstantiated information without evidentiary support. In a higher education context, accuracy is of the utmost importance.

The second cluster of codes deals with individual and organizational opinions and viewpoints. Beginning with individual attitudes, the majority of participants mentioned that they and their colleagues either were or are resistant to using AI tools in their work for various reasons. They also expressed extensive frustrations that stem from generative

AI tool use specific to time waste, capabilities of the tools, and formatting. This is followed by trepidation caused by ethical dilemmas. When discussing organizational viewpoints, participants struggled both with restrictive policies and with a lack of policy. Restrictive policies, which come both from external bodies and from institutions, impede instructional designers' work, but having no policy in place is just as challenging. A lack of policy leaves instructional designers questioning the appropriateness of the tools, whether they will be reprimanded by leadership, and whether they should keep their tool use secretive.

Data to Support Theme 1

When instructional designers use a tool, especially a tool that has received such attention and media coverage, they expect it to work. However, generative AI tools have a tendency to produce text that is not aligned with what the user needs or is far outside the parameters of the prompt. Because the tools do not provide an explanation as to how the text is generated, this can leave instructional designers feeling confused and frustrated with nonsensical or misaligned outputs. In this study, this phenomenon was coded as give me what I ask for. P9 described a situation when generative AI was challenging in this way, stating:

> It just kind of came up with things that didn't make sense. For some reason it decided to focus on STEM courses when I hadn't said anything about STEM...and then it started talking about ways that students should or shouldn't use AI even though it was clear that the workshop was for... faculty.

P9 expanded on the issue expressing frustration about the “random things that aren’t useful and that I didn’t ask for, and then I’m not really sure why.” Similarly, participants expressed confusion and aggravation when generative AI was not able to format the outputs in a useful way. P3 said, “I think the times that it has not gone well all relate to trying to have AI work within specific formats or templates... AI struggled with getting the assignment prompts correct and turning it into a rubric to begin with.” P6 expanded on this saying, “But it’s hard to get the formatting correct to copy over, so it’s hard to know whether it’s really saving time and frustration or whether it’s just equalizing in the end.” Even with iteration and reprompting, participants had to be persistent to get what they needed. Some mentioned that their prompting may be at fault for the failure to get a usable output, but they still felt challenged by the tools. P7 told me “I modified my prompt a few times and I found that it just kept presenting the same content in a different way, using different words, but overall, it was still the same thing.” These challenges with garnering useful outputs from generative AI tools, regardless of whether the prompt was to blame or not, increased the amount of time spent on task and caused participants to wonder if using the tools was even worth it.

The nonsensical and misaligned generative AI outputs were irritating to participants and caused confusion as to the best way to prompt the tools to get what they needed. Even when a detailed and well-written prompt was used, they felt that this did not guarantee a useful output. Sometimes the output generated was still very basic or lacking in quality. Regarding quality of the text generative AI produces, one participant

who had a background in writing was particularly critical, but the sentiment of what they said was shared by several others (P4, P6). P5 said

> Given my background, I am very critical of LLMs in terms of text production and recognizing and understanding their very vast limitations in that regard, so for me... AI is maybe the worst thing for writing anything real and anything particularly substantive and specific.

This was echoed by P4 who stated, "It spits out the most basic, uninspired, uncritical [text]. They're just summaries." The issue of quality was discussed by P2 as well whose expectations were more tempered stating, "it's only as smart as the information has been trained off of." There also existed issues with generative AI tools providing basic, undetailed outputs or outputs that become repetitive as more is generated. P7 described the results of one query as "very skeletal in framework," and P6 noted issues of repetitiveness, saying "eventually… [it] started to repeat the same exact questions, and so then I typed in 'can you give me 10 more,' and some of it was repeated again." Like issues with generative AI tools not giving users what they need, AI outputs that lacked in some way, caused instructional designers to waste time and energy editing extensively, thereby negating one of the biggest benefits of the tools: time savings.

Poor quality and lack of detail were mentioned as problematic for instructional designers, and these were exacerbated by the way that generative AI writes, which I coded as synthetic voice. Synthetic voice caused problems with content creation as well as with student and faculty expectations. Whether it was using the same words continuously, overusing gerunds, or creating lists that all look similar, these challenges

created a robotic and uninspired tone that was easy for instructional designers to identify. P1 described this issue, stating, “ChatGPT had a language that sounded a lot like ChatGPT. [Such as] a lot of exaggerated positives” and an overuse of certain terms. “Everything was… ‘we’re going to delve into this’... delve was it’s favorite word.” P6 also described this phenomenon, asserting “I’ve noticed with AI that it likes to write sentences in a specific way. It’ll use gerunds a lot, so it’ll do a statement and then comma, [and] a list with gerunds.” Although this may seem like a small challenge, this has led to several issues in participants’ institutions with stakeholders noticing synthetic voice and making assumptions as a result (P3, P5). P1 expressed an awkward situation involving synthetic voice in student work. “I’m reading assignments… and I’m like ‘AI… AI… AI.’” In this context, this participant worried students were not using their own thoughts in assignments. P6 struggled with synthetic voice with a subject matter expert, explaining, “I had a subject matter expert who I was pretty sure was using AI to generate some of the content… and that rubbed me the wrong way… we’re paying you to write this course… but you’re giving us the AI generated ideas.” In addition, synthetic voice has been noticed by students who have complained that their faculty are not doing their job. P9 told me:

> Faculty Senate [has] gotten quite a few student complaints... about students saying that they can tell faculty used AI to give them feedback… the same “tells” that faculty have for when a student is using AI; students will see the same things for faculty.

Noticing generative AI writing is one issue, but this is compounded by the fact that detection tools are completely unreliable. P6 discusses this by saying, “It had markers of AI, so I knew that it was [written by AI], but there’s no real way to prove it.” Regardless of how generative AI tools are used in any situation, having those markers of synthetic voice tends to yield negativity by stakeholders, whether they be students, faculty, or staff.

Instructional designers also questioned whether generative AI tools are worth using when they are required to prompt the tools with enough context to understand what is being asked. Unlike humans who can infer and deduce based on context, generative AI tools need these elements spelled out explicitly. In addition, course content in higher education is highly nuanced and dependent on contextual knowledge. Participants’ statements about these challenges were assigned the code context and nuance. Within academia, generative AI tool limitations are magnified as the tools just cannot make the same connections as a human brain. P5 explained this issue saying, “I think a lot of other academic disciplines and subject areas are much more rooted in analysis and critical thought and application of concepts and the sort of oblique human thinking that the technology is not capable of yet.” P2 also discussed circumstances when generative AI struggled to understand contextual cues. “It can be a real pain in the butt to do it [create content with AI]. You have something in mind, and it has something else in mind… it tells me it can’t do it, and I know it can” (P2). In order for generative AI tools to fully grasp what is being asked, details and context need to be included in prompts, which can be time consuming and challenging.

As generative AI tools continue to evolve, they may improve in some areas, but, currently, many of the challenges that participants in this study discussed have caused them to waste time rather than save it. Perhaps most distressing for instructional designers are issues around accuracy, evidence, and the inability to verify sources for information. Where other challenges just waste time, this challenge can render outputs completely unusable. Issues with accuracy and evidence were mentioned by over half of the participants (P1, P4, P5, P6, P7, P8). P5 explained their dissatisfaction with this issue saying the following:

> I also don't always trust the accuracy… that's a whole other frosting-on-that-can't-write cake is the fact that we now know for a fact that programs like ChatGPT will literally make up information–will literally falsify sources that do not exist, authors who are not living human beings. So in in my mind, if I know I need to cite sources and accurately represent research I'm better off doing that myself.

P8 further explained their feelings about verifying output accuracy stating, "I honestly think it's more of the opposite effect [from making people more knowledgeable] unless they're checking or fact checking the output… AI–it hallucinates a lot...you have to do your due diligence still." References and citations, in particular, have caused challenges for instructional designers. When any type of evidence is given within an output, there are often errors in the references or the references provided are fabricated. P8, P1, and P7 all mention references and citations as a major limitation with P8 saying, "I often find if it does give you [a citation], it's mixing and matching... authors are being attached to

articles and research that may not be theirs just because the AI tool is just pulling things randomly together." Any one of these issues and limitations is extremely challenging for instructional designers, but when you consider all of the issues together, it makes learning how to properly use the tools of the utmost importance.

Individual and organizational opinions and viewpoints, which is the second cluster that makes up this theme, have also played a massive role in how participants use generative AI tools. Preconceived notions about the tools or their outputs create internal struggles and barriers to successful adoptions. In general, particularly when generative AI tools were new, before many instructional designers understood the implications of generative AI tools, there was much resistance. This was seen across educational sectors with faculty and administration also practicing avoidance. P2, P5, P6, and P9 all mentioned challenges with resistance to generative AI tools either within themselves or amongst colleagues. Their comments include the following, "We still have faculty that are adamantly opposed to using it. And that's their prerogative" (P2). P6 was very honest about personal hesitation saying outright that "I was very anti using [AI]." This strong aversion to generative AI tools by some seems more passionate than resistance to other recent educational innovations. Both P9 and P10 described theirs and their colleagues' strong negative feelings. P9 was particularly colorful saying, "There are some [educators] who are just like 'AI is evil. I'm not going to teach you how to use it.'" P10 was equally passionate, explaining that "I've always in my life been an early adopter... for some reason I was very adamantly anti AI for quite a while. I didn't even want to hear those two letters uttered." Some participants hypothesized that resistance was borne from fear

of generative AI tools. P4 discussed some of the fear they saw within colleagues, commenting, “People were like, ‘Oh my God, the end of education!’” P2 also talked about fear saying, “I think faculty have just like–it’s a fear factor too–of the not knowing.” Despite fears and hesitations, though, P3 had an interesting take stating that “I think the people who are a little bit resistant to using it for creating courses, it feels like that is the… losing side of history.” Statistically, the tides have turned some with more people using generative AI tools as time goes by, but there are still many who refuse, and this can create challenges for instructional designers who either are being asked by their administration to integrate them or who struggle from fear.

Even when instructional designers move beyond their hesitations and use generative AI tools, there are a wealth of other frustrations that they have experienced when using and trying to implement the tools in their daily work. In fact, 7 out of the 10 participants in this study mentioned specific circumstances or issues with generative AI tools that caused them personal frustration (P2, P3, P4, P5, P6, P9, P10). Perhaps the most frustrating type of experience that participants mentioned was when they wasted time completing a task with generative AI that could have been completed much faster without the tools. P4 and P5 both mentioned time-wasting in their interviews. P4 said, “Sometimes it’s just not worth it… ChatGPT will offer me 3000 alternatives to a perfectly good paragraph.” P5 called this issue out as well stating, “Those negative experiences for me are… when I’ve inadvertently wasted time and realized I should have just done this myself.” Frustration was also a common emotion when the instructional designers found that generative AI tools are not capable of completing a task. P5

mentioned this issue saying, “You know [that] the output just isn’t sufficient… Claude or ChatGPT simply can’t do these tasks.” This type of frustration is also seen when random outputs are generated like P9 described. “Despite that clarity, it just gives me random things that aren’t useful and that I didn’t ask for, and then I’m not really sure why.” The tools also sometimes failed to follow the participants’ prompts, even with iteration and revision causing more frustration. P2 said, “Am I really giving it the details that it needs? So then I’ll revise it, and I’ll still get the same crap back. And then so it can be very frustrating at times.” Formatting is of particular frustration as multiple participants mentioned their issues in that area. P3 explained this:

> It could not put it together in a table for anything… It would give me an Excel document or a Word document and the table would be blank... and what’s disappointing about that is I think we really want AI to be able to take some of those repetitive copy and paste tasks away from us... but it’s not as automatic as we want it to be.

One final frustrating circumstance that one participant mentioned is around the protections that have been gradually added to the tools. These guardrails can hinder the work of an instructional designer in a way. In one such case, when trying to generate a case study with a diverse character, generative AI refused to create anything for a participant. While this may seem like a small issue, these types of guardrails can lessen the richness of content in courses. P6, who experienced this scenario, said the following:

> I was trying to type in parameters for a case study that was about someone who is quite diverse. So like an Indian woman who identified as bisexual, who is

> Muslim. I put in all this information and saying ‘can you write a case study about this individual,’ and then the copilot wrote back to me. I cannot talk about this topic [because the diversity aspect is unacceptable].

These are only some of the circumstances that participants discussed that caused them frustration. If it were only one thing that was frustrating, that would be challenging, but with multiple scenarios causing this irritation, it could be detrimental to instructional designers’ willingness to experiment and truly adopt generative AI tools.

Questions around ensuring ethicality when using generative AI tools can also cause challenges for instructional designers, particularly when there may be ethical gray area or dilemmas associated. Uncertainty about how to proceed can be paralyzing for instructional designers who would rather choose to do nothing at the risk of violating ethical standards. P5 summarized this issue by saying that “There is a lot of complex ethics in my mind involved in any and all use of AI technology... so I’m always a bit skeptical and probably should be more.” This was echoed by P2, P4, and P10 that ethical use is one of the most important considerations they think about when using generative AI tools. P5 spoke extensively about the many ethical dilemmas and considerations that they have been contemplating including, “all AI is built on unpaid labor and theft from real writers, real artists, real academics,” “inherent biases in all AI,” and “theft and intellectual property and the fact that all AI images are pilfered from actual artists doing real work.” As will be discussed further in other themes, ethics and responsible use are critical to successful integration of generative AI tools. This starts with the realization

that it is the onus of the user to ensure ethical use and not necessarily the creators of the tools. P5, again, articulated this:

> Ultimately all of this is just capitalism, it's just commerce. We can try to gussy it up and pretend that the folks making AI programs of various kinds are out to benefit the world, and they're inherently not. Their products exist to turn a profit.

Ethical gray area, similar to frustration, has a tendency to stymy creativity and innovation in instructional designers. Organizations need to help their employees deal with these issues, but there is a delicate balance between enough and too much guidance.

Conversations around organizations providing strict guidance or prohibitive policies compound the many challenges faced by instructional designers working to adopt generative AI tools. This begins with limiting policies imposed by external sources like accrediting bodies. Especially when generative AI tools were in their infancy, organizations, through a lens of fear, prohibited generated content, which was a hindrance to P7. They said, "I know early on [accreditors] were like, do not use AI for licensure prep" warning that AI-generated content was not usable. They also said that "the AI model right now isn't robust enough to actually help with that." These hindering policies also come from within. P10 discussed this saying, "The internal policies that the organization outline [dictate] what you can and cannot put where." P6 expanded on this by explaining that proprietary information as well as AI-generated images were problematic. "There was policy from the overarching organization that was like: We can't be using this because we can't put our proprietary information in... so I was scared to do anything that might compromise that." P6 continued the conversation saying,

"Another policy that we have is that we can't use images that are straight AI in our courses, which is definitely holding me back." Being told that generative AI tools are not acceptable for certain tasks or in certain ways presents challenges, but there are arguably worse issues regarding policy.

Prohibitive policies could be considered more useful than policies lacking altogether. Without guidance, instructional designers are left having to determine when and how to use the tools on their own. In nearly every interview, participants expressed confusion, concern, and irritation with the lack of policies their institution has in place that explain when generative AI tools are appropriate for students, faculty, and staff. For 7 of the 10 participants in this study, there was almost a feeling of surprise about being asked about the policies in place at their institution (P1, P2, P3, P4, P5, P9, P10). Having a lack of policy about generative AI use seemed to be more of the norm than instructional designers knowing exactly what their institution expects. P1, P2, P4, P5, P8, and P9 openly stated that their institution did not have a solid policy in place. P4 even went back to their previous employer's lack of policy stating, "We don't really have a policy yet and even coming from [previous institution] that has been thoroughly immersed and has a QEP [quality enhancement plan] around AI across the curriculum, they did not necessarily have a policy." Lack of policy, particularly when it relates to new and unfamiliar tools, can lead instructional designers to feel a loss of control, in a way. In the interviews, P2, P5, and P8 all used a similar analogy describing people using generative AI tools however they want. P5 said, "At the moment, AI kind of feels like the Wild West in that there are all these capabilities and you have a bunch of people just kind of

doing whatever they want and experimenting wildly." On the other side of that coin, missing policies caused other instructional designers to avoid the tools altogether. Without guidance, several participants felt safer waiting to learn about generative AI, or if they did use it, it was secretively. P10 said in their interview, "So I would say that maybe early on, since we didn't have like a really full version of Copilot, I questioned using it just because I needed some help clarifying things." P8 also said, "At first it had to be very secretive that we were using it. ... We were not allowed to share that we were using it." One participant, however, had a different perspective on the lack of institutional policy. Higher education is seen as the keepers of academic freedom, so limiting the use of a tool that could potentially help us learn may not be a good thing. This person, P2, stated, "We don't really have a policy in place because education, higher education in particular, [needs] academic freedom." The instructional designers interviewed for this study craved guidance in using generative AI tools effectively, but policy that is too limiting or restrictive was also found to be problematic.

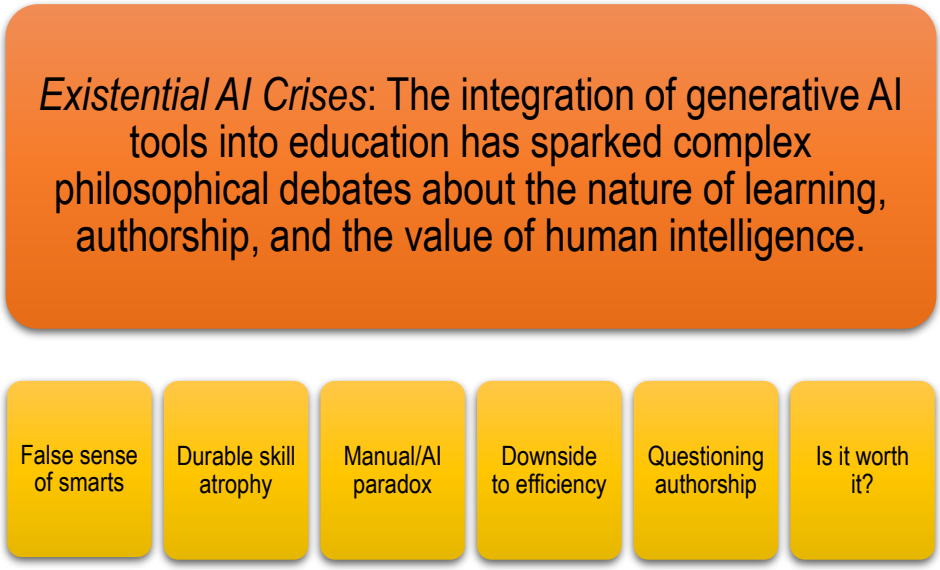
Overall, the findings within this theme illustrate the many challenges, both functional and perspective-based, that participants have faced when attempting to use and adopt generative AI tools in their daily work. The tools have well-documented limitations, which were mentioned across the 10 interviews. Some additional issues were also added to that list. On top of the tools not functioning properly, perspectives toward the tools posed additional challenges that hindered the instructional designers, and these two clusters of evidence contributed toward part of the answer to RQ1.

Theme 2: Existential AI Crises

Also answering RQ1 is the second theme: Existential AI Crises. The integration of generative AI tools into education has sparked complex philosophical debates about the nature of learning, authorship, and the value of human intelligence, and this is the crux of this theme. There is only one cluster associated with this theme, which is made up of six codes, each of which represents how participants were challenged in their beliefs. Figure 5 visually presents the codes and their relationship to Theme 2.

Figure 5

Theme 2 Code Tree: Existential AI Crises



Theme 2 Definition

In addition to the practical challenges associated with using generative AI tools, there were also philosophical and moral challenges that arose as a result of integrating the tools, and this is the main topic if Theme 2: Existential AI Crises. Generative AI tools are new, evolving, and polarizing. No one really knows what the ultimate effects will be in a

future where generative AI tools are deeply infused into daily life and work. Many speculate both positively and negatively on this dilemma, and some find that a world with generative AI gives them pause. In this theme, the deep philosophical questions that participants struggled with are discussed.

Within this theme are six codes, each of which poses a complex dilemma discussed by at least one participant. The first code is false sense of smarts, and this explores whether free and easy access of generative AI tools will cause tool users to actually learn or only gain a false sense of knowledge. This is followed by questions about whether the tools have the potential to atrophy durable skills. Without flexing the parts of brain that perform critical thinking, empathy, and communication, is there a potential to lose these skills? This is followed by the manual/AI paradox code, which is a recognition that even when AI tools can complete tasks faster and more accurately than humans, humans still need to know how to complete tasks by hand. The other side of this paradox is that, in the future, using generative AI tools in the workplace is likely going to be expected, so students also need to know how to complete tasks with the support of generative AI tools. The next code within this theme is an exploration of the downside that participants see with regard to efficiency in that more work could potentially be added to their queue since they are able to complete tasks faster. Authorship and whether individuals can call AI-generated work original is the next philosophical question that arose from the interviews. Finally, participants postulated that using the tools may not actually be worth it at times either because humans are capable or because there is potential damage associated with tool use. These questions and concerns, while they need

to be discussed, do not have a clear answer at this time, making them even more complex and challenging.

Data to Support Theme 2

When one first thinks about the challenges that go along with using generative AI tools in instructional design work, much of what initially comes to mind is about the tools not working correctly or accurately. There is, however, another side to generative AI challenges though, and it centers around the idea that generative AI tools are provocative, fascinating, and unsettling and that they have caused participants to question their beliefs and preconceived notions, particularly when it comes to teaching and learning. The first complex question that emerged from the interviews was about people gaining a false sense of intelligence. If someone crafted an entire paper using generative AI tools, several participants questioned whether that person actually learned. P2 illustrated this by saying, “You know, [the AI is] telling them something. But did they learn?... just because you can create something doesn’t necessarily [guarantee learning].” Also within this idea of learning and building knowledge is the question of what expertise means in this new technological era. When asked about building knowledge and expertise, P10 cheekily said, “It depends on what your definition of an expert is. Is AI an expert? Maybe. Am I an expert? Not at all, because I don’t know everything there is to know about my field.” Regardless of what expertise means in this new generative AI era, multiple participants discussed the concept of building a false sense of expertise through the use of the tools. P4 articulated this by saying, “It gives the perception of expertise, but I don’t think it builds real expertise at all.” P4 went on to say, “People feel like they are becoming

experts without actually gaining expertise" to really explain their point. P3, similarly, described a strange phenomenon around a false sense of expertise in their workplace:

> We have heard from the university partners that… 'with AI we can make a course in a weekend. We don't even need the LXDs [learning experience designers].' And then on our side we have the same thing, which is 'we can also make a course in a weekend without a subject matter expert'... I don't think that that necessarily has given our LXDS more experience outside of being LXDs, and I don't think that that's gonna give a [SME]… more experience on the learning experience design side.

A false sense of expertise is simple to believe as well due to generative AI tools being so easy to use and their outputs being so positive and confident. P4 discussed this calling generative AI outputs "so polished and upbeat" and remarking that "generative AI makes everything seem so easy." P1 also talked about how easy it is to fall into asking generative AI everything, saying, "You can look up information instantly...and make it look like you really know what you're doing." This desire for instant expertise and the false perception is also being adopted by companies who advertise instant expertise. P7 mentioned this, saying, "Use this prompt and become a finance guru in like 30 days... Can I really use AI to become a finance guru in 30 days with these prompts? I don't know. And if that's the case, why isn't everyone a finance guru?" While generative AI tools may hold the potential to provide fast information and explain concepts, truly learning is ultimately based on what is done with that information.

Acquisition of knowledge and skills and how that is affected by generative AI tools is a complex and multifaceted question, as is the question about whether the use of tools will cause people to lose some of the durable skills they had built previously through deep thought, patience, research, and presentation of thoughts. In the interviews, participants mentioned several skills that were in danger of being lost, the first of which is overall intellectual rigor. In acquiring information quickly and with relatively little effort, P5 and P6 both worried about the effects of using less brain power over an extended period of time. P5 articulated this concern:

> What I worry about is that folks will automatically run to ChatGPT or consult AI for solutions rather than thinking through problems critically on their own before working out much more specific prompts, like eliminating that intellectual rigor could be a problem that may get worse over time.

P6 added to the concern, saying, "There's also the fear of… giving this thing way too much credence… we're relying on this thing too much now." Taking the idea of losing intellectual rigor one step farther, P9 discussed worries about dependency on generative AI tools lessening the ability to think critically. About their own process, they said:

> It's just me wanting to kind of take a first try… before asking AI to do it for me. I've had conversations with lots of faculty about just everyone in society generally, like losing their ability to think critically and do things for themselves if we depend on AI too much. And I kind of don't want to put myself in that situation.

P7 added to the conversation about durable skill loss bringing up communication and the importance of maintaining that skill. “I’m a stickler for wanting to make sure that my sentences are complete… but a lot of people aren’t... a lot of people struggle [saying] ‘I write in tweet; I write in Instagram post’… but they can’t move beyond that.” While these styles of writing may be appropriate in some places, they are often not appropriate for professional settings. Creativity is another durable skill that participants worried generative AI tools may affect in a negative way. P6 illustrated this problem, saying, “it can be an idea generator or it can be an idea blocker.” They continued on saying that “you kind of shut down your own creativity and you’re like these are the only three options to choose from… it blocks you from doing any further effort.” P4 agreed with this potential issue, saying, “it also has the possibility to make things flatter and less creative... if the output isn’t being evaluated critically or evaluated by an experienced instructional designer, then what comes out is potentially just a bad idea that sounds confident.” A final durable skill that came up in conversation is empathy. P7 shared a story about generative AI users failing to be empathetic after practicing skills virtually.

> We’re doing virtual reality [in a nursing curriculum]. When it comes to patient engagement... even though [empathy] could be simulated as real life, when students or graduates have to do it in real life, we’re finding that their soft skills... get lost because... even though you can be empathetic on the screen, doing it in person with like cues with your body language and with your eyes - students didn’t know how to do that.

Durable skills like communication, critical thinking, and empathy are regularly sought after by employers and are often viewed as predictors of success. To think that adopting and regularly using generative AI tools could put those skills in jeopardy seems to make tool use somewhat risky.

A third philosophical question has to do with needing to know both how to perform skills manually as well as how to perform skills with the help of AI tools, which was coded as manual/AI paradox. Several participants discussed the importance of keeping manual skills in the curriculum, but as the world continues to change and evolve, many employers are also looking for graduates to know how to use generative AI tools to complete the same skills. This creates a challenging paradox of how much to teach manually and how much to allow for AI integration. First, when asked whether certain skills like coding should no longer be taught since AI tools are more efficient and accurate, every participant disagreed for various reasons. Some, like P2, simply highlighted that people need to still know manual methods. “I just feel like it’s a skill that we should still have, especially coding. Even though these AIs can do it.” P9 shared a story of students asking for AI skills even though faculty were resistant, saying, “I think that you’re doing a disservice to us as students by not showing us and teaching us how to appropriately use AI and how it can help us with this work.” Several participants likened the manual/AI paradox to the integration of the calculator into math classrooms (P1, P2, P9). While manual skills are still taught, calculators are now seen as ubiquitous in math courses. P2 said, “even though we have calculators, and we have things that’ll add for us… knowing how to do that, I think it is needed.” P1 also recalled being told, “learn

your basic math and learn long division because a calculator may not always be there." How much AI to teach is, again, a complex question that is compounded by faculty not having expertise in using generative AI tools yet.

Efficiency is generally thought of in a positive light professionally, but, in interviewing instructional designers, a new viewpoint on efficiency was unearthed. Instructional designers often have high workloads. With generative AI tools being integrated more and more into higher education, some participants feel pressure to integrate the tools to keep up, and this was coded downside to efficiency. P8 articulated this issue, saying, "I realize that to keep up with the workload that's being asked in this role, in these types of roles, that we really have no choice but to lean into these [generative AI tools]." Other participants worry that in finding efficiencies in their processes, administrators may assign more work rather than leaving time for instructional designers to be creative and think critically. P4 spoke vividly about these worries saying, "I definitely see the potential for the downside of efficiency is, well, you have ChatGPT, so why can't you produce? Why can't you work on 20 courses at a time? Why is it so hard?" The expectation of being more efficient also is not helpful for all participants. P8 found reviewing and editing generative AI outputs challenging, stating, "It does take more time to review with such a critical eye. It's different when you're proofreading your own paper, but when you're proofreading something else that's generative AI... it's sometimes harder to review with such a critical eye." Generative AI tools do bring with them the potential to save time, and this is seen by most as a huge benefit. Fear of an

increasing workload as a result of finding efficiencies, however, could lessen that benefit for instructional designers.

Authorship was another philosophical question that was mentioned by several participants as potentially problematic when generative AI is used. One participant spoke about this issue as it pertains to students (P1). They said, “I think we have an entire generation of students who are going to come up being able to produce amazing work… and it will be [called] original work, but it’s not really theirs.” P6 also spoke about this issue but related it to course content development. They wondered where generative AI use crosses the line into too much, asking, “how much can they say they authored it when it’s just every step in the process is… AI telling them what to do and giving them options?” P5 took this issue a step farther by considering the possibility that institutions may begin to sell fully AI-generated courses. They stated, “The uses can become problematic - I won’t go so far as to say nefarious, but I do kind of bristle when I see folks in other spaces peddling courses that are clearly 100% AI-generated.” As generative AI tools continue to evolve and become more integrated into life, eventually these lines are going to need to be drawn between what is acceptable and what no longer constitutes original work.

A final complex question that arose within the interviews was about whether using generative AI tools was worth it either due to uses being found unnecessary or the problems that were caused as a result. Several participants had revelations about using generative AI tools for no real reason when their writing was already adequate. P4 expressed this revelation saying, “Sometimes it’s just not worth it. Why tinker [when]...

ChatGPT will offer me 3000 alternatives to a perfectly good paragraph?" This sentiment was echoed by P8 who said, "it ended up being more work for the SME to edit the output than it was for the SME to give us content to begin with." One participant went so far as to say that there were some tasks that were done so poorly by generative AI tools that they found the tools no longer trustworthy. "Sometimes we still really have to do the work ourselves and can't trust the technology" (P5). On top of wasteful feelings are concerns about the social, economic, and environmental implications associated with using generative AI tools. P4 and P5 were particularly lively in describing some of these issues. P4 said, "I have to remind myself, this is a highly environmentally damaging process, so do you need 5 versions of this?" P5 expanded on this:

> The ecological damage that is being done by immense server farms that essentially require similar levels of power to a nuclear plant to function… these are the things that that I think of every time I submit a query to an AI program.

P5 hammered on the concept of damage and nonchalance saying, "please don't think about all of the social, economic, and ecological impacts that human beings, but Americans in particular, love to ignore." Although generative AI tools are fun, easy to use, and simple, they may not always be worth using, particularly unnecessarily considering the potential damage they may cause as they continue expanding.

The many complex questions that were gleaned from interviews with instructional designers, coupled with functional issues and negative perspectives, comprise an answer to RQ1. The integration of generative AI tools in higher education has been and continues to be challenging for a multitude of reasons. As instructional designers use the

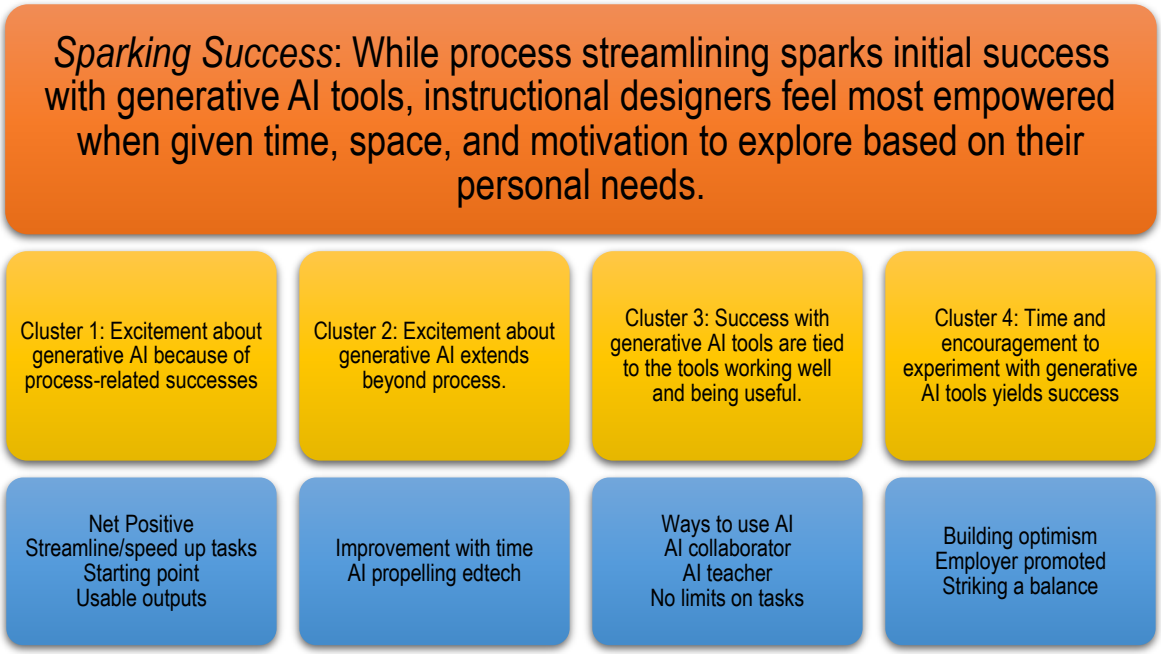
tools, integrate them into work, and see how others apply the tools, complex questions about teaching and learning will likely continue to emerge, and not all of these questions will have clear-cut answers. Constant evaluation of practice and persistence aimed at integrity and positive student outcomes will help instructional designers maintain high standards and find a balance with generative AI tools that feels comfortable to them.

Theme 3: Sparking Success

The third theme, Sparking Success, is the only theme that aligns to RQ2. Theme 3 is an examination of the successes that participants have had when using generative AI tools. While process streamlining sparks initial success with generative AI tools, instructional designers feel most empowered when they are given time, space, and motivation to explore based on their personal needs. This theme is comprised of four clusters. The first cluster explains that instructional designers are excited about generative AI because of process-related success. The second cluster extends the idea of instructional design excitement beyond process. Cluster three highlights that success with generative AI tools is tied to the tools working well and being useful. Finally, in cluster four, the codes indicate that when instructional designers are afforded time and encouragement to experiment with generative AI tools, they tend to feel more successful in their use. This theme, the clusters, and the 13 codes associated are all depicted in the code tree labeled Figure 6.

Figure 6

Theme 3 Code Tree: Sparking Success



Theme 3 Definition

Although all participants were very open about the challenges that they encountered in integrating generative AI tools in their work, each also highlighted the successes they had as well. In fact, many of these successes have led to excitement about how the tools work and how they can be useful in the instructional design process. Excitement about generative AI tools extended beyond process as well to other applications and the possibility of better technology. Overall, the participants in this study found the tools to be helpful and useful when they worked well and when they were afforded time and encouragement to explore applications of the tools.

Within this theme are four code clusters. The first cluster describes excitement about generative AI tools because of process-related success. Overall, the majority of

participants felt that the effects of generative AI tools on their daily work were positive. They spoke extensively about the ability to streamline processes and speed up tasks, which comprises the second code. Third, several participants used generative AI tools to create a starting point either for development needs, for beginning to learn about a topic, or for orienting to a new job. Finally, participants examined the ease with which they were able to use generative AI outputs and how that usability created additional efficiencies.

The second cluster within this theme is that excitement about generative AI tools extends beyond process. Although a smaller cluster, it was of note that, first, generative AI tools have improved drastically since they were first introduced. Several participants expressed excitement about how much the tools may continue to improve in the future. They also spoke about different technology in the education sector and how generative AI tools have created such comfort amongst professionals that it is actually propelling other technology as well.

Following these conversations is a cluster dealing with success with generative AI tools and how that is tied to the tools working well and offering usefulness. Within this cluster, participants expressed a wealth of ways that they use AI within their processes like brainstorming, wordsmithing, and writing goals. The second code in this cluster is AI collaborator. Multiple participants discussed the function of generative AI tools as a collaborative partner and how it can help solve issues with scheduling. AI teacher was another successful use of the tools as many participants enjoyed using generative AI to expand their knowledge around topics outside of their sphere of knowledge. Participants

found the tools so useful in so many ways that they shared their difficulty thinking of any tasks for which they would not use the tools.

The final cluster in this theme is about time and encouragement to experiment with generative AI tools and how these factors yield more success for instructional designers. As participants experimented more and saw their colleagues experiment more, the more optimism they noticed around generative AI tools. They also were more open and optimistic when their employers encouraged use of the tools either through policy or the purchasing of licenses. Finally, instructional designers see the need for balance with generative AI tools in several ways. This includes balance between institutions providing encouragement while ensuring ethics, balance between having generative AI write and maintaining the human voice, and balance between finding the positives in using the tools versus avoiding negative consequences.

Data to Support Theme 3

Throughout the interviews, participants were candid about the struggles and challenges that they experienced, but they were equally excited about successes and the ways they felt generative AI tools have helped them in their work.

Cluster 1. Despite negative sentiments that were shared, most participants agreed that the overall effects of generative AI tools on the instructional design process are or have the potential to be a net positive. P5 was the first to use the term net positive when asked about how generative AI tools were affecting the instructional design process, saying, “As a whole, I think GenAI is a net positive in that it opens up possibilities. It can be used at various stages in the design process somewhat effectively.” Participants spoke

openly about the overall positive experiences and how the tools made them feel. For example, P10 stated, “I can’t say that I have had a truly negative experience with generative AI.” P4 described an experience with the tools, musing that it “was a super positive experience because it just made me feel more confident.” P1 agreed and discussed the positive overall influence that generative AI tools were having on the course content that they were developing. “In terms of just content creation and text rubrics, things like that, it’s enhanced the courses a lot.” P4 spoke highly about the quality of content saying, “I think it offers the possibility of creating higher quality course materials… [and] improving, enhancing instructional materials, because you don’t have to be a professional to make things look good anymore.” These overall positive comments were shared by six of the 10 participants (P1, P2, P4, P5, P6, P10), and while the other four did not make general comments, they did provide specific examples of their positive thoughts.

One of the most talked about specific benefits of generative AI tools in instructional design was in streamlining and speeding up the process. In speaking with the participants, each of them marveled at the potential of generative AI to assist them in completing tasks faster. Six out of the 10 participants in this study made general statements about the ways that generative AI tools have been useful in streamlining their personal processes (P4, P5, P7, P8, P9, P10). P10 supported the use of the tools saying, “I cannot say enough about how good it can be for the process.” This was echoed by P4 who said, “It has a lot of potential I think to make the process more efficient.” P5 explained it further from the perspective of their colleagues:

> I work with some faculty who are all in on AI and really want to try to leverage that technology to save time, save effort and... through a combination of their own curiosity and a desire to streamline their own processes are very much on board with uses of AI.

These types of general statements about streamlining were also made by P7, P8, and P9, and a similar number of participants talked specifically about speeding up tasks using the tools. P2, when reflecting on their own doctoral journey, said that, "If AI had been around when I was in my dissertation... I think I could have probably shaved a year off of my program." These types of thoughts were also expressed by P5 with regard to course development with a SME who said, "He [the SME] got really excited and... I'll be honest, sometimes being annoying... asking is there a way we can speed this up using AI?" Although not as colorful, P3 expressed hope about being more efficient saying, "I am hopeful that it is going to speed up parts of it and allow us to be a little bit more efficient."

Another way that participants saw generative AI tools streamlining their processes was through saving brain power and making complex cognitive tasks easier. P8 seemed relieved to say that "It's taking a lot of the cognitive load off of me, to be honest, in a lot of ways." P9 agreed with this saying, "I think it's made the instructional design process a lot easier in terms of being less time consuming... I would take a lot of time stressing and overthinking for myself." Quality, budget, and the variety of content were also cited as ways that generative AI tools are helping to streamline the instructional design process. P1 referenced quality saying, "I think it's made courses much more content rich… [and]

what used to take hours to write you can get in basically no time now." P3 spoke about budget and using the tools to save money. "In terms of watching budget, we did use AI voice over for something… to keep the cost low on something." Creating content that is varied was mentioned by P10 who said, "It would have been helpful to have something like an AI to change things up a little bit." P10 went on to say, "We would all be remiss if we weren't taking advantage... to compare the tried-and-true methods to what might be new and evolving and how you can create something new from that." Several participants also spoke about how generative AI tools were being integrated at multiple points within their process rather than at just one point (P3, P5, P6). They also mentioned that there were certain points in the process that were not enjoyable, and that generative AI tools can be a way to offload some of those tasks (P4, P8). P5 explained a scenario when he used the tools, saying "We ended up using AI in a in a variety of ways at every stage in the course design process." P4 also said, "It automates some things that are kind of hard like creating or formatting scripts and generating... captions and it can format scripts for me way better." Finally, participants shared several stories about specific situations in their work when generative AI tools helped them to be more efficient. One such story was shared by P3:

> One of the LXDs I work with had a subject matter expert who was a little slow on returning materials... we'll record and transcribe in Teams and we'll just have them talk and then we can take that and I can put it in the in the Copilot chat... And that's the type of work that learning experience designers have always done, but on their own and with their own brain and with their own limitations.

Generative AI tools were referenced often within every interview as useful in streamlining, making tasks easier, and increasing the speed with which tasks could be done. Instructional designers find efficiency to be one of the most useful benefits of the tools, but there are other successes that have boosted excitement.

One specific generative AI tool use that was mentioned as a way to streamline the process was to provide a starting point. Getting started with writing course content can sometimes be the most challenging part, and generative AI tools were touted as helpful with brainstorming and preparing first drafts. P6 described the usefulness of a starting point in general. “It’s kind of like sometimes when we’re developing, it’s hard to start with nothing and this provides us something to start from.” Instructional designers, although usually working alongside faculty, are often writing course content that is outside their areas of expertise. Generative AI tools were mentioned as useful in providing participants with enough information about these new topics to get started. Several participants (P2, P4, P6, P7, P8) mentioned this, including P5:

> And part of it for me is just knowing enough to avoid incredibly stupid questions and in some cases knowing enough to use the proper language so that questions that I’m asking about content and delivery are easier to understand for the faculty member.

More specific to one field, P7 mentioned, “It would be nice to kind of be able to use GenAI [to explain] what are some key elements that a future nurse needs to be? Or what are some current challenges with regards to X in nursing today?” Even for faculty members who do have expertise in a subject, starting points were viewed as a positive use

case. P3 illustrated this saying, “If you’re a busy contributing faculty member, you’re not going to shoot down having something to start with.” There are also circumstances when there is too much information to sort through. Generative AI was mentioned as useful in narrowing focus, organizing notes, and providing a starting outline for development. P7 told a story to this effect:

> I was working with a subject matter expert... and I was jotting notes down furiously as we were meeting... I went to ChatGPT and kind of threw the notes in there and said can you summarize this in an engaging way as someone who has no experience in this field... the connections that were made between some of the concepts was a little bit clearer and more robust.

P5 also shared several stories about using generative AI to sort and organize and explained how useful it was. “It was really helpful to... take so much material and at the very least have a starting point to begin structuring that more concretely and with greater detail and specificity.” Finally, participants mentioned one other starting point-type use of generative AI tools, and it involves starting a new job. Although meaningful, on-the-job training is not always adequate to orient to a new position. P9 said, “There’s a new instructional designer who graduated from her undergrad two years ago, and she said that ChatGPT has kind of helped her understand some things about what it means to be an instructional designer now.” This was echoed by P4 and P7 who used generative AI tools to orient themselves in new roles. Starting from nothing can be challenging, and generative AI tools can help with that.

Another specific way that generative AI tools are improving the process is by generating outputs that follow the prompt and are accurate. These usable outputs are generally well-written and do not require a lot of effort to refine. When asked about the quality of generative AI tool outputs, four participants made statements about outputs that were immediately usable (P1, P6, P7, P8). P6 was impressed with how the tools followed their specific prompt. “Overall, I’d say it was really good and accurate to the experience that we were trying to get across.” P1 concurred saying, “I didn’t have to change much.” However, even with outputs that are very usable, participants discussed the importance of validating content and ensuring that it meets their needs. P8 said, “It does really well. The only thing that I typically have to refine is ensuring that the code is accessible.” P6 also discussed validation saying, “I did always click on the citations... I found that really helpful like if I wanted to verify what the AI was saying.” Throughout the interviews, participants expressed their excitement around generative AI tools and how useful they were within their daily work. Their excitement also felt somewhat like relief as well because instructional designers often have a heavy workload. Tools that will simplify and speed up tasks, especially tedious tasks, were seen as exhilarating.

Cluster 2. In addition to instructional designers being excited by process-related generative AI applications, there are other sources of excitement that extend beyond process. To begin, instructional designers expressed excitement about the improvement in the quality of content that the tools produce. P1 and P2 both discussed problems they experienced when the tools were new and how they have improved with time. P1 said, “I think the worst experiences I’ve had were more in the early days.” P2 agreed that the

tools had improved, saying, “The image generators - they’ve gotten a lot better.” The drastic improvement in generative AI tools over the past several years caused participants to wonder about how much they may improve in the future. P2 mused, “To think that this is the dumbest AI will ever be.” P9 also said, “It’s here to stay, and as the tool grows and evolves, it will become even more powerful and useful.” As the tools continue to evolve, it is yet unknown how useful they may become, but participants expressed excitement that this continued improvement would only help them more in their work.

Participants in this study have also mentioned that generative AI tools have helped educational professionals become more comfortable and proficient with technology overall. This has led some to explore more and propel edtech [educational technology] solutions more. P2 initially mentioned this phenomenon, stressing that faculty seemed more open to technology advancements in the AI era. “With AI coming out now, people are much more in tune, or becoming so, with educational technology in general. I think it’s really pushed the edtech sector out in the forefront.” P5 agreed and spoke highly about being encouraged to explore and try new tools by their institution:

> You know, [institution] has been, to its credit, really good about trying to analyze new technology and understand potential uses of new technology, so we’ve certainly been encouraged across the course production department to try to find ways to save time, try to find ways to make our jobs easier wherever we can.

P5 expanded on their statement saying, “That’s how we gain a better understanding of technology and how we push the uses and applications of technology.” Expansion of

technology has the potential to continue to improve higher education, so instructional designers seemed bolstered by this phenomenon.

Cluster 3. Instructional designers have used generative AI tools in myriad ways and at several points within their processes. The third cluster in this theme is about success with generative AI tools and how that is tied to the tools working well and being useful to instructional designers. The first code in this cluster includes the various ways to use AI within the instructional design process, so it is a relatively large code. In the interviews, several participants discussed the various ways that the tools can be used in their work, the first of which is to begin projects and use generative AI tools to help plan, brainstorm, gather information, and collate sources. P7 said, "I mainly use GenAI for brainstorming, kind of sparking ideas or to just kind of get ideas." P10 also used the tools to begin work, marveling at the capabilities to "draw on seminal research and up and coming research and give it to you all right at your fingertips without much work." Nine of the 10 participants also mentioned using generative AI tools to develop the various types of content for courses (P2, P3, P4, P5, P6, P7, P8, P9, P10). While each used the tools in different ways and for different course elements, there were some common uses. P2 and P3 found the tools useful for updating or drafting full courses. When explaining a recent development, P3 said, "From the outset, it's part of the SME contract like 'this one's AI assisted.'" P2 and P6 expressed that the tools were helping in brainstorming ideas for assessments with P6 explaining, "We have the general topics for the various weeks, and I fed them through Microsoft Copilot to ask for suggestions of assignments and discussions." Writing quiz questions, case studies, scripts, and outcomes were also

mentioned by multiple participants (P2, P4, P5, P8, P10). Other interesting uses included checking a course outline for gaps in content, which P9 described saying, “I use it a lot when I design workshops for faculty... ‘If you were someone attending the workshop, would this meet your expectations? Am I missing anything?’” Identifying gaps and areas where a student may struggle with tasks was also suggested by P5 who said, “Using AI at various stages to help refine some of his lesson plans and... potential points of student confusion and just generally trying to see some things that he as an expert… might miss.” Half of participants also explained that wordsmithing was a helpful use of generative AI tools (P1, P2, P5, P9, P10). P10 shared a story about this use, saying, “We were working through the original MSN... and if something doesn’t sound clear, make sense, you call attention to it... I said we should try ChatGPT... and it put together a couple paragraphs.” P9 also explained this use, saying, “Using ChatGPT and Gemini to kind of help me revise the content so I can kind of keep the core of what I want faculty to get out of it, but using words that are safer.” There were several other discrete tasks that participants suggested that generative AI tools could assist in setting goals, troubleshooting technology, refining code, and ensuring accessibility. P10 made light of the ways generative AI tools can support weaknesses saying, “I’m a terrible, terrible goal setter, so I really am going to draw on AI to help create my goals and a couple team goals in the coming year.” P5 and P8 both explained the importance of accessibility in course content and how the tools can support, with P8 saying, “I would say about how we can help improve accessibility for our students... we use it a lot for the closed captioning and also for alt text.” The potential uses for generative AI tools within instructional design are seemingly endless and are all

dependent on what individual tool users perceive as most helpful for them. Because everyone is different with varying strengths and weaknesses, the support of generative AI tools will ultimately look different for everyone.

In addition to the more discrete ways of using generative AI tools within the instructional design process, there were several larger categories of uses mentioned by participants, the first of which is to use AI as a collaboration partner. Overall, participants used several words to describe this function of generative AI tools as a partner. P2 called the tools a "personal assistant" and a "great collaborator." P4 used the terms "cognitive partner" and "brainstorming partner" to describe this same use. The collaboration function was described as very useful to participants, particularly when other humans were not available (P6, P8, P9). P2 described this use extensively saying that "AI for me has been a great collaborator since I am the only ID [instructional designer] on campus or at this college." P2 went on to say, "I really wish I had at least one other human to collaborate with, but I don't, and so I find that I collaborate with the different language models that are out there, and that's really helped." P4 explained the relationship with generative AI tools in a different way, saying, "It's almost like a stand in for a faculty member... it kind of fills a void when I have a faculty member who just can't like brainstorm ideas." In addition, one participant talked about a habit of overthinking and how generative AI tools can act as a support to mitigate this issue:

> I can at least brainstorm a little bit for myself and then have a conversation with an AI tool that kind of prevents the overthinking and the time-consuming component that overthinking takes up to do things in a way that's quicker. (P9)

Having someone or something available to ask questions, brainstorm, and refine ideas is invaluable to instructional designers, and with generative AI tools, this assistance is more convenient and quicker as well.

Generative AI tools are helpful collaboration and thought partners. They are also useful as teachers. Within several interviews, participants discussed how they use generative AI as a type of educator or instructor. P1, P5, and P7 all talked about having foundational knowledge when approaching course development and how generative AI tools can help to build baseline knowledge with relative ease. P7 said, “I think we could use generative AI again as a way to kind of like an encyclopedia... to help enhance the knowledge base of instructional designers as a whole.” P5 marveled at the possibilities, saying, “The number of things that I have been able to more quickly and easily understand on a rudimentary level because of AI is pretty impressive.” Generative AI tools can also be used to explain challenging concepts in terms that are easier to understand and retain. P4 discussed this use, stating, “So I created that GPT to help me just understand the content from a layman’s perspective… so I had like a vocabulary to go in.” Several participants used generative AI tools to take content that their SMEs give them and either translate it into something usable in the classroom or generate examples to help illustrate the content. P2 explained this use:

> Faculty are subject matter experts, and sometimes it’s hard for them to express exactly what they need to give you to help you create a good sound course, so being able to take what they have and then do yourself, do some deep dives yourself, can really help.

P4 also used the tools in this way, explaining that they "use it to generate real-world examples." The use of generative AI tools as a teacher is particularly helpful when instructional designers are developing courses that are outside of their sphere of knowledge. P1 explained the difficulty, saying, "I'm developing content about [a] field that is completely outside of what I do and what I know." P5 also found generative AI tools useful when working withing new fields or topic areas, describing it as "using AI to educate myself on at least enough to use correct verbiage and language when trying to develop materials." Using generative AI as a teacher and then commencing course development projects with foundational knowledge already required also helps to speed up the process and begin the work at a higher level.

As has been described, there are a wealth of ways that generative AI tools can be used in instructional design. There are so many uses that participants struggled to find scenarios or circumstances when generative AI tools would not be useful. This was the focus of the code termed no limits on tasks. When asked which tasks they would never use generative AI to complete, several participants were unsure how to respond because they had never encountered an application that AI could not enhance. P10 say, "I don't know if I can answer that" and P3 wondered aloud, "I'm trying to think if there's anything that would be a strict no for me." Other participants agreed by saying that generative AI tools have produced positive and useful experiences. P1 explained, "I think it's become so useful that I can't pick an area where I'd be inclined to not use it in favor of something else." P5 and P7 made similar statements saying they have "had relatively few wholly negative experiences" (P5) and that "I have not come across a specific place

in my ID work where I'm like, I'm definitely not using AI for that" (P7). Still others responded to this query by talking about all of the useful ways generative AI can be used in their individual processes. P9 responded "That's a good question. I've never thought about that. I think that in the design process, AI can help with everything." P5 went so far as to explain that "We ended up using AI in a variety of ways at every stage in the course design process." Out of the 10 participants interviewed for this study, six explained that they could see generative AI tools being useful for all parts of the instructional design process in some way (P1, P3, P5, P7, P9, P10). They felt that no tasks were completely off limits for generative AI tools, despite some tasks being more challenging than others to integrate the tools successfully.

Cluster 4. For the final cluster of codes in this theme, participants explained that they are most successful and optimistic about generative AI tools when they are encouraged to explore and apply the tools to best meet their needs. In the first code within this cluster, building optimism, participants talked about the opportunities that they envisioned after using the tools and learning more about them. P1 spoke more generally in this vein, saying, "In the instructional design process, I think it has opened up some really tremendous opportunities for us." P2 also spoke about general optimism, saying, "I am cautiously optimistic now… the more information you know about it." In exploring, using the tools, and trying different applications, there was an increasing sense of excitement at the potential for generative AI tools to increase in helpfulness. P6 recalled their initial uses of the tools, saying, "I started digging in and actually using it and it was kind of fun," and "as I'm learning to use it, I'm learning how I should be

engaging with it." P10 agreed and said, "I really saw how helpful it can be, and I got a little excited." In addition, participants saw their colleagues begin to be more open with the tools and gain excitement as well. P8 articulated this excitement, explaining, "Others embraced it and it was incredible to see." P5 told a story about a transformative experience:

> That faculty member hadn't really used any kind of AI previously but was very curious... and as soon as he started seeing the ways in which we could kind of save some time and save energy throughout the design process, he got really excited.

Although there are still many in academia who are resistant to using generative AI tools, the optimism that has built around the tools feels like it has increased and will hopefully continue on this trajectory.

One motivating factor that most participants mentioned was encouragement from their institutions. When employers promoted and encouraged them to use generative AI tools, participants became more interested and excited. Seven of the 10 participants in this study explained that their employer had pushed them in some way to adopt generative AI tools or use them to become more efficient in their work (P1, P4, P5, P6, P7, P8, P9). P1 described how their employer encouraged generative AI use, saying, "I was encouraged to use ChatGPT to generate content... I was informed that I should be using it to produce content for improvement." This was echoed by P4 who said "It is highly encouraged" and P8 who explained, "We are empowered by my director to use AI in any way we see fit." P6 wondered what work would be like if employers did not push

the tools, saying, “I guess it has affected me actually even using AI because if the organization itself had not... start[ed] embracing AI [I would not have either].” P7 was also initially driven to use the tools by their employers. “I think the initial even drive to use it was influenced by the organization.” Another way that participants explained employer motivation was through the purchasing of licenses to use the tools. Not only does this practice encourage more use, but it also in some cases allowed participants to securely input proprietary information and use the tools more extensively. Half of participants experienced this type of encouragement, with P10 saying, “With Copilot, we’re permitted to put some proprietary things in there to get it to help us.” P4 also explained the ease with which information can be input, saying, “We have an institutional .edu license... and we are encouraged to use it to be more efficient.” P2, P5, and P9 also explained that they have been encouraged through the purchasing of licenses. With encouragement from an employer, participants also grew so interested and excited that they advocated for generative AI tool use with their colleagues. P3 described their efforts to pass experience and encouragement along, saying, “It makes it easier for me to want to... share the experiences and really advocate and push for the use of [generative AI tools].” Employing institutions hold much power to encourage instructional designers to adopt generative AI tools and use them to be more efficient. Through enacting policies, purchasing licenses, and engaging in general encouragement, the participants in this study were motivated to explore and learn.

A final motivating factor for participants has to do with balance, both institutionally and personally. Institutions need to strike a balance between pushing

employees to use the tools and ensuring ethical and secure use. They also need to strike a balance between using the tools in development to be efficient and overusing them causing negative consequences. P5 articulated the importance of balance:

> As an employer, [institution] has been very good about trying to support the use of that technology while providing just enough oversight to try to ensure ethics while also ensuring freedom to both the instructional designers and the faculty that we're working with - to try to capitalize on that technology.

P6 also spoke about balance and maintaining human voice, stating that, "I don't view it as... developing the entire course with AI... we are working with a subject matter expert to validate and kind of decide the direction of the course." Balance also applies to personal use. Participants wanted to ensure that they maintained their own voice within generated course content. P6 explained this effort, saying, "I don't know how to achieve that balance of it being positive versus the negative repercussions" and "I think you always have to trust yourself and not lose yourself in the process." Generative AI tools have much potential to assist instructional designers, and in speaking with participants, it is clear that not only is exploration and empowerment necessary; differentiation and acceptance that everyone will use the tools differently is just as important.

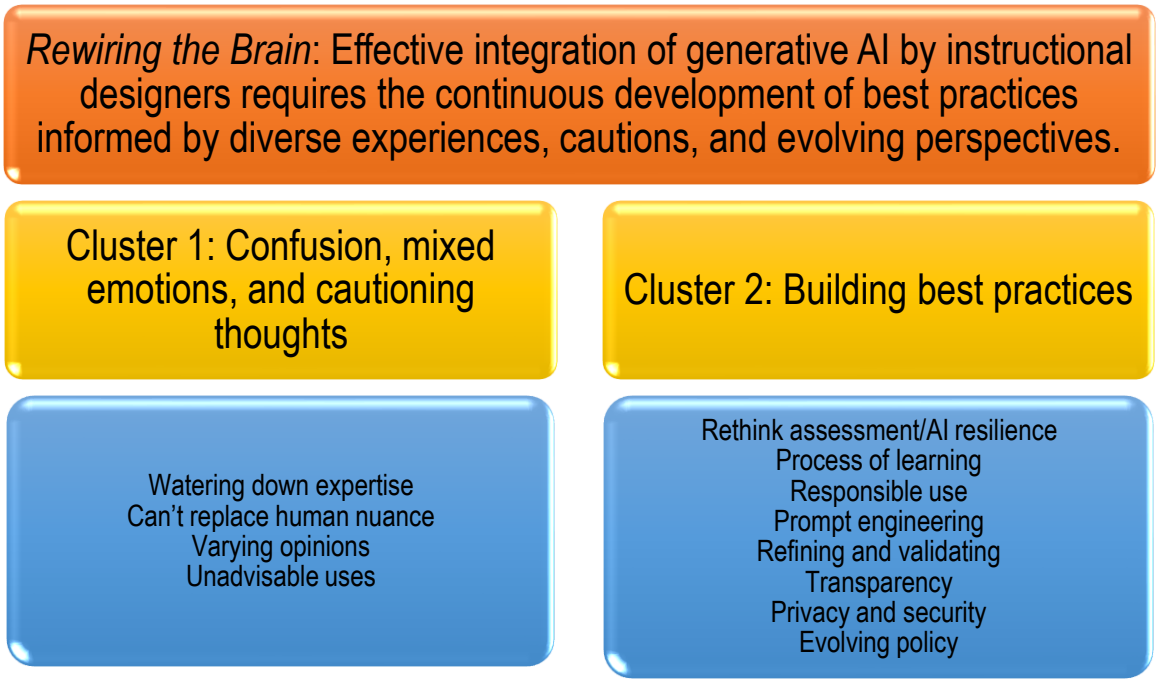
Theme 4: Rewiring the Brain

Theme 4, Rewiring the Brain, aligns with RQ3. Over the past 4 years, many instructional designers have experimented with generative AI tools both successfully and unsuccessfully, and their experiences have forced them to rethink their perspectives on teaching and learning. Effective integration of generative AI by instructional designers

requires the continuous development of best practices informed by diverse experiences, cautions, and evolving perspectives. This theme is made up of two clusters: confusion, mixed emotions, and cautioning thoughts, and building best practices. Cluster 1, confusion, mixed emotions, and cautioning thoughts, has four codes associated that explain circumstances that are causing instructional designers to question their current perceptions about teaching and learning. Cluster 2, building best practices, explains the ideal states of using generative AI tools that participants have determined through practice. This theme, the clusters, and the codes are depicted in Figure 7.

Figure 7

Theme 4 Code Tree: Rewiring the Brain



Theme 4 Definition

The generative AI era has begun to challenge some perspectives and best practices in higher education and instructional design specifically. Participants had a wide variety of experiences with using and integrating generative AI tools into their daily practices. These experiences have led instructional designers to question their pre-existing perceptions, opinions, and emotions related to teaching and learning alongside generative AI. In addition, along with changing perspectives come new best practices that participants felt instructional designers and institutions should adopt to evolve along with the tools and help maintain relevance in the field.

There are two clusters within this theme. The first is about confusion, mixed emotions, and cautioning thoughts that participants identified, which have helped to shape their opinions around generative AI best practices. First, there was concern amongst participants that the use and overuse of generative AI tools may water down expertise and cause individuals to think they are experts when, really, they are just able to generate information quickly. Following that, participants felt that even though generative AI tools are helpful and useful, they are not a good replacement for human nuance. Human experiences like connection, relationships, and interactions, which shape human nuance are not replicable by machines. Varying opinions is the next code. Across higher education, there are individuals who are spread across the spectrum of opinion on the usefulness and quality of generative AI tools, and this wide variety of perspectives creates challenges in developing best practices. Finally, participants were open about uses for generative AI tools that they felt were unadvisable due to ethical concerns, limitations of the tools, and personal beliefs.

The second cluster of codes in this theme is all about building best practices. Participants had many strong opinions on what should and should not be done with generative AI tools within a teaching and learning environment. First, they believed that in this new era, instructional designers need to rethink how assessments are approached and focus on AI resilience as a meaningful strategy. They also highlighted that the process of learning is the most important aspect of assessment rather than memorization of content. Participants felt that teaching responsible use to students and faculty was of the utmost importance moving forward in higher education. They also mentioned the

need for a new set of skills to cultivate within all higher education stakeholders including prompt engineering, refining and validating outputs, being transparent about generative AI use, and ensuring privacy and security. Finally, participants felt that the progressive nature of generative AI tools necessitate policies that are adaptable and evolving.

Data to Support Theme 4

Through experience, experimentation, and both successful and unsuccessful application of generative AI tools, instructional designers have formed mixed opinions on teaching and learning topics in light of the tools and their implications in higher education. When asked about expertise and whether generative AI tools were creating more experts, every participant disagreed for various reasons. Some participants questioned whether the tools themselves could be considered experts or if they were actually watering down the concept of expertise altogether. Some, like P10 and P6, responded by analyzing generative AI tools and their capabilities. P10 said, “Is it a generalist in everything? ... I don’t consider AI an expert in anything, but it’s really good at lots of things.” P6 had an interesting perspective as well:

> There’s only so many directions that AI can go on a given topic... it only has this box that it’s working from, but the human brain maybe has more than that box... I would be nervous if AI start[ed] to shape the content that we are teaching... versus real people who have been out and about in that field who know these are the new things on the horizon.

Some participants responded to the question by claiming that generative AI tools only contributed to understanding basic information but not expertise. P2 said, “I just don’t

think [generative AI tool users] really know or understand" and P1 said, "They're [tool users] able to transfer data, but they don't know it." P6 agreed saying, "Everybody becomes a generalist because they have AI there - they know [a little] about everything." Taking it a step further, P5 worried that relying on generative AI tools for expertise could increase mediocrity instead. "I think you will also get a lot of like aggressively mediocre versions of other things that humans with real expertise and incredibly deep experience and understanding would otherwise create." The overall sentiment from participants was that expertise was an exclusively human capability or perhaps that it ought to be exclusively human.

In addition to questions and concerns around expertise, participants found that generative AI tools were not capable of replacing human nuance, connections, or interactions. In multiple interviews, participants were quick to point out that generative AI tools cannot take over all tasks and that there was still value in knowing how to complete tasks, especially specialized tasks. P5 illustrated this by saying, "Seeing the disappointment in someone's face as the realization washes over them that AI can't do everything and definitely can't do everything better... than a human that has very intricate, discipline-specific knowledge." P7 was equally emphatic and said, "I think we're still going to need a human mind and a processing ability by someone who's considered an expert to process that and to deliver that for us. I don't know if AI can do it 100% on its own." P1 also spoke extensively on human nuance in their own experience and shared that, "In my own background... I know that I can look at the novel Invisible Man and tease out the jazz elements of it and talk about it... because I put the work in and

learned it." Other participants expounded on the fact that AI tools do not truly interact or experience things. Two participants illustrated this very well by saying "AI doesn't have the experiential learning, like all the experiences that we have as humans, like walking out into the world, interacting, touching things" (P6) and "Yes, AI is here and it's helpful, but that human to human interaction and subject matter expertise that individuals have based on their experiences is still really valuable" (P9). P3 and P4 agreed and extended the thought to reviewing course content and the importance of humans in that task. P3 provided this thought, "I think that [certain reviews] take sort of human review and intervention... there's just some tasks where we still need either the subject matter expert or the learning experience designer to be really deep in checking." P4 also said, "I've not encountered any discipline where something can be outsourced–that it still requires, and will likely always require, human review–that requires expertise." Participants truly believed that, even though generative AI tools can help support multiple tasks, the human element is still valuable and, in some cases, required.

Best practices in instructional design are also informed by varying opinions and individuals who are strongly on either side of the generative AI debate in higher education. According to participants, instructional designers have mixed opinions on generative AI use in their daily work. P7, P8, and P9 all estimated that there is about a 50/50 split between those who were willing to use the tools and those who were not:

> Within the group of folks who do instructional design work and learning experience design work, you're going to find a 50/50 [split] I think. So folks who

> are going to embrace it 100% and start exploring and folks who are a little wary of it because we've been doing this work and know how to do it. (P7)

P10 also said that "AI is going to end up being one of these things where a lot of people are going to embrace it and… people that are going to kind of lag behind and adopt late." Participants also reported that their faculty have varied opinions on using generative AI, which, according to some, is understandable. P2 provided one such opinion, saying, "I know there's faculty out there that have really large classes, and I see both sides of the coin." P5 shared a similar divide, stating that, "I work with some faculty who are all in on AI and really want to try to leverage that technology… and I also have faculty I work with who are incredibly skeptical of anything related to AI." Varied opinions force institutions to truly think through the policies that are enacted and work to compromise with requirements.

Finally, instructional designers in this study have identified multiple uses for generative AI tools that they find inappropriate or unadvisable for a number of reasons. Although this is in contrast to the six participants who claimed there was no task AI was not able to support, these unadvisable uses were more about being ethical, working around limitations, and having personal preferences. In general, several participants warned against unethical or otherwise problematic uses of generative AI tools. For example, P5 said, "Where I begin to become skeptical is when folks think that it is a magic pill that can solve every problem and can be deployed in every context and every scenario." P2 also found issue with inputs saying, "There's certain things that you don't put in an AI model." The issue of inappropriate use was also mentioned specifically to

students and their applications of the tools. P1 warned against using AI-generated sources, saying, “It’s still not good at finding sources that are actually good.” P9 also mentioned student use saying, “I think that it isn’t great if students are going to use it to just generate all of their assignments without thinking for themselves.” Faculty also need to be wary of how they use generative AI tools, according to P2. They explained one ethical issue of feedback saying, “I’m doing all the work [with feedback]. I just feel like that’s something that we owe to our students.” Several participants also spoke specifically about instructional design work and commented on uses they found unadvisable (P1, P5, P6, P9). P9 expressed caution in letting AI do all of the work saying, “I don’t really like to use AI to help me completely create something. I like to at least brainstorm and have a draft of something and then have AI help me improve it.” Although this isn’t the consensus amongst participants, there are those who prefer to use generative AI tools sparingly. For example, P6 said, “Some organizations are using AI like from start to finish... so that is really changing the whole field because it’s almost like AI is like the author of the course versus the person.” P5 was particularly sensitive to institutions selling fully AI-generated courses, saying, “I do kind of bristle when I see folks in other spaces kind of peddling courses that are clearly 100% AI-generated and trying to capitalize on [them].” Overall, “we need to be very wary of what this technology is potentially capable of and the inherent potential for either misuse or sort of unthinking, uncritical, unexamined use” (P5). While generative AI tools may be able to support nearly all tasks, participants recognized that certain uses within these tasks may be unwise.

In the second cluster of codes for this theme, participants detailed the many best practices they recommend based on their experiences and opinions. To begin, several participants spoke openly about how their approach to drafting assessments needed to be rethought and that the concept of AI resilience needed to be at the forefront of what is being designed. The beginnings of several of those conversations were around poorly written assessments and those that are simple to complete using generative AI tools. P5 illustrated this by saying, “I’m a firm believer in the fact that if students can use AI [exclusively] and earn an A in your course... it’s probably not a great course.” P1 and P6 made similar statements. “To be blunt, students are not doing much of their own work now... a lot of like discussion threads for example... kind of a waste of the students’ time” (P1). Regarding a writing course P6 said, “Pretty much all of the students were using AI to write the main product in that course... it doesn’t work anymore.” Even if assessments were well-written initially, that may not be the case anymore now that generative AI tools can draft text easily. Participants hear from faculty often about students cheating with generative AI tools with no way to prove it, and participants hope that this spurs conversations about how to proceed. Regarding rethinking assessments, P4 said, “I hope that it is forcing conversations, forcing a realization for faculty that traditional modes of assessment are just not going to cut it.” This was also mentioned by P8 who stated that, “Authentic assessments are great, but even authentic assessments can be done with AI.” When faculty are resistant to rethinking assessments, participants found that demonstrating the ease with which generative AI tools can be used to produce content could be a good strategy. P4 tried this strategy and said, “I asked instructors ‘have you

thought about AI resilience? ... are you OK if I upload your homework problems [into generative AI tools]'... they came back and he goes, 'what do the kids say? I'm shook.'" Regardless of how the conversation is started, multiple participants were adamant that the way instructional designers approach writing assessments needs to be rethought in some way (P1, P2, P3, P4, P6, P10). P10 explained that "These traditional pedagogical approaches that we use, I think it's time for them to change a little bit and it's time for us to take them to the next step." P1 an P2 made similar statements, saying, "In terms of teaching, we are going to have to rethink how we get the contents to the students and how we assess it" (P1) and "This tool has really pushed faculty to... reassess what they're doing in their classrooms" (P2). When rethinking assessments, several participants felt that the best strategy to rethink assessments was to consider ways to make them more difficult for AI to generate or build AI into the assessments, a practice termed AI resilience. P3 shared their thoughts, saying, "Ways to help make sure that if there's something where we don't want them using AI, we're developing it in such a way that would help prevent that." This strategy was also mentioned by P1 who said, "The major strategy I've worked with instructors is not trying to find ways around AI but instead try to build in assignments where students are required to use it." Although participants were not completely sure how to rethink or create more AI resilient assessments, they were aware that changes were needed and that they, as instructional designers, were in a position to affect that change.

When assessments are being rethought and reworked, participants believed that the focus should be on the process of learning more so than the content that is being

learned. Focusing on the process of learning was initially mentioned in the first interview with P1 as critical in higher education. “So much of the undergrad experience in particular is less about the content and more about the process of learning that content. Those are the habits that you build and you strengthen over time.” It was reiterated by P2 who said, “It’s not so much the product, it’s the process.” Even with assessments and approaches being rethought, participants felt that the way that students learn remains the same. P5 and P3 mentioned learning theories with P5 saying, “Some of the fundamental educational theories that undergird how and why we teach to diverse learners isn’t being changed by ChatGPT. ChatGPT and other AI are merely presenting new avenues within existing processes.” P3 agreed with this statement:

> Any of the learning theories that you have always come down to... it helps if you watch a person do it, you have a guided experience with an expert doing it, you do it on yourself and get feedback. Those things stay the same.

Overall, P1 illustrated this sentiment that learning is the most important part and that students who work hard do well by questioning, “Do I know it? No. Am I going to learn? Only if I really want to.” They went on to say, “I think you gain a deeper understanding of subject matter of any kind if you put the work in.” Many participants in this study felt that in focusing on the process of learning and asking students to track and document their learning, issues of fully generating assessments with AI tools are mitigated.

When rethinking approaches, revising assessments, and focusing more on learning, participants recommended the best practice of including several specific skills within curricula. The first of these skills is teaching responsible use to students. P2 stated

it succinctly that, “I think as an educational institution, we owe it to our students to educate them on how to use these tools appropriately, ethically.” P8 agreed, specifically mentioning that students will need to have these skills when entering the workforce. “I think we are charged as higher ed institutions to educate them on AI... as we’re going through this new world, I know the students are going to use generative AI.” Responsible use was also brought up by P9 who said, “We just need to find a way in all education spaces to guide students on how we want them to use it properly in certain contexts.” Guiding students in using the tools responsibly begins by assisting students in recognizing the limitations of the tools and how to approach generative AI use with a critical eye. P5 explained this eloquently saying, “You have to have a very critical eye when using it to spot those shortcomings and to find ways to ameliorate those issues, whether it’s through very direct intervention on your own or better prompting and synthesizing of information.” Although much of what participants said about responsible use was focused on students, colleagues and faculty also need to learn and master these skills. While faculty are often seen as the experts in academia, with generative AI tools, they are novices just like students.

Another important and relatively new skill that participants mentioned was prompt engineering. This is the art and science of drafting and iterating upon prompts that are input into generative AI tools. P7 spoke quite a bit on prompt engineering and how learning this skill has helped them in their daily work. According to P7, the prompt is everything. “It’s all dependent on the prompt. You can give it 150 different caveats to consider... I feel like that nuance in the prompt is what’s going to dictate the quality with

which you get of the results." P7 continued by discussing how the prompt affects the output:

> It's going to go back to the way in which we utilize it and the way in which prompts are generated... you and I could approach the same problem or challenge by coming up with our own prompts and we'll get vastly different outputs.

Iteration was also discussed by P5 who found it particularly vital in higher education, which requires complex and multi-faceted writing, saying, "Not quite realizing the iteration that's required both in terms of prompt engineering and in terms of revision. That is almost definitely required for anything with some complexity." P10 and P6 both shared examples of how iteration of the prompt improves the output. P10 shared that they "just kind of wordsmithed that down... 'you said this, can you clarify that?' And it… kept expanding it and clarifying it" and P6 said, "I might not put enough information at first and then it doesn't give me what I want... but then I build on it and so I'm learning as the AI is learning too." Finally, P7, who had recently been on a hiring committee, expressed the desire of employers of instructional designers to have prompt engineering experience. "Some organizations now are saying some experience with prompt engineering or demonstrated experience of using it thoroughly are starting to come in as requirements." When efficiency is the desired result of using generative AI tools, the ability to draft inputs that yield relatively usable outputs is a skill whose importance cannot be overstated.

In addition to prompting and iteration, participants expressed a need to know how to handle the outputs of generative AI tools. Every output needs to be validated for

accuracy and refined to meet the needs of the tool user. In the interviews, multiple participants discussed the need to refine outputs and edit the text to meet their needs. P10 said, “We cannot copy and paste this information in here... we have to smooth it out” and P3 said, “The output for something like that is not usable the initial way that it’s spat out. Although I will say it’s very good.” P6, who had a writing background, emphasized, “If you want varying sentence structure, which you do in good writing, you would edit that in order to be more compelling to the reader.” Ensuring that the outputs are accurate and aligned to what the participant needed was also described as a best practice by seven of the 10 participants. P1, P6, and P8 all talked about validating the accuracy of the content that was being placed in courses. P6 explained that “We are working with a subject matter expert to validate and kind of decide the direction of the course rather than AI just steamrolling and doing the direction of the course.” P8 reinforced the need to validate by saying, “AI... hallucinates a lot” and P1 mentioned content specifically, saying, “In terms of critiquing the actual content and math formulas that they use... I ran it by the SME.” P6, P7, and P8 all discussed validation from the perspective of ensuring that proper attribution was given to authors and that the tools were not infringing on those rights. P8 said:

> It does take time, and you also don’t know where the generative tools pulling the information from... it’s really hard to go fact check to ensure that it’s accurate information. It actually takes even longer to go see if this is valid information.

P6 also explained their validation process saying, “I did always click on the citations that they would provide... to verify what the AI was saying, I would go to the actual source

that it was quoting," and P7 remarked that it was the onus of the user to ensure proper attribution saying, "I'm kind of in the driver's seat of ensuring that I'm paraphrasing and not lifting 100% pieces." Participants also talked about other elements to validate like ensuring that outputs align with outcomes or that examples generative AI tools provided were accurate. P3 said, "There are a handful of things where I use it with a lot more skepticism... I would really want to check [alignment to outcomes] carefully. I think that that takes sort of human review and intervention," and P4 said that "I Google everything to make sure it's real." Finally, refining and validating are crucial when developing course content and copying and pasting outputs, according to participants, is not considered a best practice. P8 expressed frustration with this practice, saying, "They were not using it effectively in my opinion... they were truly just copying and pasting exactly what the output was without actually looking at it through an SME lens." P5 also expressed frustration with skipping the validation step:

> I'm also incredibly cynical, and I know just enough about human nature to know that there are people who are more than happy to take every shortcut available to them, and there are more than enough people who are perfectly happy being entirely uncritical when it comes to AI, its uses, and its outputs.

When generative AI tools are used to help draft content, the process of validating content for accuracy and ethical use as well as refining to ensure quality and alignment are important skills to cultivate.

The next best practice that participants found important is transparency with generative AI use. This applies to anyone who uses the tools, not just students. Across the

board in higher education, being transparent about any tools that are being used not only helped people avoid negative perceptions; transparency also yielded benefits to participants. P6 explained how a lack of transparency led to negativity saying, “It wasn’t being disclosed to me that this is AI, so I was rejecting it,” and P4 discussed the other side of the coin by explaining how they received accolades from their employer for being transparent. “It has, like you said, helped me be more like transparent with use because it’s almost like I’m rewarded.” Participants explained that transparency is needed in student work, in developing course content, and when providing feedback. P1 explained student obligations asking them to “tell the teacher exactly what the prompts were... demonstrate that you’re using [generative AI] in some kind of skillful way.” P4 felt strongly that generative AI use should be transparent and said, “I would have told instructors anyway that I was using it, but I am now... advertising it.” P4 also explained that if the desire is to use generative AI tools with someone else’s work, the user is required to get permission first. P4 said, “I always ask instructors first, like… ‘Is it OK if we use it?’” and “I would never put student material in it... It has to be transparent, and a student has to agree.” When generative AI tools were just rising in popularity, there seemed to be some feelings of shame in using them to generate content, but that has lessened in recent years, and the pendulum has swung the other way to transparency being a best practice that participants all found vital.

Many of the best practices discussed thus far by participants, have applied more to individual users, but they also addressed best practices that should be more institutionally accepted in addition to being practiced by individuals. One such best practice is ensuring

privacy and security of information. Several participants discussed the types of information that are not appropriate to input into generative AI tools due to privacy and security issues. “There’s certain things that you don’t put in an AI model” (P2) and there are “ethical considerations of not putting student data or work into any AI tool” (P8). P3 also touched on security and the policies in their institution, stating, “Workplace policy... telling us where we can put proprietary materials and that it definitely influences that I’m only using the Copilot tools.” Copyrighted materials and trade secrets were also mentioned by P8 as inappropriate to place in open generative AI tools. They said, “If it’s something coming from a publisher... I also don’t want them to put that into generative AI because you’re still infringing on their copyright.” P8 also talked about external companies and how students may not be using generative AI tools as they assume they will:

> There’s a lot of trade secrets per se out there… so they may not get to use an AI tool for coding unless you know that company pays buku money to have their own internal one that’s safe with their intellectual property.

Privacy and security need to be considered by all parties using generative AI tools, and, as some participants mentioned, included within policies where appropriate.

The final best practice mentioned in the interviews centers around institutions staying adaptable with policy to accommodate any future iterations of generative AI tools. P2 described this practice of offering policy and guidance but staying open to change, saying, “It’s sort of like writing with an erasable pen. It changes so much–you can have some great guidelines and guardrails, and it seems to be working pretty well

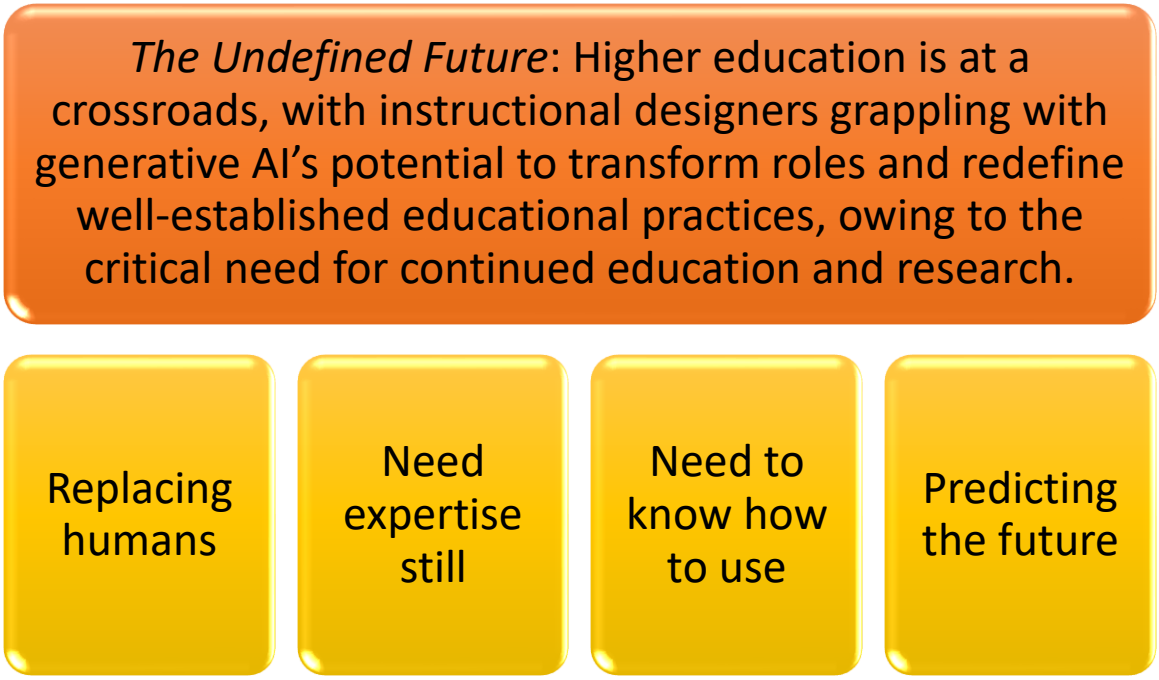
right now." P5 agreed with this practice and explained its importance by saying that no one really knows what the future holds with regard to generative AI tools. They said, "We'll see where they're at as AI guidelines continue to evolve in various sectors and spaces. You know, I might change my tune a year from now," and "some of this will have changed and there will be, you know, more rules, more oversight" (P5). Institutions have had to be adaptable since generative AI tools were popularized, and this practice will need to continue in order to account for the rapidly evolving nature of the tools.

Theme 5: The Undefined Future

The fifth and final theme for this study, The Undefined Future, is a recognition that higher education is at a crossroads. Instructional designers are grappling with generative AI's potential to transform roles and redefine well-established educational practices, owing to the critical need for continued education and research. This theme is made up of four codes: replacing humans, need expertise still, need to know how to use, and predicting the future, and partially addresses RQ3. The organization of this theme is shown in Figure 8.

Figure 8

Theme 5 Code Tree: The Undefined Future



Theme 5 Definition

The future, in general, is unpredictable. Now that generative AI tools have become popular and their integration is increasing on a daily basis, the future seems somehow even more uncertain. In every interview for this study, the participants made at least one comment about the future and how it is extremely difficult to predict what could happen in higher education as a result of integrating generative AI tools. As instructional designers face an uncertain future, they question what they will face in higher education and regarding knowledge and expertise as a whole.

There are four codes in this theme. First is replacing humans, and it encapsulates the feelings, fears, predictions, and suggestions that participants shared around the idea of

generative AI tools either replacing jobs or responsibilities. This is followed by a series of reasons why it is still important for humans to build and maintain expertise regardless of generative AI tools being more efficient at times. Participants also discussed extensively how students and professionals are going to need to know how to use generative AI tools in the future. Finally, this theme concludes with opinions, wonderings, and fears participants hold about the future and the challenge of not being able to predict what will happen.

Data to Support Theme 5

The first code in this theme is replacing humans. Throughout the interviews, eight of the 10 participants spoke about fears, predictions, and recommendations surrounding the idea of AI tools replacing humans. Several of the participants expressed fear that academic positions could be replaced by AI tools. P7 articulated this fear by saying, “I think that’s the thing that most people get scared of is we’re going to be replaced by AI, and they’re going to be able to do everything... you don’t need us anymore.” P6 and P10 also mentioned this fear with P6 saying, “This thing can write and mimic me and put me out of a job” and P10 expressed that, “I... have felt a little threatened and I kind of clammed up.” Some of the participants were hesitant to make a prediction about whether AI replacement was realistic. P1 said, “In [an] already very tight teaching market, it’s going to make jobs harder for instructors... how much we actually need them.” P1 went on to question, “If there are even jobs for them... I’m not convinced.” Others made comments in a joking manner but were somewhat serious like P4 who said, “I don’t know if I should be worried or not.” Over the course of the interviews, eight of the 10

participants made comments about potentially being replaced with five individuals warning that instructional designers ought to be prepared for some type of replacement in the future. P2 said it outright that, “I could see it taking some jobs away or maybe some processes away” and P1 added to that saying, “Eventually, it’s just gonna be AI exchanges with no actual human interaction going on.” Regarding a more specific topic, P5 said, “I do think for very specific technical skills like coding, that is an area where AI can be incredibly effective. ... A human cannot compete with a well-built chess robot.” P1 also spoke about specific faculty roles saying, “The days of online teaching and being an instructor are numbered in terms of having to be at an SME,” and P9 also said, “They’re seeing less requests coming to their teaching and learning or technology centers because faculty are using AI.” P9 also thought that with instructional designers becoming more proficient in AI use, employers may choose less experienced employees who possess generative AI skills:

> A lot of people have been getting laid off because they can hire somebody else who is less experienced, can pay them a little bit less money and kind of train them to use AI, to do the work that we’ve been doing for years.

Time will tell whether generative AI will affect faculty or instructional design jobs in the future. Regardless of the outcome, instructional designers are feeling the pressure to become proficient in using the tools to remain relevant.

Also within the interviews, many participants expressed that expertise and human elements were still important in the generative AI age and were still required in instructional design. Four of the 10 participants recognized that there is value in expertise

and gaining knowledge and skill, regardless of whether skills are considered current or not (P2, P6, P7, P8). P7 articulated this thought well by saying, “I think there’s still value in knowing how to do these things, even if they’re considered anachronistic or of the past.” This was corroborated in several other comments including P8 who said, “I do think it’s a foundational skill. They still need to know,” and P6 who believed that “there’s always room for expertise.” Another reason for needing expertise is that technology is not perfect, and humans need to troubleshoot, work through glitches, or, in the worst-case scenario, shut the AI down. Half of participants mentioned some type of troubleshooting including P6 who said, “I think there might always be something that goes wrong with AI like some glitch or like any technology, it might become unavailable for a period of time, and we’d still need to do the work.” P5 also talked about working through issues:

> We still need to have humans who are adept with that skill... because someone has to build and or repair or in worst case scenario shut down the AI... I think you still very much still need that human element because of not only limitations of technology, but because humans can inherently consider things that AI will not.

A future without experts was discussed by P4 who said, “Someone would have to troubleshoot coding, and someone would have to understand coding to review the output... then in 30 years no one can figure out what’s wrong.” The need to identify inaccuracies was also identified as a reason for needing human expertise. Fact-checking was mentioned by P7 who said, “There’s still value in having individuals understand as a way to cross-check and as a way to ensure that we don’t become so fully dependent on the automation.” P4 also said, “It just generates wrong info and then you still have to

know a little something or just be so persistent that you just query it until it finally gives you a right answer." Finally, moving away from purely practical reasons, several participants found intrinsic value in the human aspect associated with skill and expertise and felt that the need for the human touch would never fully be eliminated (P4, P6, P7. P9, P10). P4 felt very strongly about this, saying, "It [AI] has a lot of potential in the hands of experienced instructional designers who are still empowered to make instructionally sound, pedagogically sound decisions, and who are still given the time to develop high-quality, engaging courses." The value of the human brain was also mentioned by P6 who said, "I also think that if you're using AI to solely develop a course... then we might limit ourselves because there's only so many directions that AI can go on a given topic... the human brain maybe has more." P7 felt particularly strongly about the value of expertise:

> I don't think we can rely on GenAI 100% on its own to teach us. I think we're still going to need a human mind and a processing ability by someone who's considered an expert to process that and to deliver that for us. I don't know if AI can do it 100% on its own.

P10 summarized many of the thoughts on the importance of expertise, saying, "There's always going to be a human part... AI is not going to be the gold standard. We are not just going to be able to take content directly from it… there's got to be a human aspect to it." The majority of participants felt strongly about expertise and the value of the human brain over generative AI tools for many reasons. Although this may not always be the

case as the tools continue to evolve, these instructional designers led me to believe that this principle will remain.

While participants did find great value in the human brain and in expertise, they also recognized that generative AI tools are here to stay and that, in order to remain relevant in the field, instructional designers need to learn how to use them. P3 said, "Knowing how to use it is going to be very important" and "It's something new... and it is here [to stay]." P10 felt pressure to use generative AI tools in an effort to not fall behind their colleagues, saying, "I've got to jump on the wagon or I'm going to get left in the dust and I'm going to miss something." P3 also made an interesting comment about the nature of trends in education, saying, "I don't think that this is necessarily a trend so much as it is more akin to, say, like [the introduction of the] internet" and that "AI is something that really does need to be talked about a lot in the space." Participants also expressed a need to figure out different ways to integrate and use the tools effectively in their daily work, which can be challenging with the tools still being relatively new. P10 was one such participant who said, "I think that you're going to have a great 'team'... we've got to learn how to work with AI and how to help it make our processes more effective and efficient" and that "we need to find ways to utilize it and integrate it." P7 made comments to this effect as well, saying, "It does need to be considered the way we can apply it the most meaningful way. And that's hard because you're trying to do it as it's being explored and that's always the challenge." P3 and P7 also explained that in the future applicants for instructional design positions will need to have generative AI skills listed on resumes in order to be considered. P7 said, "If you look at new job postings for

instructional design work… some organizations now are saying some experience with prompt engineering or demonstrated experience of using it thoroughly are starting to come in as requirements." P3 also said, "Not enough of the [applicants] we have talked to have mentioned it and it seems like it's a very important thing in the field to mention at this point." Overall, with so much uncertainty and change, P7 felt that "we need more research" on generative AI, particularly in instructional design. The future is still unknown, but the rapid growth of generative AI tools and their increasing integration into higher education has led participants to believe that skills in using the tools are of critical importance.

All of the thoughts and opinions participants shared are fairly complicated and sometimes conflicting, and this is exacerbated by the fact that generative AI tools are still rapidly evolving, so interactions with the tools change from one moment to the next. In this final code, predicting the future, participants offered their thoughts on what the future may look like in this ever-changing generative AI era, beginning with a comment from P1 who expressed surprise over the changes that have already occurred in higher education thus far. "I think in in terms of student work and the way that they're approaching school, I think AI has blown up everything" (P1). P3, P7, and P10 felt that the topic of generative AI needed to be discussed more within higher education and that successful integration required finding the right fit. P10 explained, "I don't know how or where it's going to fit seamlessly. I have found places where it just fits, but it's not a seamless integration." The challenge, however, in finding a good fit for generative AI tools within the instructional design space is that the future is yet to be determined. What

is thought to be a good path forward may change as the tools continue to evolve. P3 explained this succinctly, saying, “All the things that we have going on that could change it are so nebulous that I don’t even think I can predict what we’ll end up with.” P6, P7, and P9 made similar comments with P9 saying, “I’m kind of wondering about what the instructional design field will look like in the future, especially outside of education spaces.” The unpredictability of the future can be unnerving to some like P1 who said, “Looking down the road to what happens when the grade schoolers and high schoolers who are growing up the in the age of AI now, they’re going to be the college professors someday.” P9 specifically worried about the fate of instructional designers, saying, “I just wonder, 10-15 years from now, how many universities will have teaching and learning centers with a full staff.” While fears and worries are common, some choose to approach uncertainty with a sense of humor, like P1 who mused, “We’re like those - the fat people in the film, WALL-E, who are just in front of their computer screens all the time not doing anything. That’s probably where we’re going to end up someday, but I hope not.” No one can predict what will happen in higher education as a result of generative AI tools being increasingly adopted and integrated into processes. By continuing to discuss, conducting research, and exploring the tools, instructional designers can further their expertise and maintain their position as thought leaders.

Findings in Context of the Conceptual Framework

Many of the findings in the results section of this study align to my interpretations of how the TK, TCK, TPK, TPACK, and XK domains of the TPACK framework align to instructional designers using generative AI tools in their work (see Mishra & Koehler,

2006). The TK domain is reflected in results around the limitations and strengths of generative AI tools and how the tools alter the student experience. This domain aligns with several clusters and codes in the results including Cluster 1 in Theme 1, which deals with functional limitations of the tools and Clusters 1 and 3 in Theme 3, which are about excitement about the tools due to process-related successes and success being due to the tools working well. The TPK domain is also reflected in the results related to using generative AI tools to enhance the effectiveness of assessments, knowing that instructional design needs to change as a result of generative AI, and applying generative AI in the classroom. TPK-related results are found in Themes 2, 3, and 4 primarily. Themes 3 and 5 also address the TCK domain of the framework as the results demonstrate that subject matter could be changed by generative AI tools and that goals should be adapted as a result of the adoption of the tools. The TPACK domain is a complex interplay between technology, pedagogy, and content, and this is complexity is seen throughout the results and in the variability and sometimes contradictions in the results. TPACK aligns most directly with Themes 2, 3, and 4. Finally, the XK domain content like policy, perceptions, and institutional circumstances were found in Cluster 2 of Theme 1 as well as in codes like employer promoted, evolving policy, and policies lacking. The TPACK framework and my interpretations around the integration of generative AI in instructional design are aligned throughout the results of this study. Because the results discuss both positive and negative aspects of integrating generative AI tools in instructional design practice, there were not any codes or patterns that were discrepant or disconfirming.

Evidence of Trustworthiness

During data collection and analysis, I used multiple strategies to ensure trustworthiness. In this section, I will describe how credibility, transferability, dependability, and confirmability were upheld. To ensure credibility, I engaged often with another qualitative researcher sharing raw data, codes, clusters, themes, and the flow of the narrative. I used the strategy of rich contextualization to ensure transferability as well. Throughout data collection and analysis, I worked to include as much context as possible in my narrative as well as in my reflexive journal. I also intentionally recruited participants from a variety of institutions with differing levels of experience. To ensure dependability of my data, I employed an audit trail strategy and kept detailed record of all participant interactions in my reflexive journal. Finally, I ensured that confirmability was accounted for by reflecting often on interviews and analysis procedures. In my reflexive journal, I was sure to include both positives and negatives and attempt to challenge my personal opinions and biases throughout.

Summary

In this chapter, I reported the results of this inquiry into the experiences and perceptions of online higher education instructional design professionals in using generative AI tools. My analysis of the data yielded five themes organized into 10 clusters made up of 49 codes. The full list of codes and descriptions can be found in Appendix A. The first two themes help to answer RQ1, and the key finding around that RQ is that there are a wealth of challenges that instructional designers associated with using generative AI tools including functional issues, issues related to perceptions of the

tools, and deep philosophical dilemmas. Theme 3 is aligned to RQ2, which is about successes in using generative AI tools. The overall finding for this theme is that instructional designers are excited to learn more and use the tools when they function well and speed up their processes, and success is somewhat dependent on employer actions or lack of actions. The final RQ is addressed with Themes 4 and 5. Generative AI tools are changing higher education teaching and learning, and instructional designers' beliefs, opinions, and behaviors are also changing as a result. Participants felt that, at this point when the tools are better understood, policies and best practices need to be constructed to facilitate successful use. In the next chapter, Chapter 5, I will provide an interpretation of the findings, discuss the limitations of the study, and deliver recommendations, implications of the study, and a final conclusion.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this qualitative study was to explore the perceptions of online higher education instructional design professionals on what challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development and how these experiences have shaped their current perceptions about teaching and learning. To address this purpose, I conducted a basic qualitative study comprised of semistructured interviews with online higher education instructional design professionals. I employed reflexive thematic analysis to analyze the data, and several key findings developed as a result. The key finding associated with RQ1 is that challenges associated with adopting generative AI tools in course design work arise from technological issues as well as perception-based issues, and that these challenges have sparked complex philosophical debates amongst instructional designers. Regarding RQ2, the key finding from this study was that success in adopting generative AI tools stems from streamlining processes, often resulting from employers motivating instructional designers to explore these tools. Finally, the key finding related to RQ3 is that perceptions of teaching and learning are evolving in tandem with generative AI tools, and that, while the future remains uncertain, instructional designers believe they and others in higher education need to develop a new set of best practices to achieve success.

Interpretation of the Findings

The exploration of instructional design perceptions on the challenges and successes they are experiencing in integrating generative AI is one that has not been well explored extensively thus far in scholarly literature, nor have their current perceptions

about teaching and learning in this generative AI era been explored. This study aimed to contribute to the body of knowledge on instructional design practice, thereby enhancing the understanding of this topic. Although the results are not generalizable, they provide both confirming and disconfirming findings. In this section, I provide my interpretations of the findings organized by RQ.

RQ1: Challenges

When reviewing the literature related to instructional designers and their perceptions of generative AI tools in their work, several challenges were noted that were confirmed by participants in this study. Accuracy of generated content was mentioned extensively as a functional limitation of generative AI tools (Choi et al., 2024; DaCosta & Kinsell, 2024; Davis & Lee, 2024; Karpouzis et al., 2024; Kostikova et al., 2024; Kozan et al., 2025; Kumar et al., 2024; Madunić & Sovulj, 2024; McNeill, 2024; Okulu & Muslu, 2024; Tupper et al., 2025; van den Berg & du Plessis, 2023), and this was confirmed by over half of all participants in this study who mentioned accuracy or failure of generative AI tools to provide evidence as a limiting factor. Quality and ethics were also cited as limiting factors in published literature (Choi et al., 2024; Karpouzis et al., 2024; Küchemann et al., 2023; Kumar et al., 2024; Madunić & Sovulj, 2024; Mikroyannidis et al., 2024; Sridhar et al., 2023), and this was confirmed by many of the participants in my study. However, participants in McNeill's (2024) study reported the quality of AI-generated work to be higher than that of human work, which was disconfirmed by my study participants. Issues with context and nuance not being understood by generative AI tools were another confirmed finding in this study. Choi et

al. (2024), Davis and Lee (2024), Hu et al. (2024), Khademi (2023), Kostikova et al. (2024), and Meron and Araci (2023) reported issues with generative AI tools understanding context and nuance, and these sentiments were repeated by multiple participants in this study. Several other functional limitations were discussed in the literature that were confirmed or extended by this study. For example, multiple studies reported that generative AI outputs were basic, generic or vague (Choi et al., 2024; Davis & Lee, 2024; Küchemann et al., 2023; Meron & Araci, 2023; Rutecka et al., 2025), and participants in this study extended that thought by stating that outputs were so basic or generic that they fail to adequately respond to the prompt and often yield outputs written in a redundant or synthetic voice.

Challenges associated with negative perceptions and fears were also confirmed, disconfirmed, and extended by the results of this study. Several authors mentioned maintaining ethicality as a significant fear of instructional designers in their research (Amando-Salvatierra et al., 2023; DaCosta & Kinsell, 2024; Kostikova et al., 2024; Kumar et al., 2024; McNeill, 2024). This was confirmed as a considerable challenge by multiple participants, as was the challenge of resistance to AI-generated content (Tokita, 2024). Another key topic mentioned in the literature concerned durable skills and how generative AI tools will affect those in the future. Baytak (2024), Kumar et al. (2024), and Meron and Araci (2023) all reported worries that using generative AI tools may stifle creativity. Others specifically called out critical thinking and reasoning as durable skills that could potentially atrophy (Bolick & da Silva, 2023; Choi et al., 2024; Kostikova et al., 2024). Participants in this study confirmed these worries, but there were a few studies

that were disconfirmed as well. Mikroyannidis et al. (2024) and van den Berg and du Plessis (2023) found that using generative AI tools could facilitate and develop critical thinking skills, which is contrary to what my participants stated. In addition to the confirming and disconfirming results related to creativity and critical thinking, participants brought up the atrophy of durable skills to overall intellectual capabilities, communication skills, and empathy, which are issues around practice that have not previously been addressed in the literature.

RQ2: Successes

The literature related to successes that instructional designers experience when integrating generative AI tools in their work was also extensive, and, in fact, the majority of existing literature on the topic included findings on both challenges and successes. One of the successes cited most often in the literature was about streamlining or speeding up tasks using generative AI tools (Amando-Salvatierra et al., 2023; Bolick & da Silva, 2023; Choi et al., 2024; Davis & Lee, 2024; Karpouzis et al., 2024; Kostikova et al., 2024; Kozan et al., 2025; Krushinskaia et al., 2023; Kumar et al., 2024; Madunić & Sovulj, 2024; McNeill, 2024; Meron & Araci, 2023; Mikeladze, 2023; Morales-Chan et al., 2023; Nagy et al., 2024; Ryall & Abblitt, 2023; Tupper et al., 2025; van den Berg & du Plessis, 2023). While these studies were confirmed by the results of this research, there were also studies that were disconfirmed. Krushinskaia et al. (2023) and Madunić and Sovulj (2024) both seemed to report contradictory findings that some participants found that generative AI tools did speed up processes while others found that the process of validation and refinement of generative AI outputs negated the efficiencies. Authors

were somewhat split on other success-related topics discussed by participants in this study. For example, Baytak (2024) found AI-generated lesson plans usable without much revision, and this was confirmed in statements by several participants. However, other research found that AI-generated content was only usable as a template that can be edited by a human (Meron & Araci, 2023), which was disconfirmed by this study.

In addition, many research studies in the literature review discussed the various ways that AI tools can be used in the instructional design process. Applications like creating course materials, developing media, writing learning outcomes, and building media items were all explained as valuable and useful (Amando-Salvatierra et al., 2023; Kozan et al., 2025; Kumar et al., 2024; McNeill, 2024; Rister & Velez, 2025; Ryall & Abblitt, 2023). Participants confirmed these uses as beneficial within their processes. Lammert et al. (2024), however, found that AI-generated lesson plans were not useful, and this was disconfirmed by this study. Several studies also mentioned the concept of balance as critical in the adoption of generative AI tools in higher education (Amando-Salvatierra et al., 2023; DaCosta & Kinsell, 2024; Kostikova et al., 2024; Mangaroska et al., 2024; Morales-Chan et al., 2023; Okulu & Muslu, 2024; Nagy et al., 2024). The importance of balance was confirmed within this study as significant to success with using generative AI tools.

RQ3: Perceptions of Teaching and Learning

Regarding current perceptions about teaching and learning, this study's results confirmed much of what has already been published on the topic, starting with statements about varying opinions within the field. McNeill (2024) and Nagy et al. (2024)

specifically discussed differing levels of comfort with generative AI tools, and this was confirmed by more than half of the participants in this study. Other beliefs like the inability to replace human nuance with generative AI tools (Amando-Salvatierra et al., 2023; Dogan, 2025; Morales-Chan et al., 2023; Nagy et al., 2024; Tupper et al., 2025; van den Berg & du Plessis, 2023) were also confirmed. Regarding best practices that need to be adopted to successfully use and adopt generative AI tools, much of what participants in this study recommended was also included in the results of previous studies. For example, successful use necessitates the practice of refining and validating generative AI outputs (Choi et al., 2024; Davis & Lee, 2024; Kostikova et al., 2024; Kozan et al., 2025; Krushinskaia et al., 2023; Kumar et al., 2024; Madunić & Sovulj, 2024; McNeill, 2024; Mikeladze, 2023; Okulu & Muslu, 2024; van den Berg & du Plessis, 2023), learning prompt engineering (Bolick & da Silva, 2023; Chen et al., 2025; Davis & Lee, 2024; Kostikova et al., 2024; Lammert et al., 2024; Meron & Araci, 2023; Morales-Chan et al., 2023; Tupper et al., 2025), and practicing transparency (McNeill, 2024; Mikroyannidis et al., 2024). Rethinking assessments and building in AI-resilient techniques were also best practices that were confirmed by this study (Baytak, 2024; Bolick & da Silva, 2023; Mangaroska et al., 2024; Ryall & Abblitt, 2023).

The final theme dealing with the future contained both confirming and disconfirming statements from participants as well. Throughout the literature, instructional designers reported that generative AI tools could not replace humans, although roles and responsibilities may shift (Amando-Salvatierra et al., 2023; Dogan, 2025; Kostikova et al., 2024; Kumar et al., 2024; Meron & Araci, 2023; Morales-Chan et

al., 2023; Nagy et al., 2024; Ryall & Abblitt, 2023; Sridhar et al., 2023; van den Berg & du Plessis, 2023). Many participants in this study agreed with this, but there were several who expressed fear and concern that this may not always be the case. In this way, this study both confirmed and disconfirmed that humans could be replaced by AI. There was, however, full agreement across the literature review and interviews that instructional designers will need to know how to use generative AI tools in the future and require training (Lammert et al., 2024; Mikeladze, 2023; Morales-Chan et al., 2023; Nagy et al., 2024; Ryall & Abblitt, 2023). The necessity of knowledge and training was confirmed in this study as was the continued need for humans to acquire and hold expertise (Choi et al., 2024; Davis & Lee, 2024; DaCosta & Kinsell, 2024; Dogan, 2025; Khademi, 2023; Kumar et al., 2024; Lammert et al., 2024; Madunić & Sovulj, 2024; McNeill, 2024; Meron & Araci, 2023; Mikeladze, 2023; Mikroyannidis et al., 2024; Okulu & Muslu, 2024; Sridhar et al., 2023). Finally, and perhaps most importantly, authors expressed that the future is yet unknown regarding generative AI, how it might affect higher education, and how instructional designers need to be adaptable (Amando-Salvatierra et al., 2023; Bolick & da Silva, 2023; Mikroyannidis et al., 2024; Nagy et al., 2024; Ryall & Abblitt, 2023). Sentiments about the nebulousness of the future were confirmed in this study as participants are both wary and excited about how higher education and instructional design may change.

Limitations of the Study

According to Burkholder et al. (2020), weaknesses or limitations are associated with all research studies, stemming from design, methodology, or both. This study is not

an exception. First, the research design I chose for this study was limited. In this basic qualitative study, I conducted semistructured interviews of 10 participants. This small sample size could limit the transferability of the findings. In addition, this study was limited to only higher education instructional designers whose primary job function was creating course content. In limiting the type of instructional designers that fit the criteria, I may have missed additional insights about the challenges and successes other types of instructional designers experienced in integrating generative AI tools in their work. Another limitation of this study was that the participants had varying levels of experience with generative AI tools. While this did provide a wide array of perceptions, the time engaged with the tools may also have altered their perceptions. A final limitation is that, as with any basic qualitative study, there is potential for researcher bias to affect the findings. Although Braun and Clarke (2022) disagree with categorizing researcher bias as a limitation, I have worked in the instructional design field in the past and have preconceived notions that may have influenced my interpretations of the results. In an effort to manage bias and ensure the trustworthiness of this study, I adopted multiple strategies that are outlined in Chapter 3, including rich contextualization and reflexive journaling.

Recommendations

Recommendations for future research on this and adjacent topics are numerous considering the relative novelty of generative AI tools, the limited research on their use in instructional design, and the many other applications of generative AI tools in higher education. The first recommendation is based on the limitations of this study. Only 10

instructional designers were interviewed and their perceptions analyzed. In addition, among the 10 participants, I only considered one an innovator and none as laggards. Instructional designers who design training materials and other non-course content were also excluded. I recommend that this study be replicated with a larger and more diverse sample of instructional designers and that other sources of data on the topic be collected as that may provide additional depth to the phenomena.

The second recommendation for future research on this topic is related to the findings of the study. Across the 10 participants, there was agreement that the way instructional designers approach the development of assessments in online higher education needs to be rethought. They did not, however, provide details on how assessments should be rethought, however, other than saying that building AI resilient assessments was important. Based on this finding, I recommend that additional research be carried out that explores new and innovative approaches to assessment design that take generative AI into account.

A final recommendation, which is also related to the findings of this study, is around the building of best practices in using generative AI tools. Multiple participants expressed concern about the lack of policy and guidance their institution provides relating to best practices. This has led many to build their own non-evidence-based ideas about best practices to this point. To better guide instructional designers and assuage fears about improper use, I recommend that research be designed that systematically tests best practices in using generative AI tools in instructional design.

Implications

This study may contribute to positive social change in multiple ways and at multiple levels. The application of generative AI tools in online higher education instructional design is a fairly new and unexplored topic. At the individual level, this study has contributed to instructional design practice and knowledge about how instructional designers perceive the tools, how they are currently integrating the tools in their daily work, and what benefits and drawbacks they are finding as they put the tools into practice. This increased body of knowledge also applies to positive implications at the institutional level. In better understanding instructional designers' experiences and perceptions, best practices can be better informed, and training and guidance could be more targeted. Institutions could also use this information to design or redesign policy to better meet the needs of various stakeholders. At the societal level, this study has the potential to help advance instructional design practice as a whole. Several participants in this study discussed the paradigm-shifting potential of generative AI tools likening it to other innovations like the internet. In better understanding the experiences of instructional designers in integrating the tools, broader guidance and training from outside individual institutions can be developed. In collating these experiences, perceptions, and concerns with generative AI tools across institutions, the practice of developing course content could be changed, thereby affecting multiple stakeholders in higher education.

Conclusion

This study, which was an exploration of the perceptions of online higher education instructional designers on the challenges and successes they are experiencing in integrating rapidly evolving generative AI tools in course design and development, yielded several key findings that have the potential to guide further practice and policy. Instructional designers have a wealth of varying experiences with generative AI tools that both exhilarate and alarm them. In addition, experiences with using generative AI tools have caused instructional designers to question their current perceptions about teaching and learning as a whole.

The key findings related to RQ1 are that instructional designers experienced multiple challenges in using generative AI tools both functionally and due to opinions and viewpoints about the tools and their outputs. The integration of the tools, in addition, have sparked complex philosophical debates about the nature of learning, authorship, and the value of human intelligence. Related to RQ2, successes that instructional designers are experiencing, the key findings demonstrate that excitement about generative AI tools are related to the tools being useful within the instructional design process and beyond that. Participants noted that their most successful applications of generative AI tools came from finding the uses that worked well within the tools' limitations and that it was easier to find successes when employers encourage generative AI tool use. The key findings related to RQ3 involve using experience to guide best practices and look toward the future. Despite whether experiences were positive or negative, each helped to shape participants' current perceptions of teaching and learning. Not only are structured best

practices desired by instructional designers; they need to be experience-based and adaptable to account for the rapidly evolving nature of the tools. In addition, participants spoke extensively about the future and the many unknowns that exist as a result of generative AI tool integration. In looking toward the future, participants stressed that humans would always have a place in instructional design and that the future, while undecided, should be informed by continuing education and research.

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Appendix A: Codes and Descriptions

Code	Description
Accuracy and evidence	Outputs are not accurate or fail to provide evidence.
AI collaborator	Using AI as a collaborative partner, particularly when others are not available.
AI frustrations	Ways that AI can be frustrating to use.
AI propelling edtech	The "AI era" is also propelling other forms of EdTech amongst faculty and by the institution to be more efficient.
AI resistance	Some people fear AI because they just don't understand it.
AI teacher	Using AI to explain concepts, learn more, or put in layman's terms.
Benefits and Successes	Ways that AI tools are positively impacting ID.
Building optimism	The more people play around with and get comfortable with AI tools, the more optimistic they get.
Can't replace human nuance	Human nuance, connection, or interaction are not things that AI can replace.
Context and nuance	AI tools are not good with human-only skills like nuance, context, and things based on experience.
Diversity guardrails	AI isn't allowed to respond to queries about diversity, which can be a problem in education.
Downside to efficiency	Efficiency can lead employers to increase workloads.
Durable skill atrophy	Using AI rather than experiencing things in person can affect durable skills like empathy and communication.
Employer promoted	Participant uses AI because their employer encourages it either through policy, motivation, or buying licenses.
Ensuring ethicality	Talking about the AI and ethics as well as the gray area associated with it.
Evolving policy	AI policy is and should be adaptable and changeable to keep pace with AI evolution.
False sense of smarts	Some folks think that being able to use GenAI to explain something or create content makes them an expert, but did they learn at all?
Give me what I ask for	Outputs are not what the prompt asked for or what the user needs.
Improvement with time	AI tools are getting better as time goes by.
Is it worth it?	Sometimes it isn't worth it to use AI when you could just do it yourself.
Manual/AI paradox	The paradox where you need to know how to do things manually, but AI is going to be used in future careers, so you also need to know that.
Need expertise still	Why we still need human expertise/not all jobs can be replaced.
Need to know how to use	Knowing how to use AI will be necessary in the future.
Net positive	The perception is that AI tools have a net positive effect on course development.
No limits on tasks	No tasks they would definitely NOT use AI for.
Orienting to a topic/job	Using AI to gain comfort in a new job or new topic.
Outputs are lacking	Some outputs lack detail or are low quality.
Policies lacking	Institutions not having solid policy in place for AI use.
Predicting the future	Pondering on how AI popularization will affect us in the future.
Privacy and security	Considerations of both privacy and security.

Process of learning	The content isn't as important as the process of learning-this is important to keep in mind during development that we want to create learning experiences.
Prohibited by policy	Several actions are not allowed because of either workplace or accreditor policies.
Prompt engineering	Prompt engineering dictates the quality of the output you get/ importance of prompting.
Questioning authorship	Can we say AI-generated content is authored by people?
Refining and validating	Outputs do need to be refined and validated in order to make them work.
Replacing humans	Will AI tools replace humans in the future or at least aspects of human work?
Responsible use	We should be working to teach responsible use to students (and faculty for that matter).
Rethink assessment/AI resilience	How we approach assessments will need to be rethought.
Starting point	When folks have trouble getting going, AI can provide a starting point off which you can build.
Streamline/speed up tasks	A benefit of using AI tools is that they streamline aspects of the ID process and speed things up.
Striking a balance	People and institutions both need to find a balance with AI tools between them being used for anything and having guardrails, between helping support and losing your voice.
Synthetic voice	Easy to tell when AI is being used without any kind of detection software because AI has a particular way of writing.
Transparency	Letting folks know you are using it is important.
Unadvisable uses	Certain tasks that seem inappropriate for AI use.
Usable outputs	Some outputs don't require a lot of effort, and these are the ones that save us time.
Using it anyway	Folks are not affected by external factors -they are going to use the tools anyway.
Varying opinions	Not everyone agrees on the usability of outputs.
Watering down expertise	Opinions that using AI generated content waters down knowledge and expertise.
Ways to use AI	Examples of ways to use AI that are helpful, cool, useful.

Appendix B: Full Interview Protocol

Template for Interview Protocol

Introductory script:

Thank you for agreeing to participate in this interview for my dissertation. Before we get started, I wanted to share a bit about myself and why I am doing this study as part of my doctoral research.

I have worked in the instructional design field for more than a decade and was involved in creating course content for many years prior to that as well. I'm passionate about instructional design and creating high quality content for students. I'm sure you know that in recent years generative AI tools have changed the way we approach course content creation, and I anticipate that these changes are going to continue. I think it is important to learn more about the experiences that instructional designers have had thus far so we can steer the ship moving forward to a place where we are leveraging the strengths of people and generative AI tools and using them to their full potential.

During this interview, I will be asking about your experiences in using generative AI tools within the instructional design process. Just so you know, you can end this interview at any time, and you can skip questions that you do not want to answer. This interview is expected to last for 30-60 minutes.

I will be audio recording our interview today so that I can make a transcript for analysis. This will ensure that I have an accurate record of what you share with me today. Before we get started, do you have any questions?

[START RECORDING]

Today's date is [DATE] and it is [TIME].

Background, Screening, and Introductory Questions

To get started, I wanted to ask a few questions about the type of work you do and how your workplace approaches instructional design.

- *First, tell me about your employer.*
- *What type of work do you normally do?*
- *Explain the level of AI integration your workplace currently has.*
- *What instructional design models do you use when designing courses?*
- *Which general tools and specific tools have you tried out?*

Option A: *Thank you, Let's go ahead and move into the interview questions.*

Option B: *Thank you so much for your willingness to participate. But after talking with you, I'm not sure you have the depth of experiences on using generative AI tools in instructional design that I need to answer my research questions. Thank you for time.*

Table of Interview Questions

Transition Statement: *My first few questions relate to just your general experiences, both good and bad.*

Interview Questions (IQs)	My Notes & Alignment to framework/literature
IQ 1: I'd like to start out with you just telling me some stories about times you used generative AI tools to create course content. Let's start with a positive story.	TK, TCK, TPK, TPACK, XK
Prompts: I hear you saying X is something that benefitted from generative AI tool use. Why do you think that is? Tell me more about…	
IQ 2: Now, let's think about the other side of the coin. Can you share a story of a time that using generative AI for creating course content went wrong.	TK, TCK, TPK, TPACK, XK
Prompts: It sounds like X is maybe a limitation of using generative AI tools. Why do you think that's the case?	

Transition Statement: *Now that you've shared a few stories about experiences, I want to get a little bit into why you choose to use or not use generative AI tools in your work.*

Interview Questions	My Notes & Alignment to framework/literature
IQ 3: In your experience, how have personal or institutional perceptions affected your generative AI use? This could be perceptions of the tools themselves or of AI-generated content.	XK
Prompts: Can you tell a story to illustrate how perceptions have affected your generative AI use?	

That's really interesting that X. Can you explain how that has affected your tool use?	
IQ 4: What is your experience with determining when to not use generative AI tools within the course design process? Like are there certain tasks you definitely would not use generative AI tools?	TPACK
Prompts: So, I hear you saying you don't like to use the tools for X. Why do you think this way? I hear what you are saying about other people's opinions, but how does your opinion differ or align?	
IQ 5: In your experience, how have external factors like policies or accreditation affected your use of generative AI in course content creation?	XK
Prompts: I hear you saying that X has contributed/hindered to your use. Can you tell me more about that? You shared about how X was an external factor that contributed, are there any factors that have hindered to your Gen AI use? Does your company have any type of policy on generative AI use? How has that influenced your use?	

Transition Statement: *This next set of questions are related to the impact of generative AI tools on instructional design processes and on personal behaviors in learning and designing course content.*

Interview Questions	My Notes & Alignment to framework/literature
IQ 6: What is your opinion on the impact of the integration of generative AI tools on the ID process as a whole?	TPK
Prompts: Which ID processes do you think have undergone the most significant changes as a result of generative AI integration? I hear you saying the impact is small/large. Can you explain more about why you think this is the case?	
IQ 7: What are your thoughts on the impact of generative AI tools on traditional pedagogical approaches or teaching strategies?	TPK
Prompts:	

Just so I am clear, you find the impact big/small? Do you have a story to illustrate how you used generative AI to find or refine teaching/pedagogical approaches?	
IQ 8: What is your experience with using generative AI tools as a way to deepen subject area knowledge?	TCK
Prompts: Can you tell me more about X experience? Regarding X experience, how was this different from how you would have gained subject matter knowledge in the past?	
IQ 9: Explain whether you think the integration of generative AI tools led to any changes in the subject area content that is included in course work? For example, if AI can generate code with better accuracy than a human, do we still need to teach coding?	TCK
Prompts: Can you tell me more about why you think this way?	
IQ 10: Do you think that access to or expertise in subject area knowledge has changed with generative AI tools becoming more widely used? For example, do you think that generative AI tools are contributing to more people being knowledgeable about more topics or is it having the opposite effect?	TCK
Prompts: I hear you saying X, can you tell me more about why you think that?	

Transition Statement: *I have one more question for you, and it involves the instructional design process as a whole as well as the intersection of multiple knowledge types. Think of it as kind of a compilation of all of the other questions.*

Interview Questions	My Notes & Alignment to framework/literature
IQ 11: Some educational experts think that to effectively integrate technology into the classroom, one needs to understand the technology, the subject area, and effective ways to teach the content and how all these things work together. With the integration of generative AI in the instructional design process, how do you see the three elements interrelating?	
Prompts:	

Final IQ.

Is there anything else about generative AI use in the instructional design process that we have not yet had a chance to discuss or that you want to add?

Closing Script: *I really appreciate your time today. Your experiences and insights are critically important to the purpose of this study, so thank you very much. If you have any questions or would like to reach me, I will share my email address and phone number in the chat. Again, I truly appreciate you taking the time to talk with me today.*

As needed: *I am still looking for additional participants for my study. If possible, could you share contact information for any instructional designers that you know who have experience using generative AI tools in creating course content. If it is easier, would you be willing to forward my study invitation to others you think might be interested? Thanks so much for considering that.*