From Pilot to Global Scale: Iterative Teaching and Curriculum Design for Introduction to Generative Artificial Intelligence

by

Larissa Schwartz

B.A., University of Iowa, 2007

M.S., University of Colorado Boulder, 2023

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Department of Engineering Education

2026

Committee Members:

Tom Yeh, Chair

Angela R. Bielefeldt

Diane Sieber

Lee Frankel-Goldwater

Bo Wu

Schwartz, Larissa (Ph.D., Engineering Education)

From Pilot to Global Scale: Iterative Teaching and Curriculum Design for Introduction to Generative Artificial Intelligence

Thesis directed by Prof. Tom Yeh

This dissertation examines the design, iterative refinement, and global scaling of a pioneering introductory course on Generative Artificial Intelligence (GenAI) for engineering education. Across four iterations from January 2024 through September 2025, the course evolved from a 25-student undergraduate pilot at the University of Colorado Boulder into a five-day workshop reaching over four thousand registered global participants. The study uses curriculum-as-research and design-based research methodologies grounded in constructivist learning theory and self-determination theory to surface three curriculum-design principles that emerged across the iterations: modularity, learner choice, and continuous feedback. The dissertation contributes to engineering education scholarship by documenting how a curriculum for a rapidly evolving (black swan) technology can maintain pedagogical coherence while adapting at the pace of the underlying technology, and by demonstrating the value of treating each course offering as a unit of inquiry rather than as a discrete delivery event.

To the students, colleagues, and family who made this work possible.

Acknowledgements

Acknowledgements will be added in the final version.

Contents

Chapter 1

Introduction

1.1 Background and Rationale

1.1.1 The Rise of Generative AI as a Black Swan Event

I remember the first time I saw a Generative Artificial Intelligence (GenAI) application create images that looked almost as if they were made by human artists. The moment made me feel curious, excited but also nervous. GenAI seemed to appear almost overnight, changing creative work and education in ways none of us expected. As a visual arts educator who helps students explore and create artistic ideas, I observed tools such as OpenAI's GPT-3 and DALL · E produce original stories and visuals with incredible efficiency and accuracy. GenAI was more than a new technology, it was what Taleb (2007) calls a "black swan" event, an unexpected development with major and lasting effects.

My advisor, Professor Tom Yeh, asked me to redesign parts of my curriculum to help students understand how these tools work and how to use them ethically and responsibly. With these GenAI tools starting to appear, new questions about authorship, originality, and what it means to be creative were brought up daily. In the creative industry and classroom, I now present GenAI content as a starting point for brainstorming and human imagination rather than a replacement for it. These tools have changed how I teach and encourage new conversations about ethics, technical skills, and the future of creative work in the industry and classroom (Brown et al., 2020).

1.1.2 Unprecedented Speed and Breadth of Adoption

I've never witnessed a technology spread so quickly. Within weeks of GPT-3's release, social media, classrooms, and the creative industry were chaotic with people testing prompts and sharing AI-generated drafts (Brown et al., 2020). Educators who hesitated to introduce AI into their curriculum, now assign students to use the tools as collaborative partners. Artists who spent months/years on concept sketches began using DALL · E to explore dozens of ideas in minutes (Ramesh et al., 2021). Even small non-profits, Title 1 and local schools have free or low-cost access to these powerful GenAI models, which make this technology accessible to more people than ever imagined. This quick, global adoption, along with the variety of users, from teachers, politicians, and industry leaders, proves how GenAI truly shook up every professional industry and educational institution almost overnight.

1.1.3 Rapid Technological Evolution, Demanding Responsiveness

I've observed GenAI move and evolve at record pace, with each new model release bringing capabilities we hadn't even imagined weeks prior. When GPT-3 amazed us with their technical abilities, it felt cutting-edge. Then GPT-4 arrived, expanding into image creation, coding assistance, and reasoning in ways that made my course materials obsolete overnight (OpenAI, 2023). As a creative educator, I've learned to build flexibility into my curriculum, planning time each week to explore and research the latest tools and adjust my teaching materials on the fly. This constant change in GenAI tools, forces me to stay curious and responsive, demonstrating for students how to learn alongside technology rather than fall behind it.

1.1.4 Why Engineering Needs to Address GenAI Now

I've spent years teaching students how to combine art and technology, and I've never worked with a tool so powerful as GenAI. In engineering classrooms, this new technology can automate routine coding tasks, generate design prototypes, and even suggest original solutions. With these new technological advancements, the tool also introduces new risks around accuracy, bias, and copyright infringement, which are issues that need to be addressed.

By integrating GenAI into our curriculum now, we give future engineers the chance to learn how to successfully use these tools responsibly and evaluate and critique their outputs. When students experiment with code generation prompting, they discover both the efficiencies and the downfalls, such as subtle errors that can cause safety or ethical concerns when GenAI models reproduce biased data (Brown et al., 2020).

Teaching GenAI tools and skills helps engineers collaborate more effectively with other disciplines which can create interdisciplinary innovations (Ramesh et al., 2021). It also prepares students for a job market where fluency in AI-driven workflows is becoming an essential.

Addressing GenAI today means building an adaptable curriculum that combines hands-on projects and demonstrations, ethics discussions, and regular updates on the latest GenAI models. This approach not only equips students with cutting-edge competencies but also instills a mindset of continuous learning, which is crucial in a world where technological evolution never stops (OpenAI, 2023). Engineering education that embraces GenAI now will help empower graduates to shape technology's future.

1.1.5 The Opportunity: A Pioneering Introductory Course Designed, Taught, and Studied as a Scholarly Contribution

I was honored to pilot an Introduction to Generative AI course through the school of Engineering and Applied Science at The University of Colorado Boulder in the spring of 2024. I continued to teach the course for a second time during the spring of 2025. During the courses, every student project was used for collective data discovery. From week one, students experimented with a range of tools, such as text generators like ChatGPT and Microsoft Copilot, image generators like DALL · E and Midjourney, music generators like Soundful and Suno, video generators like Runway and Pika, recording prompts, outputs, and reflections in a specific module for their assignments in Canvas, which is a learning management system (Bommasani et al., 2021).

Each module centers on a different topic: prompt engineering, image, video, sound, human centered AI, and vibe coding. Students compare how different models handle the same assignment, identify patterns in specific styles and errors, and discuss ethical considerations around bias and ownership. Their assignments become the foundation for a future research paper that outlines best practices across tools and highlights areas for improvement (Marcus & Davis, 2020).

By positioning the course as a scholarly contribution, students learn GenAI skills and concepts through hands-on demonstrations rather than just lectures. Weekly classes introduce emerging research, such as new approaches to prompt engineering, updates on existing GenAI models, and new GenAI tools, while providing guest lecturers and workshops from industry and academia deliver real-world insights. Assessment focuses on students' assignments and research contributions, data analyses, and reflective essays, that help draft sections of the scholarly paper, so by the end of the semester, everyone has built both practical skills and a publishable artifact.

The pioneering structure of the course not only provides aspiring creatives and engineers with GenAI tool fluency but also trains them as significant scholars, ready to shape GenAI's technological future through evidence-based exploration.

1.2 Literature Review

This section reviews existing research on three interrelated topics: the use of GenAI in education, the curriculum-as-research approach, and frameworks for teaching ever-changing technologies. Basing research on studies from engineering education, instructional design, and technology-integrated learning, this literature review highlights the essential findings and identifies holes and gaps that this dissertation addresses.

1.2.1 GenAI in Education

GenAI, applications that produce text, images, code, or other artifacts based on data-driven models, has rapidly entered educational settings. Early studies focused on using GenAI as a tutor or content generator. For example, Huang et al. (2023) demonstrated how AI chatbots can answer student questions in large online courses, improving response times and perceived instructor presence. More recent work explores GenAI's role in creative assignments. Dehouche and Dehouche (2023) illustrated how art and design courses used text-to-image models to help students brainstorm design concepts, reporting increases in creative ideation and student confidence. However, most implementations highlight tool demonstrations rather than the underlying pedagogy, leaving a space in understanding how to integrate GenAI into curriculum design systematically.

Researchers have also examined ethical and equity concerns. Baker and Hawn (2022) investigated how GenAI assignments might reproduce biases present in training data and recommended inclusive design practices, such as diverse prompt examples and reflective discussions, to mitigate harm. Kelly and Sullivan (2023) found that students with limited technical backgrounds can struggle with blurred AI behaviors, emphasizing the need for transparency and scaffolded explanations.

Despite these advances, there remains a lack of cohort studies documenting full course development cycles. Few works trace iterative refinements across multiple offerings or analyze how student feedback drives curriculum development. This dissertation fills that void by presenting a systematic account of course design, implementation, and revision in GenAI education.

1.2.2 Frameworks for Teaching Disruptive Technologies

Disruptive technologies, innovations that fundamentally change industries and the skills they demand, create a unique challenge for educators. Christensen, Grossman, and Hwang's (2009) concept of disruptive innovation has been adapted to showcase the need for curricula that can change rapidly as new tools appear.

Modular course design supports flexible content updates by breaking curricula into independent units or modules. Salmon's (2002) e-tivities model demonstrates how self-contained online activities can be updated individually, such as substituting in new case studies on developing AI ethics, without revising the entire syllabus.

Community engagement involves co-creating curriculum with learners to ensure relevance and ownership. Healey and Jenkins (2009) show that partnerships between students and faculty, involving learners in curriculum planning and review, lead to deeper engagement and improved learning outcomes. By involving students in selecting GenAI tools and refining module objectives, educators build a shared responsibility for curriculum development.

Although each element, modularity, transferability, and engagement, has strong support, few frameworks integrate all three into a cohesive methodology for the fast-moving technical field. This dissertation proposes an integrated framework that combines curriculum-as-research documentation, iterative teaching inquiry, and these three pillars to address the specific demands of GenAI education.

1.3 Problem Statement

1.3.1 Traditional Curriculum Assumes Gradual Change; GenAI Requires Rapid Adaptation

I currently work in the creative industry and also teach students how to explore ideas and express themselves artistically. The traditional curriculum I'm used to working with in educational settings, is built around the expectation that tools and methods evolve slowly. I normally would plan lessons months in advance, refine projects over an entire semester, and trust that the outside world and professional industry would remain mostly the same as when I started the course. With GenAI, everything is constantly changing at rapid speed as new tools and models are arriving daily to weekly. If I don't update my lessons immediately, students miss out on the newest innovations that I want them to learn.

The rapid shift forces me to rethink how I design my GenAI courses. I need a specific framework that allows me to switch in fresh content on the fly, teach students to adapt to new tools, and encourage resilience and excitement when technology pivots overnight. I also must monitor GenAI developments continuously and build flexible modules that can be reconfigured and designed in hours and days, not years. This curriculum transformation isn't just about adding an "GenAI Tools" lecture, it means embracing ongoing change as the core part of learning. With these adaptations, I'll help students become more successful in their agile thinking while growing alongside GenAI rather than falling behind it (Luckin et al., 2016; UNESCO, 2021).

Two unique challenges follow from this condition: contextual diversity, addressed in §1.3.2, and technological volatility, addressed in §1.3.3.

1.3.2 Contextual Diversity: Different Learner Populations Require Different Approaches

I work at the intersection of art and education, and I've learned that contextual diversity is one of the hardest parts of designing creative learning experiences. Every group of students brings their own cultural background, prior knowledge, learning styles, and access to resources. When I plan a project for a class that includes students from different countries, socioeconomic levels, and learning abilities, I can't use only one approach. I have to think about language support, technology access, and the variety of ways each person creates their meaningful solution (Tomlinson, 2014).

For example, a digital illustration assignment might be exciting for students with high-speed internet and tablets but feel impossible for someone using only a basic smartphone and does not have the proper equipment. Similarly, cultural references that inspire one group of students might confuse another. In my coursework, I adapt prompts by providing low-tech alternatives, like notebooks instead of tablets, and by creating assignments broadly so that every student can connect to their own story (UNESCO, 2021).

With these adjustments and adaptations, I spend extra time researching each student group and creating flexible lesson plans. This is about honoring each student's unique way of learning, observing and expressing the world. When the lesson is successful, the classroom becomes a successful mix of perspectives, and that diversity fuels deeper creativity and collaboration (Tomlinson, 2014; UNESCO, 2021).

1.3.3 Technological Volatility: The Landscape Changes Faster than Static Syllabi Allow

I've built my career combining creativity and teaching, and I've found that technological volatility is one of the biggest hurdles in education today. When I create a syllabus, I plan out software tools, digital platforms, and multimedia projects months in advance. But, by the time the course launches, new GenAI apps, updates, or entirely different delivery formats have emerged. This makes my carefully planned activities instantly feel outdated.

For example, I once designed a lesson around a video generation tool that was popular when I created the syllabus. Halfway throughout the semester, the application moved to a subscription model that the students couldn't afford, and an update changed the interface completely. I was scrambling to try to find free video alternatives, redesign my instructions, and provide a new demonstration for students during the middle of the semester (Prensky, 2001).

To help with this issue, I build flexibility into my courses. Instead of specifying one GenAI app, I introduce a range of possible tools and focus on core creative principles that transfer across platforms. I also assign "teach out" sessions at the start of each class to explore recent technological updates together (Redecker & Punie, 2017). Students have to provide a demonstration or presentation on a new GenAI tool. This approach allows students to take ownership and agency of their learning outcomes while staying relevant amongst the new technology throughout the semester.

1.3.4 No Current Models for Teaching a Black Swan Technology in Engineering

I've found that introducing a black swan technology in engineering feels like a fish out of water. Traditional course models, assessment checklists, step-by-step projects, assume we know the curriculum in advance. But a black swan arrives unannounced, reshaping everything before publications even exist (Taleb, 2007).

With no tested syllabus or assessment guides, I focus on metaskills: adaptability, creativity, and critical thinking. Instead of fixed assignments, I create open-ended labs where students explore the new GenAI tool together, document what works (and what doesn't), and reflect on failures and successes as lessons. The week-by-week planning mirrors the GenAI technology and teaches students to learn as they go (Prince & Felder, 2006).

It can be chaotic and time-consuming, but it builds the resilience engineers need to face whatever comes next. By embracing uncertainty and learning through discovery, I prepare students not just for the current black swan but for the next one in the future.

1.4 Purpose of the Study

This is a study of a curriculum — the syllabi, slide decks, modules, and assignment designs of an introductory GenAI course across four iterations — and not a study of the students who took the course. The purposes that follow are stated in those terms.

1.4.1 To Design, Implement, and Iteratively Refine an Introductory Course on GenAI

I piloted the introductory course on GenAI because I believe artists, designers, and engineers can all benefit from understanding how these tools work and how to use them creatively and responsibly. As someone who bridges the creative industry and engineering education, I saw a need for a hands-on, beginner friendly class where students don't become overwhelmed by technical terminology. My goal was and is to help students gain confidence using GenAI tools for class projects, educational assignments and everyday tasks, while also giving them a basic understanding of how the underlying models function (Basgen, 2023).

While designing the course, I focused on real-world examples from the creative and engineering industries. I organized content into short lessons (modules) featuring simple explanations, guided demos, and individual and collaborative assignments. After each lesson, I gathered feedback from students through written reflections to find out what they found to be successful and confusing. I then made small improvements and adjustments, tweaking instructions, adding new examples, and rearranging topics, to help the learning process run more smoothly.

Ultimately, I wanted this course to be a friendly introduction that provokes curiosity and empowers students and learners to experiment with GenAI tools in their own professional fields. By iterating on design and content based on direct feedback, I continue to strive to create a course that truly meets the needs of both creative professionals and engineering students, giving them the practical skills and confidence to explore GenAI tools on their own.

1.4.2 To Document the Evolution of the Curriculum Across Four Distinct Iterations

In the first iteration, I piloted the course with approximately 25 creative technology and design majors, students already familiar with engineering principles and excited to explore new GenAI tools. The small, specialized class allowed me to test core lessons on GenAI in a hands-on lab environment, observe where the assignment instructions read clearly and where they did not, and refine class activities and assignment designs accordingly.

For the second iteration, I opened enrollment to approximately 25 students from diverse engineering departments. By incorporating mechanical, electrical, and biomedical engineers, I learned which examples resonated across disciplines and adjusted curriculum and content to emphasize cross-departmental applications. I also scaffolded the assignments for students to use for real world applications within their domain. I provided guest lecturers from different engineering backgrounds so the students could gain knowledge from their future professional industry.

The third iteration scaled the course online to a global audience of 411 registered participants with 129 attending live, offered for free. To address varied time zones and educational backgrounds, I broke lessons into shorter modules with recorded demos. This iteration was for an hour a day for a week with different topics each day. It was branded as GenAI in Five, sponsored by the College of Engineering and Applied Science at The University of Colorado Boulder. The five GenAI topics I discussed and demonstrated were image generation, video generation, sound/music generation, research tools and human-centered AI. This curriculum assigned daily activities so participants could learn from each other's solutions and perspectives. The participants earned a badge for each assignment completed and a certificate for completion of all assignments.

In the fourth iteration, the course expanded to 4,731 registered participants worldwide, with

2,654 attending live on Day 1. At this scale, I focused on managing accessibility, inclusivity, and community support, with a team from GenAI Works who provided additional learning resources, breakout sessions, discussion forums, to reinforce learning. Each change was driven by feedback and data through polls and surveys conducted at the end of each class, ensuring that the curriculum remained practical, engaging, and relevant from pilot to global release.

1.4.3 To Surface Principles and Practices that Enable Curricula to Adapt Across Contexts and Technological Change

I believe effective curricula must be flexible, learner-centered, and data-informed to expand across different contexts and keep pace with the ever evolving GenAI technology. First, flexibility means creating modules so that future instructors can substitute in new examples, tools, or case studies without rewriting the entire course. I design each lesson with a clear learning objective and optional extra credit activities, allowing educators to customize content for art studios, engineering labs, online workshops, etc.

Secondly, a learner-centered approach ensures that diverse backgrounds and skills are respected and inclusive. I include multiple entry points for each assignment, visual tutorials, step-by-step guides and demonstrations, and open-ended challenges, so participants can choose the learning path that best matches their experience and interests. This practice not only improves engagement but also encourages peer learning, as students bring unique perspectives to group critiques and projects.

Finally, being data-informed means collecting feedback through course evaluation surveys and reflections. I review which assignment designs produced the widest range of submitted work and which assignment prompts were repeatedly flagged as unclear in course evaluation feedback. Then I refine the curriculum accordingly, whether that's clarifying instructions, reordering topics, or introducing new GenAI tools. Over time, this cycle of feedback and revision creates a living curriculum that adapts to different class sizes, cultural contexts, and GenAI advancements.

1.5 Significance of the Study

The contributions stated below are curriculum-design contributions: they concern how a course of this kind can be built, adapted, and scaled, rather than claims about the students who took any specific offering.

1.5.1 Novelty: Among the First Systematic Documentations of an Introductory GenAI Course in Engineering Education

This study is significant because it provides one of the first systematic, step-by-step records of how to design, implement, and modify an introductory course on GenAI within engineering education. By documenting every iteration, from a pilot with approximately 25 creative technology and design majors to successive lessons with diverse engineering cohorts, an online cohort of 411 registered participants (129 attending live), and finally a global launch with 4,731 registered participants (2,654 attending live on Day 1), this research provides a successful outline for course creation. It details how to select real-world examples, structure hands-on activities, and integrate reflective exercises and assignments so that learners with varying backgrounds can comprehend and apply GenAI concepts.

GenAI progresses at a rapid pace, and instructors often struggle to keep content current and accessible. This study addresses that challenge by introducing modular curriculum design: organizing the syllabus into independent units or modules that can be individually updated when new models, platforms, or ethical considerations arrive. It also allows for a collaborative learning experience, where students contribute to new GenAI tool discoveries, recommendations, and feedback that form subsequent iterations. Simple visual graphics, demonstration videos and workshops on how to use new GenAI tools, further prove how small changes can drastically improve clarity and engagement. Educators can adapt these methods to their own contexts, whether in art studios, engineering labs, online classrooms, or corporate professional development training settings.

Moving beyond the course design, this research uses the curriculum as a scholarly contribution. Every syllabus revision, assignment modification, and curriculum adjustment is documented and analyzed to reveal underlying principles that support effective learning. The resulting framework combines creative practice with technical instruction, demonstrating how hands-on projects, collaborative critiques, and iterative feedback create deeper understanding and creative innovation. By sharing both successes and challenges through conference presentations, peer-reviewed articles, and faculty and community workshops, this work broadens the conversation in engineering education and offers evidence-based strategies for teaching rapidly changing technologies.

This study provides educators and institutions with a tested model for developing flexible, inclusive, and continuously improving GenAI courses. It fills an essential need for beginner-level resources, makes sure that courses remain relevant amongst technological advances, and contributes new knowledge on how adaptive curricula can prepare students for the real-world creative and technical challenges produced by GenAI.

1.5.2 Scholarly Contribution: Shows how to Design Curricula that are Inherently Adaptive to Context and Technological Change

This study makes an original contribution to engineering education by providing a detailed, evidence-based framework for designing curricula that is adaptive to instructional context and the accelerated development of GenAI technologies. The framework emphasizes three interrelated practices.

Modular curriculum design splits the course into independent units with clearly defined learning objectives, assignments and activities, and assessment criteria. Each module is organized indicating the GenAI tools, models, and ethical topics it covers. When a new GenAI model or platform emerges, instructors can update just the affected module, refining lecture slides, substituting demonstrations, and refreshing assignments, without disrupting the overall course structure. This targeted approach to updates minimizes downtime, reduces work load on instructors, and makes sure that students always engage with the latest GenAI technology and research.

Student-led feedback places students as active contributors to the curriculum process. Throughout each cohort, learners share GenAI tool discoveries, use cases, and successes and challenges through discussion forums, surveys, and peer-review sessions. Instructors verify these contributions through hands-on activities and analysis of student work. This co-creative process accelerates content refinements but also encourages an agile mindset among participants, preparing them to become lifelong learners in a constantly changing field.

The curriculum is built on a platform independent conceptual framework. Rather than teaching students a single GenAI tool, the curriculum focuses on universal principles and skills, such as responsible use, ethics, fairness, transparency, safety, and effective prompt engineering that apply across GenAI platforms. This universal approach guarantees that learners can quickly adapt their skills when new GenAI tools gain recognition or existing ones progress.

By documenting every syllabus revision, pedagogical refinement, and update process as research data, this work provides actionable insights into what pedagogical strategies best support creativity, technical understanding, and inclusive learning.

This study contributes to the knowledge of engineering education by offering a reproducible, scalable model for adaptive curriculum design. Educators at research universities, institutions, corporate training programs, and online learning platforms can adopt these principles to build or refine GenAI courses that remain relevant, inclusive, and effective among the technical advancements.

1.5.3 Practical Impact: Provides a Model for Scaling from Small Pilot Classes to Large Global Audiences

This study delivers a model for scaling an introductory GenAI course from a small pilot to a large global audience. The process begins with a specialized pilot of approximately 25 creative technology and design majors, allowing instructors to test core lessons against course evaluation feedback and refine hands-on activities. Insights from this phase inform the design of foundational modules, such as prompt engineering exercises and ethical case studies, that are clear, engaging, and relevant to learners with diverse backgrounds and technical skills.

The second phase expands the course to a broader engineering cohort of approximately 25 students from mechanical, electrical, and biomedical backgrounds. This provides cross-disciplinary examples and highlights areas where course content requires adjustments. By incorporating feedback from engineers with varied experience, the curriculum progresses to emphasize transferable skills, such as prompt engineering, and integrating GenAI tools into traditional engineering work procedures.

In the third phase, the course moves online to provide instruction to 411 registered participants with 129 attending live, across different time zones and educational contexts. To address various needs, lessons are broken into 30–35 minute live demonstrations and video modules, daily participant surveys, peer-review assignments, presentation of student work, and live Q&A with open dialogue. These design choices maintain engagement and create a sense of community despite the lack of face-to-face interaction. Automated assessment tools provide immediate feedback, while weekly live tutoring hours offer real-time support and help to reinforce the key objective.

The final phase scales the course to 4,731 registered participants with 2,654 attending live on Day 1, requiring a strong infrastructure for community management, assessment, and course content updates. Modular curriculum design allows each lesson unit to be independent, so updates only affect the relevant module without changing the entire syllabus. Student-led feedback continues at scale, with discussion and chat forums and daily “teach outs” and presentation of participants’ assignments, encouraging students to share new GenAI tool discoveries and suggest course improvements.

Throughout all stages, the curriculum focuses on universal principles and skills, such as responsible use, ethics, fairness, transparency, safety, and effective prompt engineering that apply across GenAI platforms. This combination of small-scale piloting, cross-disciplinary refinement, online engagement strategies, and modular updates provides a replicable framework for educators looking to grow GenAI programs from workshops to large-scale offerings. By documenting each iteration’s outcomes and adaptations, this study prepares institutions with solid practices for maintaining curriculum relevance, providing learner autonomy, and managing complex operations as enrollment grows.

1.5.4 Broader Implications: Offers Transferable Insights for Education in Other Disruptive, Fast-Changing Domains

The methods used to teach this GenAI course can help educators in many fast-changing fields. By following these steps, teachers can build programs that stay up to date and work well for students and learners at any scale.

Modular design breaks a course into small, independent units. If a new prompt engineering technique appears, an instructor updates only that one lesson. If a new GenAI research tool is released, only the related module needs refreshing. This targeted updating means courses stay current and relevant without rewriting everything, saving time and reducing confusion for teachers and students.

Student feedback turns learners into active contributors. In class or during workshops, students might share links to the latest GenAI video tool or present a new feature in a model that was just released. By collecting real-world suggestions through surveys, forum posts, or written/audio/video reflections, instructors learn which topics matter most and can adjust lessons simultaneously. This practice not only keeps content relevant but also makes students feel ownership and agency of their learning.

Focusing on GenAI universal principles, such as responsible use, ethics, fairness, transparency and safety apply no matter which tool is being used. For example, learners need to understand how to effectively prompt the models, whether they use one application or the other. These skills and principles transfer across GenAI platforms. By teaching core methods instead of specific tools, students can adapt quickly when new applications and models become available.

This approach works whether you teach a small class or a massive online program. In a pilot of approximately 25 undergraduate students, instructors can provide detailed feedback in person. When the course expands to approximately 4,700 registered participants worldwide, instructors use a mix of peer reviews, surveys, and live support sessions. Short surveys check for basic understanding, while scheduled support sessions provide learners with scaffolded instruction. These different support systems help keep everyone engaged, no matter the course size.

These practices together create a repeatable model for any field facing accelerated change. Teachers begin with a small cohort to test core ideas, gather feedback from students, and update modules as needed. They then scale up to larger groups, using automated tools and peer support to maintain quality. By documenting each step, updates made, and feedback received, educators build a clear playbook. Other instructors can follow this guide to create flexible, inclusive, and effective courses that evolve alongside technology.

1.6 Research Questions

Research Question 1 (RQ1): What principles and practices emerge in the design and iterative teaching of an early introductory course on generative AI offered through engineering education at the University of Colorado Boulder, particularly in response to varying contexts and the rapidly evolving generative AI landscape?

Research Question 2 has two parts, one which deals with contextual adaptation and one which deals with technological responsiveness.

Research Question 2A (RQ2A): How does the Course Adapt to Different Instructional Contexts (Student Cohorts, Institutional Settings, Delivery Modes)?

Research Question 2B (RQ2B): How does the Curriculum Adapt to the Rapidly Changing GenAI Technology Landscape?

1.7 Theoretical Framework

Building on the research questions, this section outlines the narrow theoretical framework that guides how I designed, iteratively refined, and analyzed the Introduction to GenAI course across four iterations. This study uses a small set of ideas to guide it. First, I draw on constructivist learning and motivation theories, especially self-determination theory, to explain differences between students enrolled in for-credit university classes and adults enrolled in free, online global courses. Second, I use ideas from curriculum-as-research and design-based research to treat the course itself as something I can study and improve over time. Third, I pay close attention to ethics, accessibility, and my own role and biases as a teacher and researcher.

1.7.1 Learning and Motivation Across Contexts

The study is constructed in a practical, constructivist view of learning in which students build knowledge through active engagement with GenAI tools, peers, and original creative and engineering tasks rather than passively receiving information (Schunk, 2020). The Introduction GenAI course curriculum integrates social constructivist theory, where knowledge is built through active problem-solving and engagement with tools and communities. This theoretical alignment supports the course's emphasis on experiential learning, collaborative peer evaluation, and the application of real-world projects across various global instructional environments (Prince & Felder, 2006).

Across the four iterations, participants engaged in different formal and informal structures, including university courses for credit and large-scale global offerings that emphasized badges and certificates rather than transcripts. Table 1 summarizes these structures below:

Table 1. Four iterations of course structures.

Iteration	Participants	Credits, badges, certifications
1	Creative Technology and Design undergraduate students	3 credits
2	General Engineering undergraduate students	3 credits
3	Global Course 1 (411 registered, 129 live, Aug 2025)	1 daily badge per task completed (5 total), and certification from AI by Hand for completing all 5 tasks
4	Global Course 2 (4,731 registered, 2,654 live Day 1, Sept 2025)	Certification from GenAI Works and AI by Hand for completing each daily task (5 total)

The framework relies on self-determination theory (SDT), which assumes that high-quality motivation depended on supporting learners' needs for autonomy, competence, and relatedness (Deci & Ryan, 1985; Ryan & Deci, 2000). In the first two iterations, creative technology and design majors and then mixed-discipline engineering undergraduates (mechanical, electrical, biomedical, physics, and others) engaged in formal, accredited courses. Their learning experiences were shaped by a combination of extrinsic motivators (grades, transcripts, degree progress) and intrinsic motivators (curiosity, creative exploration, desire to build portfolio pieces). The curriculum adapted by incorporating intrinsically meaningful projects, open-ended GenAI media explorations, cross-disciplinary design challenges, and student-led "teach outs", within an assessment structure that still met institutional expectations. This design explicitly focused on supporting autonomy, competence, and relatedness aligned with SDT, even within a graded environment (Ryan & Deci, 2000).

When the course pivoted online to reach 411 and then 4,731 registered adults worldwide, the motivational account changed. Participants did not receive university credit and participated with varied professional backgrounds, time zones, and no prior technical preparation, often driven by interest in GenAI, professional development, or a general love of learning. To support these intrinsic motivations, the online versions emphasized short, focused modules; daily, achievable tasks; visible recognition through badges and certificates; and spaces where participants could share work and learn from a diverse international community. These design choices were intended to create a sense of autonomy (choice in projects and tools), competence (scaffolded tasks), and relatedness (community interaction), consistent with SDT's emphasis on basic psychological needs (Ryan & Deci, 2000). This course structure focused on making engagement feel worthwhile even without formal credit, while still encouraging deep exploration of various GenAI tools.

Across all course iterations, I intentionally tried to design for intrinsic engagement even as the balance between intrinsic and extrinsic motivators shifted. In the university Introduction to GenAI courses, assignments were created as contributions to a shared research project and as artifacts students could reuse in portfolios or job applications, not only as graded tasks. In the online offerings, where external pressure was lower, I focused on creating activities connected to each person's real life and offered options so adults could choose projects that aligned with their work, creative interests, or personal goals. These motivational considerations, informed by SDT and constructivist views of meaningful learning, are key to how I interpret learner participation and outcomes across formal and informal settings (Schunk, 2020; Ryan & Deci, 2000).

1.7.2 Curriculum-as-Research and Iterative Inquiry

A second pillar of the framework is curriculum-as-research, supported by educational design research and iterative teaching-as-inquiry practices (McKenney & Reeves, 2018; Kemmis et al., 2014). Instead of viewing the syllabus, assignments, and teaching methods as constant, I managed each one as something I could carefully record, explore, and improve. This approach is similar to work in STEM education where teachers and researchers repeatedly design and revise curriculum with students to improve learning and to build new knowledge about teaching (Burrows et al., 2018; Wendell et al., 2021).

Each of the four iterations; pilot, refinement, initial online scaling, and global launch, functioned as a planning, teaching, observing, and reflection cycle. In the smaller, in-person classes, I recorded how creative technology and design majors and then mixed engineering cohorts responded to modules on prompt engineering, image and video generation, sound, human-centered AI, and vibe coding, and used their feedback and assignments to refine instructions, scaffolds, and examples. As the course expanded online, these cycles extended to synchronous demos, asynchronous discussion forums, which allowed for continuous improvements in pacing, explanation, tools, and activity design.

Design-based research and curriculum-as-research also informed how I conceptualized scaling from a 25-student pilot to approximately 4,700 registered participants worldwide. Modular design, treating each unit as an independent "building block" with clear learning objectives and flexible tools, enabled quick replacements of examples and platforms as GenAI technologies continued evolving (Salmon, 2002; Redecker & Punie, 2017). Student and participant input, peer critiques, and "teach out" sessions created opportunities for learners to shape the evolving curriculum, resonating with work on student-faculty collaborations and co-created curricula (Healey & Jenkins, 2009). This perspective helps explain how the course maintained its core goals while adapting to different institutional settings, delivery modes, and learner populations.

1.7.3 Technology, Ethics, and Access as Lenses

Because GenAI is what Taleb (2007) calls a "black swan" technology; sudden, very disruptive, and unpredictable; the framework also uses ideas from research on innovation, educational technology, ethics, and equity. Studies about disruptive technologies address that courses need to stay flexible, adaptable and easy to update, rather than relying on syllabi that change slowly over many years (Christensen et al., 2009; Selwyn, 2021). This view directly shaped my choice to design modules that can easily incorporate new tools, models, and ethics examples without needing to rebuild the entire course each iteration.

Frameworks for ethics and equity in AI education show that GenAI is powerful and risky, raising concerns about bias, transparency, and unequal access to technology (Baker & Hawn, 2022; UNESCO, 2021). These ideas formed four main themes in this course and study: industry, education, accessibility, and ethics. Industry-focused activities explored how GenAI changes professional workflows including questions ownership, and intellectual property (Bommasani et al., 2021; Marcus & Davis, 2020). Education-focused activities addressed GenAI as a learning tool, prompting discussions about academic integrity and the future of teaching (Huang et al., 2023; Kelly & Sullivan, 2023). Accessibility-focused activities concentrated on differences in technology access, leading to assignments that explored user experiences across different groups of people and locations (Tomlinson, 2014; UNESCO, 2021). Ethics discussions and assignments emphasized fairness, safety, and responsible use, encouraging students to reflect on potential harms and best practices of GenAI.

These four themes also helped explain how different groups of learners, from creative technology and design, and engineering students to global adult learners, experienced the course, and how the curriculum evolved as GenAI tools and conversations continued to change.

1.7.4 Reflexivity, Positionality, and Bias

Finally, the framework includes reflexivity and positionality, recognizing that my role as both instructor and researcher, along with my background in creative technology, design, and engineering education, shapes what I notice, prioritize, and document in the course (Schön, 1983; Finlay, 2002). Qualitative research practices guided me to keep revision logs, analytic notes, and reflections alongside more traditional data sources such as surveys, student work, and activity data (Yin, 2014).

Because this study is qualitative and self-reflective, and based on curriculum materials I created, I recognized that my excitement for GenAI and focus on modular, student-centered design could influence how I interpreted the data. To address this concern, I used multiple data sources, gathered feedback from colleagues in engineering and related fields, and documented events of uncertainty, surprise, and failure in my notes (McKenney & Reeves, 2018; Finlay, 2002). These steps did not eliminate bias but made it more visible and open to rigorous examination. In summary, this framework brings together ideas about how people learn and what motivates them, especially self-determination theory, along with curriculum-as-research and design-based approaches that support ongoing, adaptive changes to the course. It also uses technology, ethics, and accessibility as different perspectives to understand GenAI as a rapidly changing technology and includes a reflexive approach to qualitative research. These different perspectives supported how the GenAI course was designed, implemented, and scaled across diverse contexts, and how learners' motivations and backgrounds influenced its changes over each iteration.

Chapter 2

Methodology

2.1 Research Approach and Framework

This study is curriculum-design research. The unit of analysis is the curriculum itself — the syllabi, modules, slide decks, assignment designs, and revisions I authored as the instructor across four iterations of the Introduction to GenAI course — not the students who took the course. Student-facing inputs (course feedback surveys, written reflections, learner-produced artifacts) functioned as course evaluation under my normal instructor authority and informed **when and why** I revised the curriculum, rather than serving as research data about students. The methodological framework that follows is built around that orientation: design-based research and curriculum-as-research applied to the instructor-authored artifacts, with course evaluation inputs treated as the contextual trigger for iterative revision. The human-subjects scope of this work is named explicitly in §2.6.5.

2.1.1 Iterative Teaching as Inquiry: Each Course Offering as Instruction and Research

In this course, each new cohort functioned as an ongoing experimentation. Every lesson, activity, and assignment was both a learning experience for students and a qualitative data point. By structuring teaching around questions and exploration, I witnessed what was successful, what needed improvement, and how different contexts influenced learning.

At the start of each class, I identified clear design questions: Which GenAI examples drew the most discussion in class? Where did the assignment instructions repeatedly need to be clarified?

How did different delivery formats (in-person workshops, hybrid sessions, or fully online modules) affect the artifact-design choices I had to make? With these questions in mind, I gathered evidence through several different methods. Course evaluation surveys recorded written responses about clarity, relevance, and course pacing. Classroom notes recorded which demonstrations took the most time to walk through. Assignment-submission patterns indicated when an assignment prompt was working as designed and when the prompt needed to be rewritten. In-person and virtual discussion threads surfaced new GenAI tool discoveries and recurring questions that more formal end-of-module surveys did not catch.

After each module, I reviewed these different data points to identify commonalities. If a prompt-engineering exercise continually led to confusion, I rewrote the instructions or added a step-by-step demonstration video. When peer critiques consistently led to strong cross-disciplinary ideas, I created more structured reflection around those activities. If an assignment showed mastery of one concept but weakness in another, I designed additional mini-lessons or offered optional office hours to support those areas.

This planning, teaching, observing, and reflecting cycle operated at two levels. Within a single cohort, it guided small, day-to-day or week-to-week adjustments that improved clarity and workflow. Between cohorts, it informed larger curriculum revisions, such as removing and adding modules on new GenAI tools or restructuring the order of topics based on repeated patterns in the data.

By documenting all lesson and assignment changes linked to the collected data, I maintained a clear record of curriculum updates. This record traced the course's development over time and served as a basis for sharing best practices with other educators. Through this process, iterative teaching as practice made the course an ongoing research project, with continuous improvement guided by coursework, reflection, and collaboration with learners.

2.1.2 Curriculum as Scholarly Contribution: The Evolving Syllabus, Assignments, and Pedagogy as Primary Research Products

I managed the course syllabus, assignments, and teaching methods as strong research artifacts rather than consistent instructional materials. Whatever change I created in the lessons, whether it was modifying an assignment prompt, reorganizing a module sequence, or adding a collaborative peer critique session, was carefully documented. Over time, these documented iterations form an audit trail showing how different pedagogical strategies and tool choices were retained, revised, or replaced in subsequent iterations of the curriculum.

I analyzed these artifacts by looking for repeated revision patterns. For example, when I added instructional videos on specific GenAI tools to a module, I observed in subsequent submissions that the same recurring errors appeared less often and that the assignment prompt did not need to be repeated as frequently — both signals that the revised slide deck and instruction set were clearer. Adding structured peer reviews became a stable feature of the next-iteration assignment design, which I retained based on course evaluation feedback that flagged peer review as a useful element of the iteration.

To share the results, I presented at various academic conferences, provided GenAI workshops for professional development throughout the community, guest lectured in classrooms, special events, and clubs. These venues allowed me to discuss how modular curriculum design supported quick implementation of new GenAI tools, and to display case studies where hands-on projects appeared to lead to successful student innovations.

Collaboration with colleagues helped strengthen this scholarly contribution. I sought feedback on draft syllabi, observed co-taught sessions, and co-authored reflective papers examining which adaptations worked across different institutions. I also used GenAI tools as a co-collaborator to help edit and brainstorm. The co-creative process provided best practices for inclusive design, such as providing multiple options within lessons and ensuring accessibility for learners with varied technical backgrounds.

The adaptive curriculum became the main research product. By approaching teaching as a reflective practice and sharing both successes and challenges, I helped develop principles that can guide future education for Introduction to GenAI courses. These contributions aimed to help educators worldwide design adaptive, learner-centered programs that kept pace with the ever-changing GenAI industry, supporting students in developing both practical skills and flexible mindsets needed for future creative and technical challenges.

2.2 Curriculum-as-Research

Curriculum-as-research theory uses instructional materials and pedagogical practices as main data sources that can be analyzed to improve teaching and learning. Unlike traditional research that studies curriculum impact from outside the classroom, curriculum-as-research places inquiry directly into the design process. McKenney and Reeves (2018) describe educational design research as closely aligned with this approach, emphasizing iterative cycles of implementation, evaluation, and revision in educational settings. However, design-based research often focuses on specific learning outcomes rather than examining the curriculum as a whole.

Documentation and analysis of curriculum artifacts, such as syllabi, lesson plans, slide deck and module revisions, created a living record of instructional decisions.

Observational work in STEM education showed how this approach looks in practice. Burrows et al. (2018), used iterative, participatory design with teachers to build a problem-based STEM curriculum for young children and found that teacher involvement increased both confidence and long-term use of the materials. Wendell et al. (2021) used design-based research over three years to develop an integrated technology design unit, documenting how it changed across iterations and identifying design strategies that supported students' participation in science, engineering, and computational thinking practices.

Although these studies showed the value of treating curriculum as research in STEM settings, they rarely focused on rapidly changing technological fields. The speed of GenAI development, combined with the need for flexible curricula, calls for new approaches that combine ongoing tracking of emerging tools with careful, detailed documentation of curriculum changes.

2.3 Curriculum-as-Research Framework

The educational design research framework (McKenney & Reeves, 2018) arranged every course element; course overview, weekly lesson plans, class activities, assignments, and supplemental resources; as an object of study. Each artifact was:

- Documented: Different versions were archived with details indicating dates, intended learning outcomes, and the reason for the change.
- Tested: Artifacts were placed in real world teaching cycles across different cohorts and delivery methods.
- Analyzed: Evidence of how artifacts performed in practice informed the identification of design principles.

For example, when a lesson plan on prompt engineering was introduced, the study followed which step in the instructions caused the most questions. After adding a short video demonstration, the same lesson was observed again to see if confusion appeared to decrease. Each iteration gave new data that refined subsequent lesson plans, creating a cycle of real time curriculum improvement.

2.4 Design-Based Research

Design-Based Research uses an iterative research methodology primarily in education to develop, test, and refine innovative learning environments or course materials in real-world settings (Schunk, 2020). In this study, DBR cycles refined the curriculum artifacts themselves — slide decks, modules, syllabi, and assignment designs — across four iterations. Each cycle asked what the artifact was meant to do, observed how it performed in the classroom and the online cohort, and produced a revised artifact. The research questions focused on how specific curriculum revisions (adding visuals, reorganizing modules, swapping a GenAI tool, simplifying an assignment prompt) reshaped the curriculum so that it could remain responsive to a fast-changing technology landscape and to a wider range of learner contexts. Course evaluation inputs (§2.6.2–2.6.4) identified **where** a revision was needed; the revision itself, captured in a dated slide-deck or module change, is the artifact under analysis.

2.5 Iterative Teaching as Inquiry

Incorporating design-based research practices, the study implemented iterative teaching as inquiry, where each course offering became a mini research project (Kemmis, McTaggart, & Nixon, 2014). Over four different cycles (pilot, curriculum refinement, course scaling, and global launch), the methodology followed a four-stage planning, teaching, observing, and reflecting cycle. Each stage included specific practices:

- **Planning**
  - ∗ Establish learning objectives and key inquiry questions (e.g., "How does adding peer-review assessments improve critical thinking?").
  - ∗ Select or revise curriculum artifacts to test new ideas (e.g., adding visuals and short demonstration videos).
- **Teaching**
  - ∗ Deliver the module to a defined cohort (approximately 25 creative technology and design majors in Iteration 1, approximately 25 mixed-discipline engineering students in Iteration 2, 411 registered participants with 129 attending live in Iteration 3, and 4,731 registered participants with 2,654 attending live on Day 1 in Iteration 4).
  - ∗ Use consistent facilitation protocols to support comparability across cohorts.
- **Observing**
  - ∗ Collect data through surveys, reflections, and assignments.

    * Record how students interacted with course materials, where they struggled, and which activities engaged creativity.

- **Reflecting**
    * Analyze data to identify successes and challenges.
    * Document curriculum changes in slide decks and module revisions.
    * Plan the next lesson and course iteration's improvements.

This ongoing cycle positioned research into everyday teaching, generating a strong dataset of curriculum artifacts and student and learner responses. Continuously, patterns appeared that revealed which design strategies consistently supported learning and engagement.

2.6 Curriculum Artifacts and Course Evaluation Inputs

To address the research questions, this study analyzed two kinds of materials: the curriculum artifacts I authored as the instructor across four iterations, and the course evaluation inputs that informed my decisions to revise those artifacts. The primary data are the artifacts (§2.6.1). Course evaluation inputs (§2.6.2 through §2.6.4) functioned as the contextual trigger for revision and are described here to make the iterative cycle auditable. §2.6.5 names the human-subjects scope of the work explicitly.

2.6.1 Curriculum Artifacts (Primary Data)

The primary data for this study are the instructor-authored curriculum artifacts: syllabi, slide decks, module structures, weekly lesson plans, in-class activities, and assignment designs across the four iterations. Each artifact carries dated revision history that traces what was kept, what was rewritten, what was reordered, and what was swapped in or out from one iteration to the next. Slide deck and module revisions are the densest record: across the four iterations I produced revised versions of every weekly lesson, recording in each version what tool was being taught, what example was being used, and how the assignment was framed. These revisions provide the artifact trail that supports the analysis for RQ1 (principles and practices that emerged through iterative design) and RQ2 (contextual and technological adaptation).

Alongside slide decks and modules, I also analyzed the broader instructor-authored corpus: the Iteration 1 Final Project assignment, the Iteration 2 syllabus, the GenAI in Five workshop decks for the global cohorts, and the cross-iteration reflective writing I authored (the Keep Up Newsletter and Keep Up Podcast series). All of these are my own intellectual products, and analyzing them does not constitute research on human subjects.

2.6.2 Course Evaluation Inputs · Feedback Surveys

Across the for-credit and global iterations, students completed short post-module feedback surveys that asked them to rate clarity of instructions, relevance of examples, perceived difficulty, and overall satisfaction (Daniel, 2014). Open-ended fields invited suggestions for improvement. These surveys were collected under my normal teaching authority as the instructor of record and were used as routine course evaluation: I read them between modules, identified clarity gaps and tool-access frustrations, and revised the next iteration of the slide deck or assignment to address what came up. In this dissertation, the surveys are described as evaluation inputs that triggered specific curriculum revisions; the surveys themselves are not analyzed as research data about students.

2.6.3 Course Evaluation Inputs · Learner-Produced Artifacts

Student work — prompt-engineering submissions, multimodal GenAI projects, peer feedback, and end-of-iteration assignments — was reviewed across cohorts as part of my normal teaching practice. Reviewing learner work let me identify where the assignment prompts were unclear, where the scaffolding was thin, and where new GenAI tools were beginning to be discovered. These insights informed the next round of assignment-design revisions and the next slide-deck update. As with the surveys, the learner artifacts are treated here as evaluation inputs rather than as research data about learners. Where individual student outputs appear as figures in this dissertation, they are presented as instructional examples of the assignment, with the student's consent for educational use.

2.6.4 Course Evaluation Inputs · Written Reflections

Students completed short written reflections after specific assignments, particularly the video and sound modules. The reflection prompts asked what they had learned, whether the GenAI tools were useful in their fields, what challenges they encountered, and what ethical concerns surfaced. The length and topics were specific to each assignment. I read these reflections as part of standard end-of-assignment review and used the patterns I noticed to refine the next iteration's pacing and emphasis. As with the surveys and the work artifacts, the reflections are treated as evaluation inputs that surfaced curriculum-design issues, not as research data about students. Any quoted reflective text in this dissertation appears anonymized.

2.6.5 Human Subjects Scope

This study is curriculum-design research analyzing instructor-authored materials. The unit of analysis is the curriculum — the slide decks, modules, syllabi, and assignment designs that I built and revised across four iterations of the Introduction to GenAI course — not the students who took the course. Course feedback surveys, written reflections, and learner-produced artifacts referenced above were collected under my normal teaching authority for the purpose of improving the course and are treated here as program-evaluation inputs that informed curriculum revisions. This stance is consistent with the scholarship of teaching and learning tradition (Boyer, 1990; Hutchings and Shulman, 1999), with practitioner research conducted from inside the instructor's role (Cochran-Smith and Lytle, 2009), and with the design-based-research framing developed in §2.4 (McKenney and Reeves, 2018).

As the instructor of record, I held student records (rosters, submissions, survey responses) for course-administration purposes. Those records remained under my teaching authority and were not redistributed; nothing identifiable about any individual student is publicly released in this dissertation. Quoted feedback appears anonymized, with no name, cohort identifier, or other detail that would allow re-identification. Any student-produced image that appears in a slide-deck figure is included as an instructional example with the student's consent for educational use. Handling of student records throughout has been consistent with the Family Educational Rights and Privacy Act (FERPA, 20 U.S.C. § 1232g; 34 CFR Part 99) and the University of Colorado Boulder's policies on the protection of student records.

Because the analytic target is the instructor-authored curriculum and the analytic claims do not rest on individual student data, and because the student-facing inputs collected during the iterations served the course's own improvement under standard teaching authority rather than a research protocol designed to generate generalizable knowledge about students, this work falls outside the scope of human-subjects research as defined by the federal Common Rule (45 CFR 46.102(l)), which limits the term **research** to systematic investigation designed to develop or contribute to generalizable knowledge about human subjects. Course evaluation conducted by an instructor to improve her own course falls outside that scope, a distinction the OHRP (2014) makes explicit in its guidance on quality improvement versus research.

2.7 Data Analysis Procedures

Data analysis was applied to the curriculum artifact trail (§2.6.1) and used the course evaluation inputs (§2.6.2–§2.6.4) as contextual triggers explaining why specific revisions occurred. The analysis is qualitative and developed an account of how the curriculum changed across iterations and what design moves recurred. Reflexive practices, including positionality statements and ongoing peer feedback, were used to examine my assumptions as an instructor-researcher.

2.7.1 Thematic Coding of Curriculum Revisions

Curriculum revisions, captured in dated slide-deck and module changes, were coded thematically using procedures informed by Lungu (2022). Open coding generated descriptive codes for each revision (for example: tool swap, accessibility adjustment, prompt clarification, example update, pacing change, ethics framing addition). Axial coding then grouped related codes into higher-order themes that surfaced the recurring design moves across the four iterations.

The coding analyzed the revisions themselves — what changed in each slide deck, module, or assignment, and what kind of trigger preceded the change. Where course evaluation feedback noted a recurring student-side issue (a confusing instruction, a tool that had become inaccessible, a missing scaffold), that issue is treated as the contextual trigger for the next-iteration revision and is recorded alongside the revision in the artifact trail. The thematic analysis surfaced repeated reasons for curriculum changes that explain the design thinking behind how the course was revised and scaled (RQ1), and it surfaced patterns of contextual and technological adaptation visible across iterations (RQ2A, RQ2B).

2.8 Ensuring Trustworthiness

Multiple strategies were used to strengthen the trustworthiness of the study and to ensure that interpretations fairly represented the curriculum's changes across iterations. Trustworthiness for this curriculum-design research rests primarily on the auditability of the artifact trail: dated slide-deck revisions, module reorderings, syllabus updates, and assignment-design changes are all instructor-authored documents that an external reviewer can examine to verify the analytic claims. Course evaluation inputs are used to contextualize **why** a given revision occurred. These strategies followed established standards for excellent qualitative research and purposely included reflexive practices.

A record was maintained, including organized archives of curriculum artifacts, slide deck and module revisions, data-collection tools, coding themes, analytic memos, and reflexive notes, allowing outside reviewers to trace the evidence from original artifacts to conclusions and strengthening trustworthiness (RQ1, RQ2).

Peer feedback with colleagues in related fields provided additional exploration of methodological choices and new findings. This feedback included discussions of my positionality and reflexive memos as an instructor and researcher, supporting ongoing examination of how my experiences as an artist, educator, and GenAI practitioner formed research questions, design decisions, and interpretations (Schön, 1983). These strategies placed the study within a reflexive, practice-based research method in which curriculum design, teaching, and inquiry were linked, and where my reflective researcher stance was managed as a resource for understanding of iterative GenAI curriculum design and learner experience.

Chapter 3

Results

3.1 Overview of Course Iterations and Data Sources

This chapter presents the findings from the iterative design, implementation, and refinement of the Introduction to Generative AI course across four different iterations. Aligned with the curriculum-as-research and design-based research frameworks described in Chapter 2, the results focus on how changes to the syllabus, instructional materials, and learner experiences addressed the research questions about adaptive GenAI curriculum design.

The chapter is organized around the research questions introduced in §1.6. First, I describe the principles and practices that emerged in the design and iterative teaching of the course (RQ1, §3.2). Next, I examine how the curriculum adapted to different learning environments, including two for-credit university offerings and two large-scale global courses (RQ2A, §3.3). Finally, I document how the course responded to the rapidly changing GenAI technology landscape, including tool updates, new platforms, and student discoveries of new technological applications (RQ2B, §3.4).

Across all four iterations, the analysis uses slide deck and module revisions, student surveys, student work, and written reflections described in Chapter 2. I examined these materials using thematic coding to find recurring patterns in course design and learner experiences.

Figure 1 visualizes the practitioner-pioneer trajectory across the four iterations and the six concurrent delivery channels that ran alongside them from January 2024 through May 2026.

Table 2 summarizes the four course iterations that generated data for this study, including participant characteristics, institutional setting, delivery mode, and data sources. The first

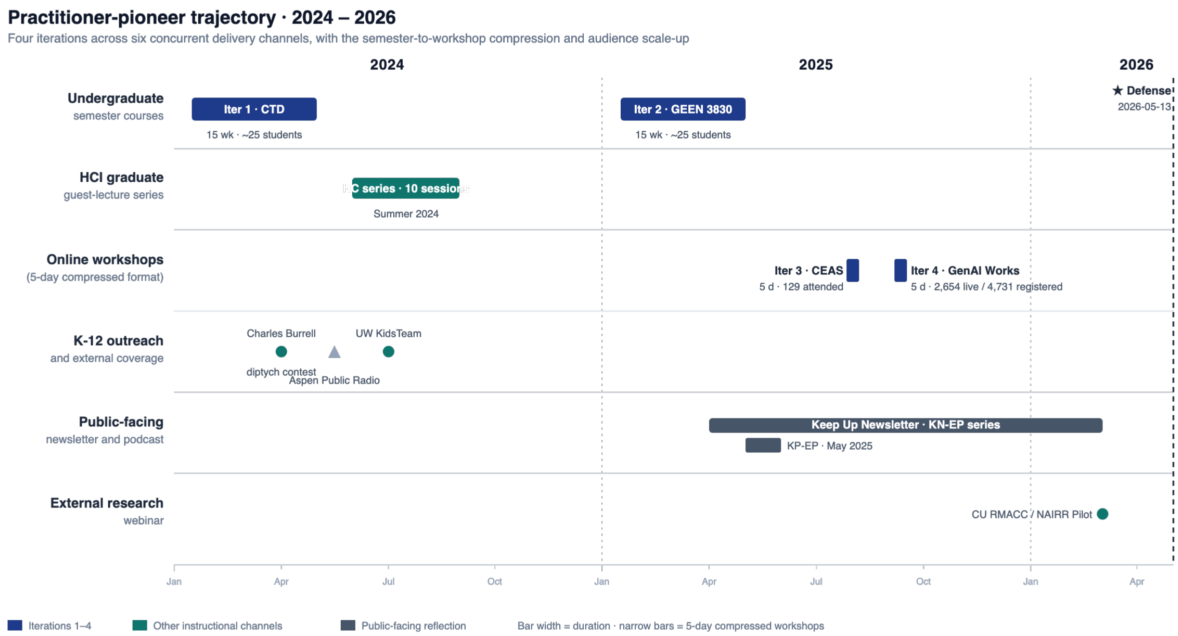


Figure 3.1: Practitioner-pioneer trajectory across six concurrent delivery channels, January 2024 through May 2026. The four iterations of the generative-AI course (Iterations 1 and 2 as 15-week semester courses; Iterations 3 and 4 as 5-day compressed workshops) appear alongside the HCI graduate guest-lecture series, K-12 outreach with Aspen Public Radio coverage and the UW KidsTeam collaboration, the Keep Up Newsletter and Podcast as public-facing reflection, and the CU RMACC federal-research webinar. Bar width is proportional to duration; narrow bars mark the five-day workshop compression of Iterations 3 and 4.

and second iterations were for-credit university courses with approximately 25 creative technology and design majors and approximately 25 mixed-discipline engineering students. The third and fourth iterations were free, non-credit global offerings: the third enrolled 411 participants with 129 attending live, and the fourth enrolled 4,731 participants with 2,654 attending live on Day 1.

Table 2. Overview of course iterations and data sources.

Iteration	Setting	Delivery mode	GenAI topics	Data sources
CTD Pilot (~25 students)	For-credit, university	In-person	Image, video, sound	Modules, slide decks, surveys, written reflections, student work
Mixed Engineering Pilot (~25 students)	For-credit, university	In-person	Image, video, sound	Modules, slide decks, surveys, written reflections, student work
Global Course 1 (411 registered, 129 live)	Non-credit, badges, certificates	Virtual	Image, video, sound	Slide decks, surveys, student work
Global Course 2 (4,731 registered, 2,654 live Day 1)	Non-credit, certificates	Virtual	Image, video, sound	Slide decks, surveys, student work

From these iterations, I collected revised slide decks and modules per lesson, student feedback surveys, student work artifacts, and written reflections, which created a detailed record of how the curriculum developed and how learners experienced image, video, and sound creation with GenAI tools. These data sources are the foundation for the qualitative analyses presented in the remainder of this chapter.

3.2 RQ1 · Principles and Practices

Using slide deck and module revisions, student surveys and artifacts, and written reflections, three core principles emerged in the design and iterative teaching process across all four courses: modularity, learner choice, and continuous feedback.

3.2.1 Modularity as a Design Principle

Modularity means breaking the course into independent units or modules with clear objectives, examples, and activities. Each module was updated independently as new GenAI tools arrived or were switched out to match the resources of an AI lab. I provided lessons alongside optional add-ons so I could customize their content without rebuilding the syllabus.

The modules functioned as independent building blocks, as each week provided one or two specific GenAI subjects based on education, industry, ethics or accessibility. The modules could be moved around and not disrupt the flow of the course. Image generation was used in the first module in all four iterations. Sound was used in the seventh and eighth module with an optional add-on assignment for pilot 1, but was used in the eleventh module with an optional add-on assignment for pilot 2. Sound was used as the third module for both the global courses. Video generation was used in the sixth and seventh module in pilot 1, but used in the fourteenth module in pilot 2. Video generation was used second in both global courses.

The different module arrangements for video generation in pilot 1 and pilot 2 are highlighted in yellow below in Figures 1, 2, and 3. These modules are located in Canvas for the students to access the course curriculum. As you can see from Figures 1 and 2, video generation was towards the beginning of the curriculum in pilot 1, and in Figure 3, video generation was organized towards the end of the course in pilot 2. During pilot 1, I felt that I needed to keep image generation and video generation close to each other in the module organization and curriculum design. For pilot 2, I felt that I needed to cover new tools and resources that I found to be more beneficially aligned with the student demographic and technological advancements before introducing the video generation module.

Figure 1. Highlighting Video Generation location in Module 6 for Pilot 1.

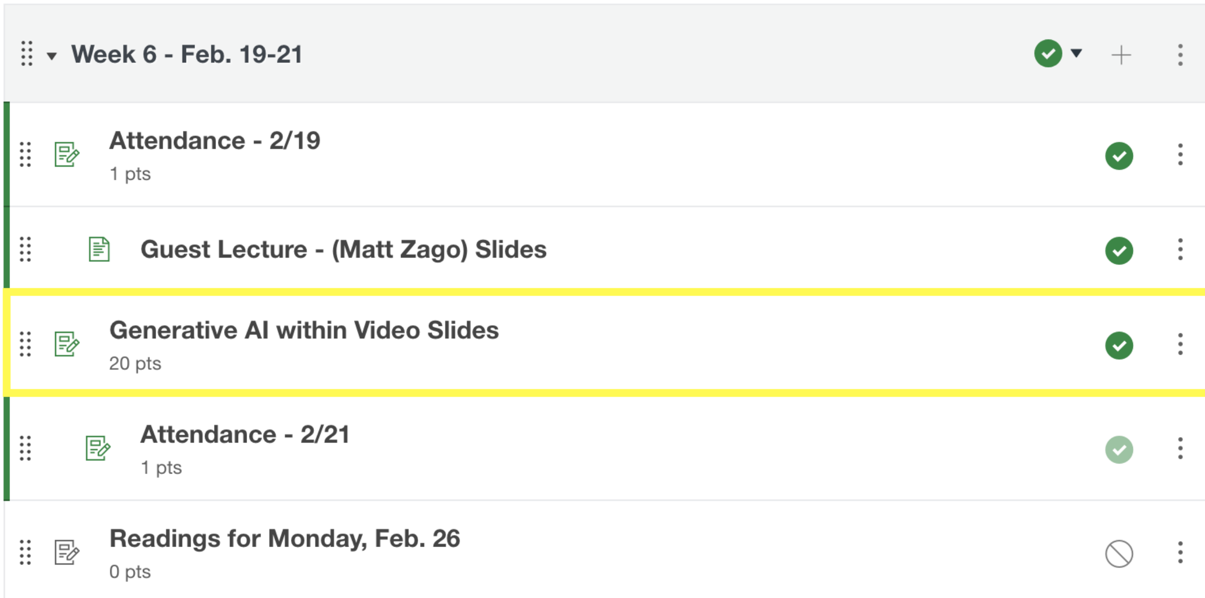


Figure 2. Highlighting Video Generation location in Module 7 for Pilot 1.

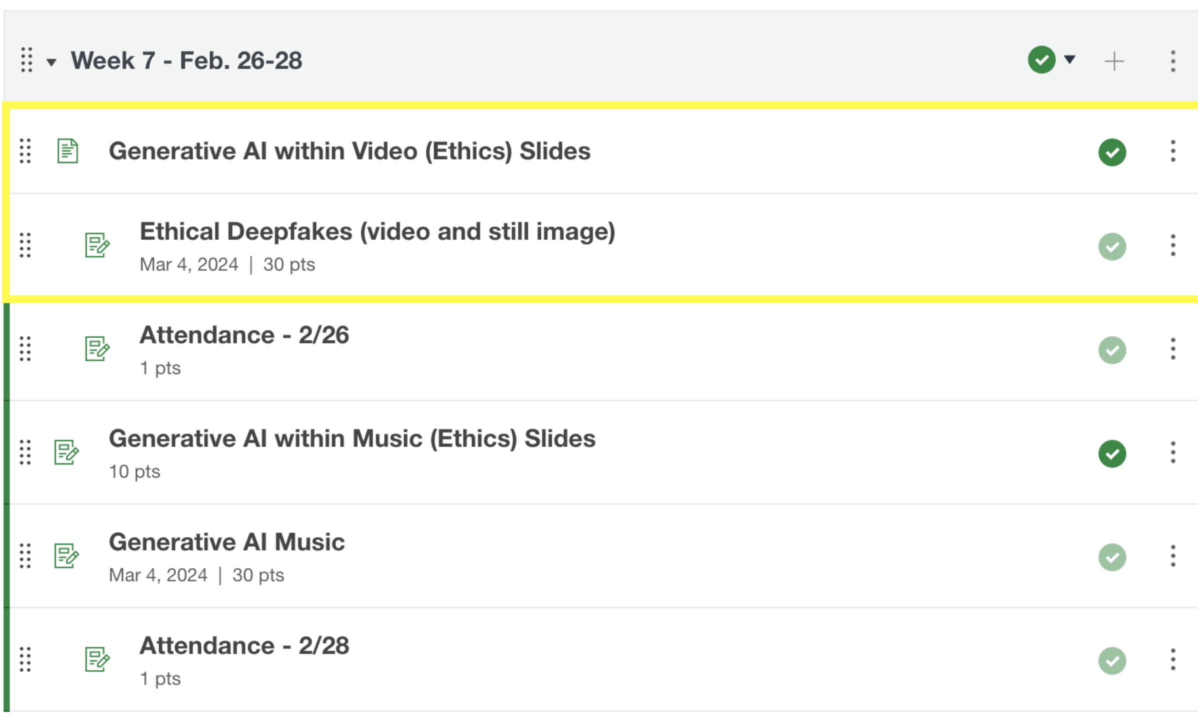
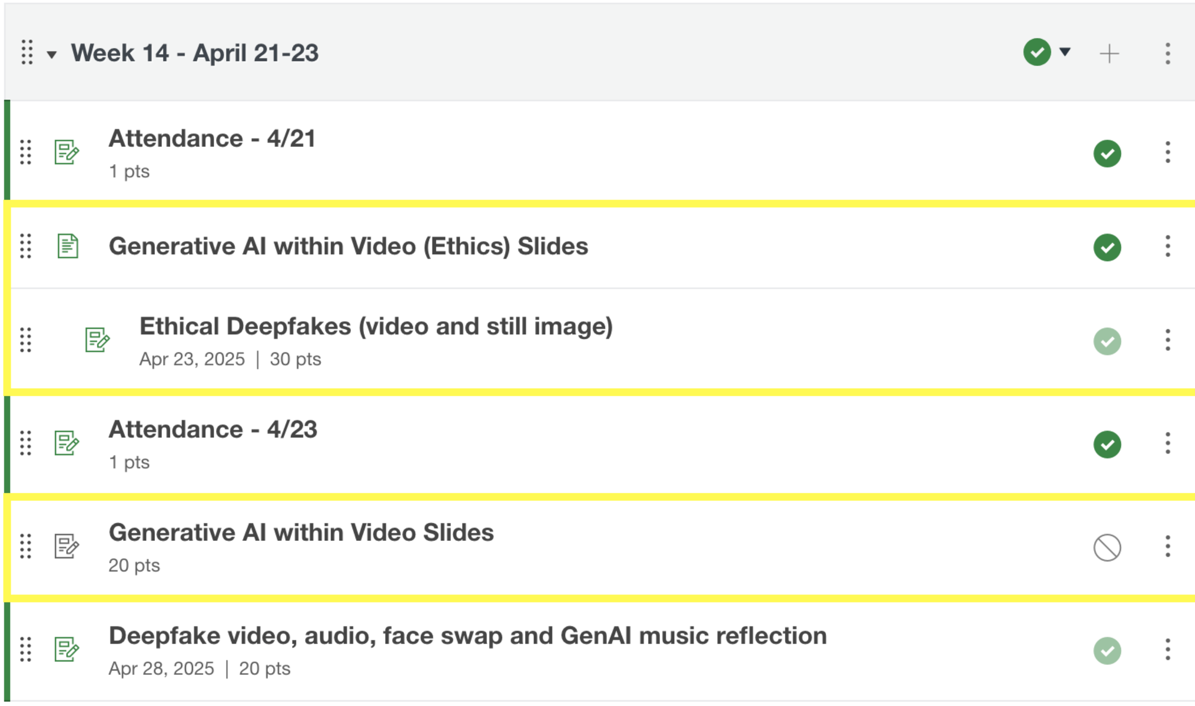
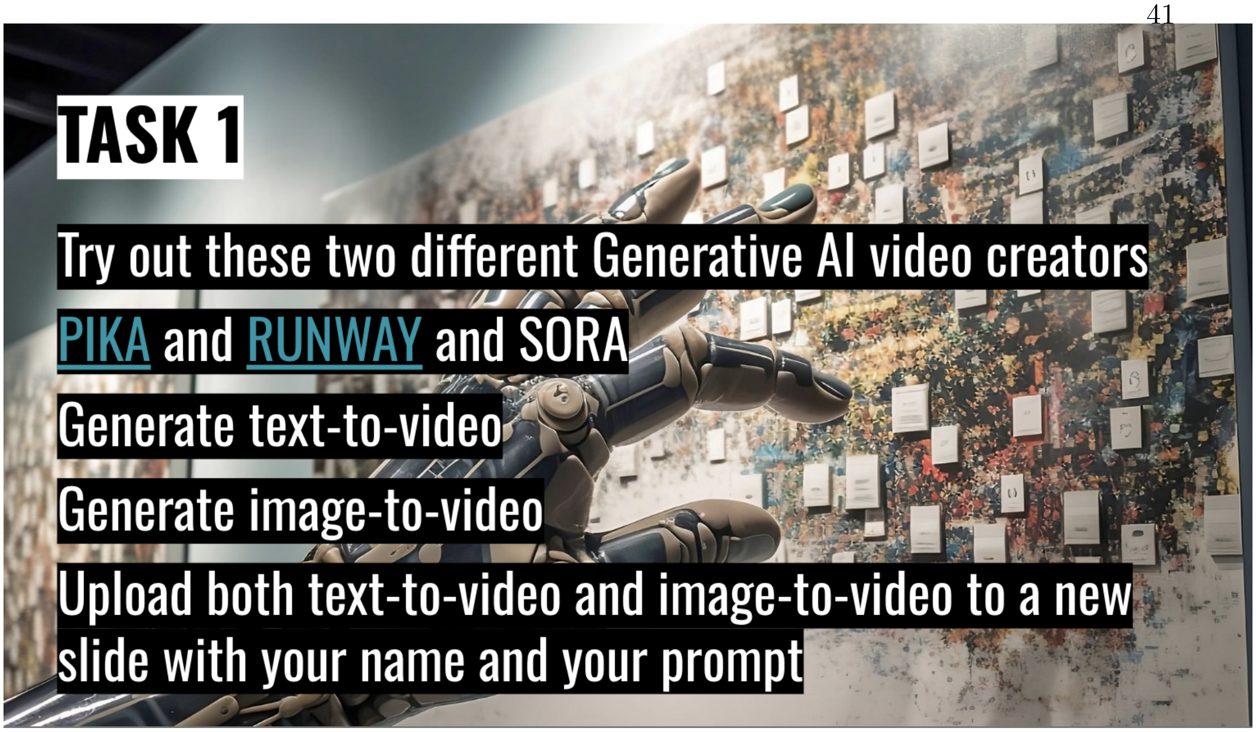


Figure 3. Highlighting Video Generation location in Module 14 for Pilot 2.



In the next several examples, you will see the different image generation revisions in the slide decks for the pilot and global courses. Due to new and emerging GenAI tools, pricing and accessibility, these tools were changed within the years of 2024–2025. In Figure 4, the video generation task slide did not change from pilot 1 in 2024 to pilot 2 in 2025.

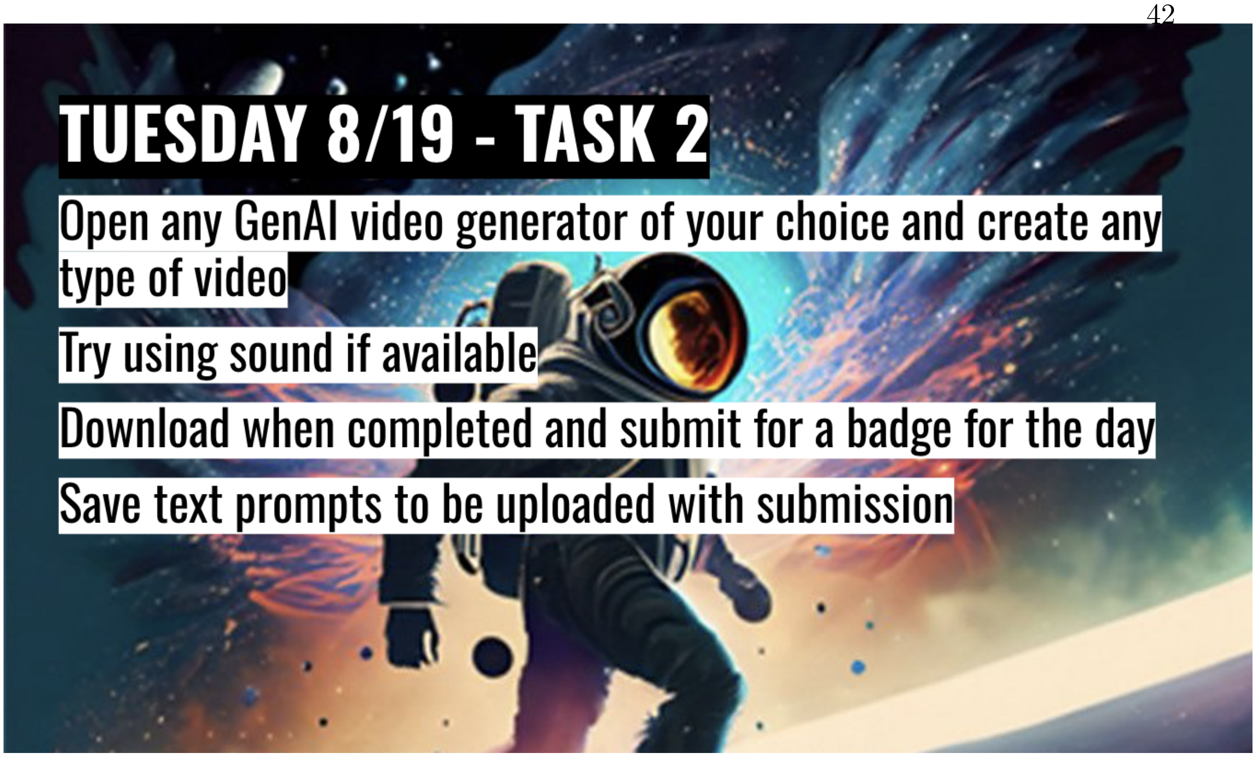
Figure 4. Video generation task slide for Pilot 1 and Pilot 2.



In Figures 5 and 6, the video generation slides did not change from global course 1 to global course 2, considering they were only three weeks apart. But, the slides and tools did change from pilot 1 and 2 to global 1 and 2.

Figure 5. GenAI video generation tools slide for Global 1 and Global 2.

Figure 6. Video generation task slide for Global 1 and Global 2.



Thematic coding of my slide deck and module revisions showed repeated reasons for change, such as resolving student confusion, tool accessibility issues, and incorporating new GenAI tools. It also revealed consistent patterns in how modules were updated over time, including simplifying instructions, adding or revising demonstration materials, and swapping specific GenAI tools while keeping core learning objectives consistent. These recurring reasons and update patterns created a set of practical principles and practices that directly informed my response to RQ1.

3.2.2 Learner Choice and Multiple Entry Points

Learner choice allowed participants to be in control of how they engaged with the course material. I offered short videos, written guides, live demonstrations and hands-on assignments in every module, letting students select the format or tool that best fits learning style, whether they come from visual design, mechanical engineering, or any other field. This teaching approach not only respects diverse learning styles but also encourages peer teaching, as learners compare insights from different solutions.

Students were given the choice to submit any type of assignment format, such as a link, video, screen recording, or audio file, which allowed students to learn and feel comfortable turning in assignments that aligned with their learning style.

For the sound and music assignment, students had the choice to choose whatever music or audio tools they preferred to use. I provided a hands-on workshop and live demonstration of the GenAI tools Soundful, Suno, Udio, Cartesia, HeyGen, and Eleven Labs. For the pilot courses, the students had to create their own GenAI music composition using Soundful, Suno, or any other music application of their choice. An article was also linked in the assignment for them to read and try out new GenAI tools. In Figure 7, pilot 1 only provided one GenAI music tool suggestion, Soundful. In Figure 8, pilot 2 provided two GenAI music tool suggestions. In the global courses, shown in Figures 9 and 10, the students had the choice to create a musical composition or a voice clone, along with many more options and suggestions for GenAI sound and audio tools in comparison to pilot 1 and pilot 2.

Figure 7. GenAI Music assignment from Pilot 1.

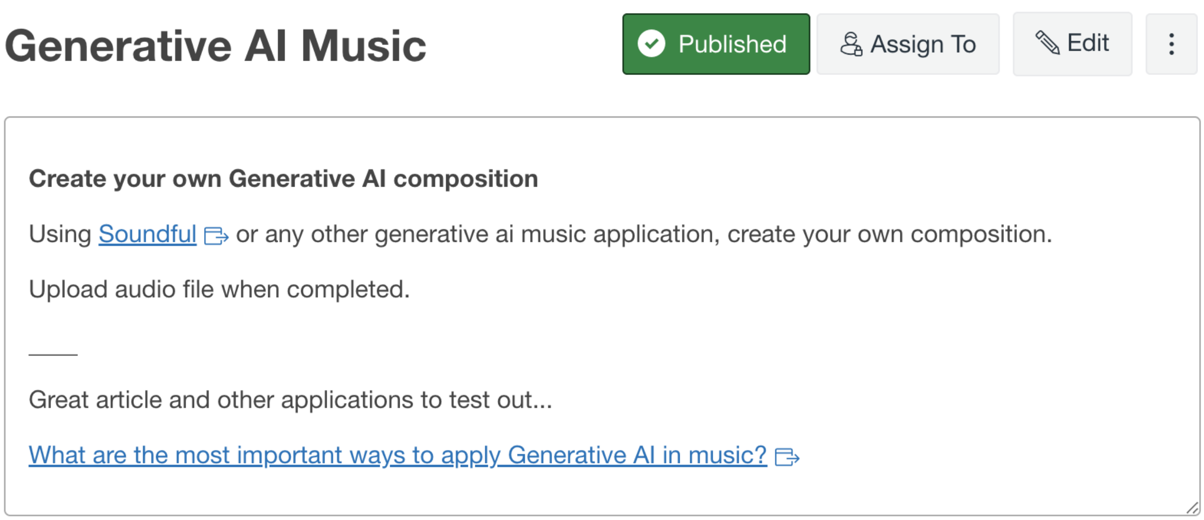


Figure 8. GenAI Music assignment from Pilot 2.

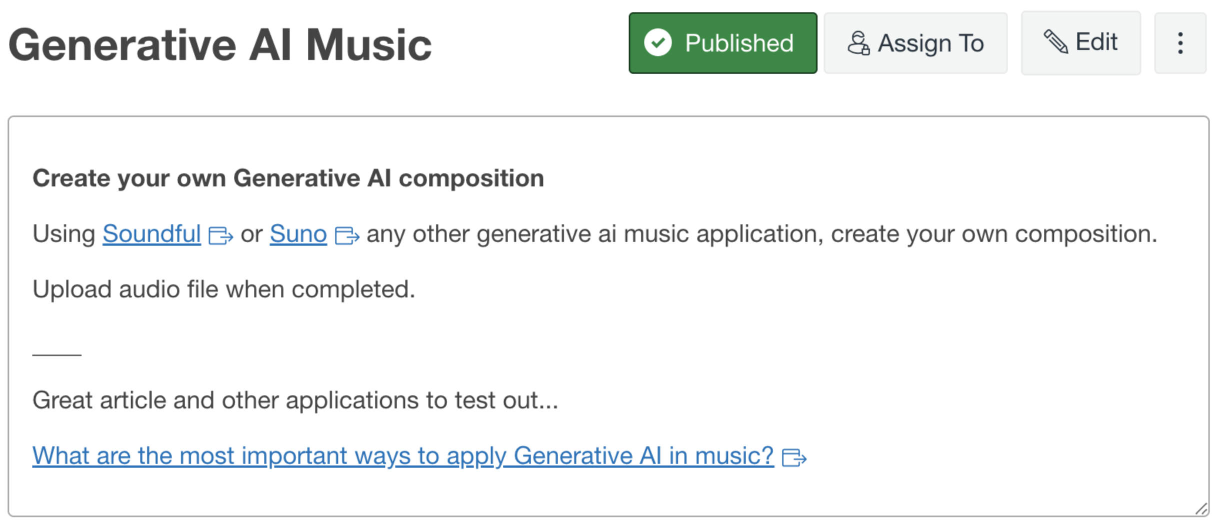


Figure 9. GenAI sound tools from Global 1 and Global 2.

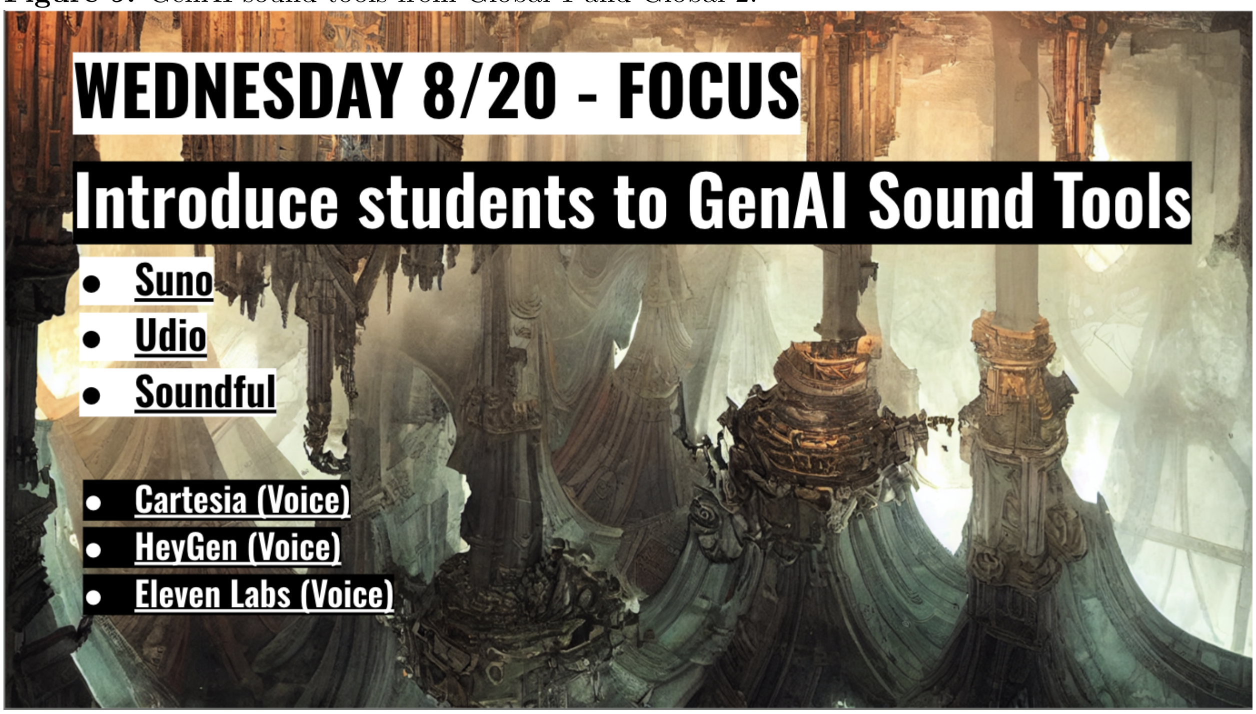
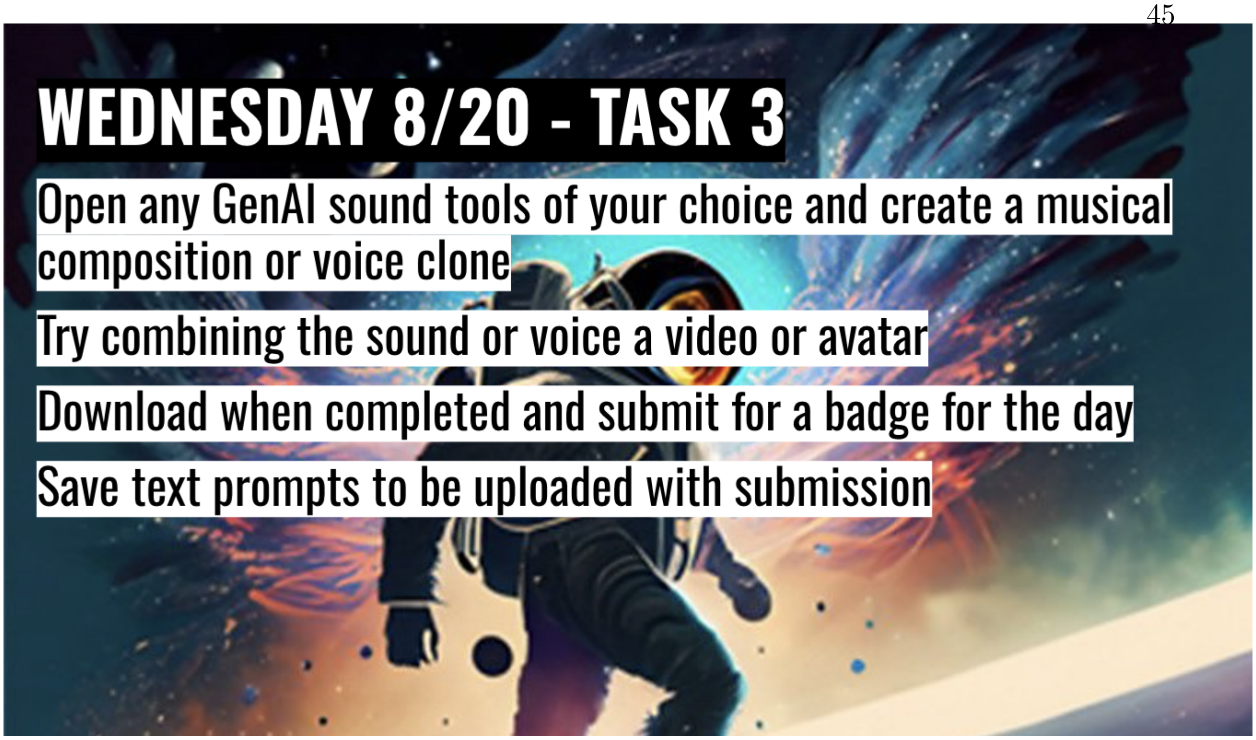


Figure 10. GenAI Music task from Global 1 and Global 2.



An end-of-course evaluation response from pilot 2 noted: "The AI Music lecture was really interesting, I enjoyed seeing and using the different generation options" — feedback that supported keeping the multi-tool walkthrough format in the next iteration.

3.2.3 Continuous Feedback and Living Curriculum

Continuous feedback helped drive learner experience. After each pilot or global iteration, I collected survey responses, and reviewed project submissions to identify main points. Those insights assisted me with weekly updates to assignment instructions, example projects, creating a living curriculum that adapts alongside GenAI technological developments which adjusts for new participants.

I collected surveys and written reflections after tasks and assignments in the pilot and global courses. For the global courses, the students had to turn in a survey each day with their assignment attached. From these surveys, I was able to collect data on comprehension of the lesson taught, suggestions, and technological challenges.

One pattern in the course evaluation feedback for the image generation global 1 module flagged the absence of worked-example prompts for the introductory magazine-cover assignment.

The next-iteration slide deck added a worked-example block: sample prompts paired with the resulting magazine-cover images, included with the contributing student's consent for educational use. In Figure 11, the task in the slide deck for the first global course for image generation is shown below. Two of the worked-example slides added in response to the feedback are shown in Figures 12 and 13.

Figure 11. Image generation task from Global 1 and Global 2.

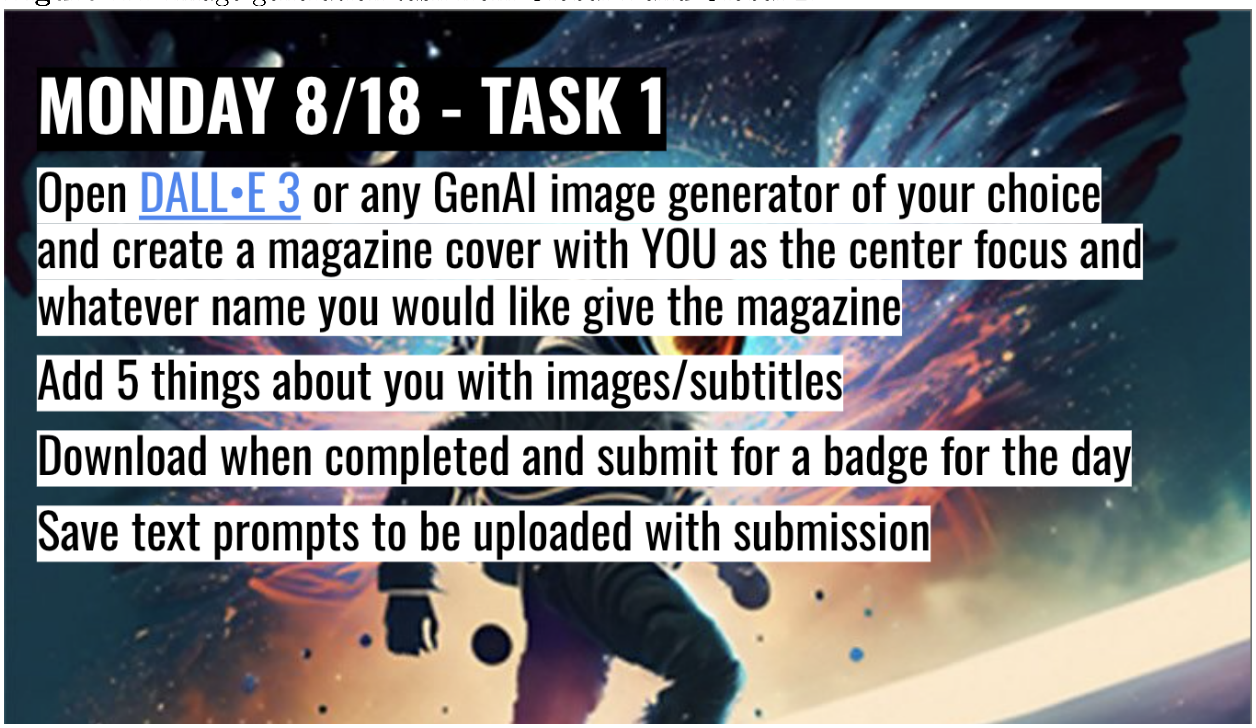


Figure 12. Example of the image generation task (Magazine Cover) from Global 1 and Global 2.

Text Prompt:
Create a Magazine cover with my own photo as attached as the center focus, name of Magazine is : "AI for Everyone", Add the points on the cover 1. Ethical AI 2. AI for Societal Good. 3. AI for Education 4. AI Expert 5. Harnessing Power of AI

Figure 13. Example of the image generation task (Magazine Cover) from Global 1 and Global 2.

Text Prompt:

Generate a magazine cover of a monkey that is a student, loves watching Law and Order episodes, loves coding, listening to music, and playing merge games, with the name: "A Day in the life of your average college student" with vertical aspect ratio

Across all four iterations, the course operated as a living curriculum that I adjusted continuously in response to learners' needs and new GenAI tools, rather than something revised only between semesters.

3.3 RQ2A · Adapting to Different Learning Environments

The course adapted to different instructional contexts by offering a flexible structure, customizable examples, and varied delivery options that met the needs of diverse learners.

3.3.1 Flexible Structure

Each module was designed as an independent "building block" with clear learning objectives and standalone activities. In a small classroom setting, such as with creative technology and design majors, I could provide hands-on workshops, expand into live demos and group critiques. When taught virtually, slide decks accompanied live GenAI tool demonstrations, keeping the same learning objectives across all different formats.

3.3.2 Customizable Examples

To connect with different student cohorts, example projects changed to match learners' diverse backgrounds. For an art-focused cohort, assignments emphasized GenAI multimedia skills. For mechanical, electrical, or biomedical engineering students, projects shifted towards GenAI CAD tools and code-based skills and assignments. In interdisciplinary offerings, examples combined design and engineering perspectives, such as vibe coding for creating and building mobile applications that also met aesthetic outcomes.

3.3.3 Varied Delivery Modes

- In-person workshops alongside live GenAI demonstrations.
- Virtual formats use recorded Zoom meetings, discussion forums, and peer reviews.

3.4 RQ2B · Responding to the GenAI Technology Landscape

I made sure the course stayed up to date with the fast pace of GenAI by keeping an eye on new developments, consistently updating lessons, and focusing on ideas and projects that could work with any GenAI tool.

3.4.1 Technology-Driven Module Revisions

First, I spent each week researching the latest GenAI models and tools. I read newsletters, followed social media, watched webinars and project updates, and tracked announcements from GenAI companies. This way, I knew when a new model or tool was released and could decide if it belonged in the next lesson for the curriculum.

Next, I split the syllabus into small units or modules so I only needed to change one lesson at a time. For example, if a GenAI model or tool changed or updated, I switched out the demonstration materials for that module without touching the rest of the coursework. This kept everything fresh without disrupting the overall flow of the class.

Then, I taught lessons that applied across different GenAI tools, like how to be successful at prompt engineering or check if a GenAI tool's output made sense, rather than focusing on a single platform. By showing students similar examples with different GenAI tools, they learned skills they could use no matter which GenAI application becomes popular next.

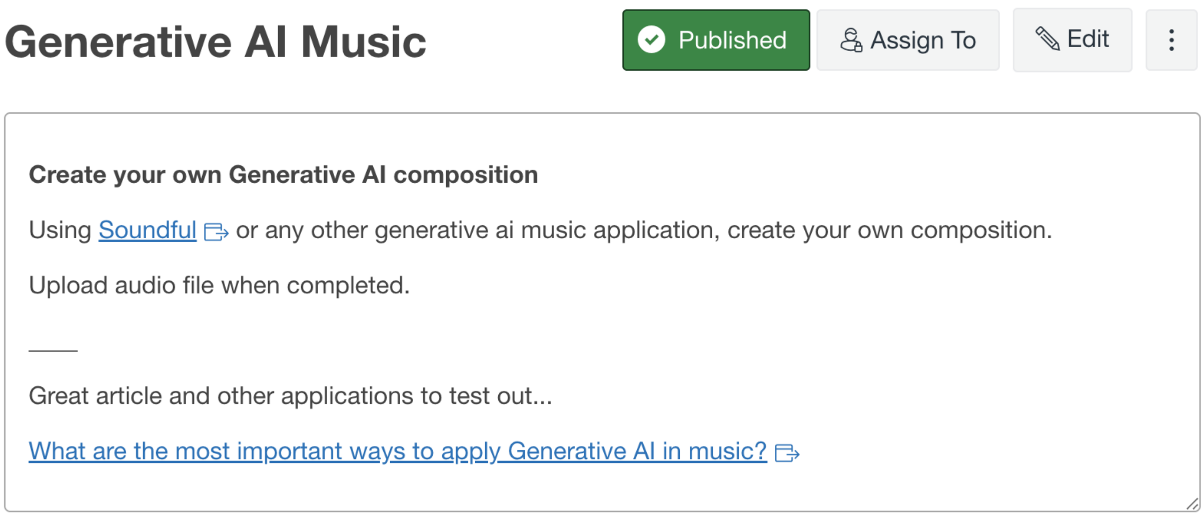
This continuous cycle of checking new tools, updating modules, and focusing on technological skills that work across platforms directly answers RQ2B by showing how the course stayed up to date with the fast-changing GenAI landscape.

3.4.2 Co-Discovery Through Teach-Out Slots and Course Evaluation Feedback

A scheduled teach-out slot at the start of each class invited students to present a recent GenAI tool they had encountered, and the post-module course evaluation prompts included an explicit field for new tools the curriculum should consider. I treated the teach-out content and that evaluation field as a recurring channel for surfacing new tools that needed to enter the curriculum. Each cycle I reviewed what had been surfaced, researched the most promising candidates, and revised the next iteration's slide deck to incorporate them. This pattern kept the course content current and is itself an instance of the modularity principle in §3.2.1: a single module can be refreshed with a new tool without rewriting the surrounding syllabus.

For example, a teach-out presentation in pilot 1 surfaced the GenAI music tool Soundful, which I subsequently added to the GenAI Music assignment in the next iteration's slide deck, shown in Figure 14.

Figure 14. GenAI Music assignment using Soundful, from Pilot 1.



The end-of-course evaluation comments from pilot 2 included reflections such as "From LLM resources such as NotebookLM to things like Lovable. The most useful things I learned this semester were from this class," and "The knowledge from this class is arguably the most valuable in today's age, as ChatGPT and other AI tools are such a common thing within the workspace. Knowing how to effectively and ethically employ these tools will be vital knowledge moving forward into industry, as they are able to accelerate workflows and make things a lot easier." Comments of this kind supported keeping the multi-tool, ethics-anchored framing in the next iteration of the curriculum.

Chapter 4

Discussion

4.1 Cross-cutting patterns

Amongst RQ1, RQ2A, and RQ2B, three major patterns appeared numerous times. The first pattern was how the modular design and continuous student feedback worked together to support timely changes. Breaking the course into separate modules within education, industry, ethics and accessibility, focusing on prompt engineering, image generation, video generation, sound generation, research tools, vibe coding, agents, etc., meant that I could revise one unit at a time without disrupting the entire syllabus. After each module, I reviewed surveys, written reflections, and student projects. When students communicated confusion or struggled with a task, I simplified instructions, added a short demo, or moved content to a different week. When tools changed pricing, access, or interfaces, I replaced and/or added in a different GenAI tool but kept the same learning objectives. This pattern of ongoing adjustments showed that modularity and feedback provided a practical way for the course to stay responsive.

The second pattern was the central role of learner choice and multiple entry points in the curriculum design across different learning contexts. The for-credit university courses operated under outside pressures like grades and degree progress; the global courses ran without credit or grades and were free to participate in. Offering choices in both learning settings, such as letting participants choose which GenAI tools to use for a given assignment, what topic to focus on, and whether to engage through written, visual, or multimodal outputs, was a design move I retained across all four iterations. This pattern aligns with what self-determination theory predicts about autonomy, competence, and relatedness as supports for engagement. When the assignment design surfaced clear connections to learner-stated interests, the course evaluation feedback for that assignment was more positive and the assignment was retained in the next iteration.

The third pattern was the consistent role of shared GenAI principles and ethics. Even though specific tools and models changed quickly, the course kept coming back to the same core ideas: responsible use, fairness, transparency, safety, checking outputs carefully, and prompt-engineering skills that work across various GenAI tools. When one tool changed or disappeared, I could swap in another and still teach the curriculum through the same core concepts. When students introduced new GenAI applications, I could observe using the same questions about bias, ownership, accessibility, and human-AI collaboration. This pattern suggests that in fast-moving technological fields, what stays consistent is the shared principles and ways of evaluating them.

4.2 Unexpected Findings

The study revealed several surprises and unexpected findings that helped me understand how an adaptive GenAI course actually works. One unexpected finding was that some activity designs that worked well at small scale required substantial redesign at large scale. In the first two university offerings, long in-person labs and detailed peer critiques produced extensive in-class artifact-review activity. When the course grew to 100 and then 1,000 global participants, those same activity designs became difficult to manage at scale because of time limits and platform constraints. I redesigned peer review to use clearer prompts, simple rubrics, and fewer artifacts per person, and I leaned more on asynchronous discussions and short, focused feedback. This change showed that as the cohort size grows, some depth has to be balanced with more structure and breadth in the curriculum design, even when the core goals of collaboration and reflection stay the same.

Another surprise involved how particular tools rose and fell in importance over time. At several points, tools that I expected to be central lost their place because of pricing changes, access restrictions, or interface redesigns that made them less feasible for students with limited resources or time. At the same time, learners frequently brought new tools to class during “teach out" sessions and discussions. Some of these student-introduced tools quickly became important examples in assignments and demos, especially when they offered more accessible interfaces, free tiers, or features that better fit project goals. This pattern highlighted how student co-discovery was not just a nice extra, but a practical mechanism for keeping the course current with the GenAI landscape. It also reminded me that my own preferences and professional habits could not fully predict which tools would matter most to learners.

These surprises reinforce the framing of GenAI as a black swan technology and support the decision to use curriculum-as-research and iterative teaching-as-inquiry as the core approach. Rather than searching for a single, stable "best" design, the course needed to be flexible enough to absorb surprises, let go of tools or practices that no longer served learners, and incorporate new possibilities surfaced by students. At the same time, these tensions made my positionality as an instructor-researcher more visible. My excitement about certain tools, my background in art and engineering, and my assumptions about what "good" GenAI work looks like all shaped early choices and interpretations. Reflexive notes, peer feedback, and student input helped me notice these influences and adjust, but they did not remove them. In this way, the unexpected findings do not just say something about the course; they also say something about what it means to study a disruptive technology from the inside, while actively teaching and designing with it.

Chapter 5

Conclusion

5.1 Contributions to theory and research

This study contributes to several strands of educational theory and research. First, it extends constructivist and self-determination theory perspectives by showing how a curriculum can be designed to support motivation, autonomy, and meaningful learning in both credit-bearing university contexts and large, non-credit global offerings focused on GenAI. In all four iterations, the curriculum was designed to invite learners to connect GenAI projects to their own interests, disciplines, and professional goals, and to share their work with peers. The artifact trail across iterations shows that the curriculum was designed and refined to offer learners genuine choices in tools and topics, scaffolded tasks for competence-building, and spaces to connect with others, and that these design choices were retained as the curriculum scaled from for-credit to large global formats. The design choices are consistent with what self-determination theory predicts will support high-quality motivation; whether the predicted motivational outcomes occurred at the learner level is a question for follow-up research with an IRB-reviewed protocol.

Second, the study deepens work on curriculum-as-research and design-based research by treating the Introduction to GenAI course as a research object over multiple iterations. The analysis drew on slide-deck and module revisions and other instructor-authored curriculum artifacts as the primary data sources, with course evaluation feedback used as a contextual trigger explaining why specific revisions occurred (§2.6). Iterative cycles of planning, teaching, observing, and reflecting were used not only to improve the course locally, but also to surface broader curriculum-design principles such as modularity, learner choice, and the value of universal GenAI concepts. This approach shows how a course in a rapidly changing technical area can serve both as an educational experience and as a living, evolving research artifact that generates knowledge about curriculum design.

Third, the study adds to literature on disruptive technologies in education by offering an empirically documented model from one institutional context for teaching a black swan technology in engineering. Rather than treating GenAI as a temporary add-on or a single lecture topic, the course was designed from the start to handle volatility through modular design, continuous feedback, and shared responsibility between instructor and learners. The findings illustrate how these design choices can make room for unpredictability while still providing structure, ethical grounding, and opportunities for deep learning. This model can inform future work on how engineering education and related fields respond to sudden, large-scale technological shifts.

5.2 Implications for practice

For practitioners designing GenAI or other fast-changing technology courses, the study suggests several practical design principles. One implication is the importance of building modules that can be updated quickly without rewriting the entire syllabus. When each module has clear learning objectives, activities, and assessment criteria, instructors can swap tools, adjust examples, or refine explanations within that module in a matter of hours, while keeping the overall course flow intact. This approach is especially helpful when tools move to paid plans, change interfaces, or are replaced by new models mid-semester.

A second implication is the value of multiple entry points and real choice for learners. Allowing students to select among several tools for a given task, choose project topics that relate to their field or interests, and present their work in different formats makes it easier to include learners with varied backgrounds, resources, and comfort levels. This flexibility aligns with differentiated instruction and supports more equitable participation by recognizing that not all students have the same hardware, connectivity, or prior experience.

A third implication is the usefulness of simple but steady feedback systems. Short surveys after each module, brief reflection prompts tied to assignments, and a habit of maintaining revision notes and timelines together form a feedback loop that keeps the curriculum aligned with learner needs. Instructors do not need complex analytics to benefit from this; even a few targeted questions about clarity, pacing, and relevance can reveal patterns that guide meaningful improvements.

A fourth implication is the need to center universal principles and ethics rather than any one GenAI platform. Teaching students how to think about bias, ownership, transparency, and responsible use, and how to design and critique prompts and outputs across multiple tools, prepares them to adapt as the technology shifts. This orientation encourages learners to see GenAI not just as a set of features, but as a space where human judgment, values, and creativity still matter.

5.3 Limitations and directions for future research

Several limitations should be acknowledged when interpreting these findings. The course was developed and studied within one institutional setting, which shaped available technologies, support structures, and student populations. Other institutions may face different constraints or opportunities. My dual role as instructor and researcher, and my professional background in creative technology and engineering education, also influenced both design choices and interpretations. Reflexive notes and peer feedback were used to examine these influences, but they remain part of the study's context.

This study was scoped as curriculum-design research analyzing instructor-authored artifacts (§2.6). It did not include IRB-approved instruments for measuring student outcomes, and it does not claim findings about student-level learning, motivation, or skill gain. The analysis focused on the curriculum's artifact trail and on course evaluation inputs collected during teaching. It did not track learners over longer periods to see how they applied GenAI in their careers, further studies, or personal projects. In addition, the global offerings involved self-selected participants who chose to enroll in a free GenAI course, which likely shifted the audience composition toward more motivated or curious participants than the general potential learner population.

Future research can build on this work in several directions. Multi-institutional studies with IRB-reviewed protocols could adapt and test the curriculum-design framework in different universities, countries, and disciplines and provide a stronger sense of how generalizable these design principles are. Longitudinal studies, also IRB-reviewed, that follow learners into internships, industry positions, or further education could offer insight into how GenAI skills, ethical considerations, and collaborative habits developed in the course show up in real practice. More focused studies on equity and access, including differences in internet access, device availability, language, disability, and cultural backgrounds, could help refine how modular, learner-centered GenAI curricula might reduce or unintentionally widen participation gaps. Finally, applying a similar curriculum-as-research approach to other rapidly changing domains, such as cybersecurity, climate technology, or robotics, could test whether modular design, continuous feedback, and co-discovery are useful more broadly for teaching disruptive technologies.

5.4 Closing synthesis

Framing GenAI as a black swan technology, this dissertation has argued and shown that curriculum-as-research, modular course design, and co-created learning communities offer a practical way to keep teaching aligned with both rapid technological change and diverse learner contexts. By treating the Introduction to GenAI course as a living curriculum, revised in real time with input from course evaluation feedback and informed by theory, the project demonstrates that educators do not have to choose between stability and responsiveness. Instead, they can build courses that are stable in their core principles and values, yet flexible in their tools, examples, and activities. The curriculum aims to support learners not only in using today's GenAI tools but also in approaching whatever disruptive technologies appear next; testing whether the curriculum delivers that broader adaptability is a question for follow-up research with IRB-reviewed protocols measuring student-level outcomes.

Chapter 6

References

References

Adler, P. A., & Adler, P. (1987). **Membership roles in field research**. Qualitative Research Methods Series. Sage Publications.

Anderson, L. (2006). Analytic autoethnography. **Journal of Contemporary Ethnography**, 35(4).

Baker, R. S., & Hawn, A. (2022). Algorithmic bias in education. **International Journal of Artificial Intelligence in Education**, 32(4), 1052–1092.

Basgen, B. (2023). **A generative AI primer**. EDUCAUSE Review (Online).

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In **Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency (FAccT '21)**. ACM.

Bommasani, R., Hudson, D. A., Adjeroh, D., Altman, R., Arora, S., von Arx, S., ... Zhang, Y. (2021). **On the opportunities and risks of foundation models**. arXiv preprint arXiv:2108.07258.

Boyer, E. L. (1990). **Scholarship reconsidered: Priorities of the professoriate**. Carnegie Foundation for the Advancement of Teaching.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... Amodei, D. (2020). Language models are few-shot learners. **Advances in Neural Information Processing Systems**, 33, 1877–1901.

Burrows, A. C., Lockwood, M., Borowczak, M., Janak, E., & Barber, B. (2018). An iterative participatory approach to developing an early childhood problem-based STEM curriculum. **Journal of Educational Research**, 111(3), 256–266.

Chang, H. (2008). **Autoethnography as method**. Left Coast Press.

Chang, H., Ngunjiri, F. W., & Hernandez, K.-A. C. (2013). **Collaborative autoethnography**. Left Coast Press.

Christensen, C. M., Grossman, J. H., & Hwang, J. (2009). **The innovator's prescription: A disruptive solution for health care**. McGraw-Hill.

Cochran-Smith, M., & Lytle, S. L. (2009). **Inquiry as stance: Practitioner research for the next generation**. Teachers College Press.

Code of Federal Regulations. (2018). **Federal Policy for the Protection of Human Subjects (Common Rule), 45 CFR 46.102(l)**. U.S. Department of Health and Human Services.

Daniel, B. (2014). Big data and analytics in higher education: Opportunities and challenges. **British Journal of Educational Technology**, 46(5).

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. **Psychological Inquiry**, 11(4).

Deci, E. L., & Ryan, R. M. (1985). **Intrinsic motivation and self-determination in human behavior**. Plenum Press.

Dehouche, N., & Dehouche, K. (2023). What's in a text-to-image prompt? The potential of stable diffusion in visual arts education. **Heliyon**, 9(6).

Ellis, C., Adams, T. E., & Bochner, A. P. (2011). Autoethnography: An overview. **Forum: Qualitative Social Research**, 12(1).

U.S. Department of Education. (1974). **Family Educational Rights and Privacy Act (FERPA), 20 U.S.C. § 1232g; 34 CFR Part 99**. United States Code and Code of Federal Regulations.

Finlay, L. (2002). Negotiating the swamp: The opportunity and challenge of reflexivity in research practice. **Qualitative Research**, 2(2), 209–230.

Healey, M., & Jenkins, A. (2009). **Developing undergraduate research and inquiry**. The Higher Education Academy.

Hutchings, P., & Shulman, L. S. (1999). The scholarship of teaching: New elaborations, new developments. **Change: The Magazine of Higher Learning**, 31(5), 10–15.

Kelly, A., & Sullivan, M. (2023). **ChatGPT in higher education: Considerations for academic integrity and student learning**. Journal of Applied Learning and Teaching.

Kemmis, S., McTaggart, R., & Nixon, R. (2014). **The action research planner: Doing critical participatory action research**. Springer.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In **Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems**. ACM.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). **Intelligence unleashed: An argument for AI in education**. UCL Knowledge Lab.

Lungu, M. (2022). The coding manual for qualitative researchers. **American Journal of Qualitative Research**, 6(1), 232–237.

Marcus, G., & Davis, E. (2020). **Rebooting AI: Building artificial intelligence we can trust**. Pantheon Books.

McKenney, S., & Reeves, T. C. (2018). **Conducting educational design research** (2nd ed.). Routledge.

Mishra, P., & Koehler, M. J. (2006). Technological Pedagogical Content Knowledge: A framework for teacher knowledge. **Teachers College Record**, 108(6), 1017–1054.

Mollick, E. R., & Mollick, L. (2023). **Assigning AI: Seven approaches for students, with prompts**. Working paper.

Office for Human Research Protections. (2014). **Guidance on distinguishing quality improvement and research**. U.S. Department of Health and Human Services.

OpenAI. (2023). **GPT-4 technical report**. Retrieved from https://openai.com/research/gpt-4

Prensky, M. (2001). Digital natives, digital immigrants. **On the Horizon**, 9(5), 1–6.

Prince, M. J., & Felder, R. M. (2006). Inductive teaching and learning methods: Definitions, comparisons, and research bases. **Journal of Engineering Education**, 95(2), 123–138.

Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., & Sutskever, I. (2021). Zero-shot text-to-image generation. **Proceedings of the 38th International Conference on Machine Learning**, 8821–8831.

Redecker, C., & Punie, Y. (2017). **European Framework for the Digital Competence of Educators: DigCompEdu**. Publications Office of the European Union.

Reed-Danahay, D. (Ed.). (1997). **Auto/Ethnography: Rewriting the self and the social**. Berg.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. **American Psychologist**, 55(1), 68–78.

Ryan, R. M., & Deci, E. L. (2017). **Self-determination theory: Basic psychological needs in motivation, development, and wellness**. Guilford Press.

Salmon, G. (2002). **E-tivities: The key to active online learning**. RoutledgeFalmer.

Schön, D. A. (1983). **The reflective practitioner: How professionals think in action**. Basic Books.

Schunk, D. H. (2020). **Learning Theories: Educational Perspectives** (8th ed.). Pearson.

Selwyn, N. (2021). **Education and technology: Key issues and debates**. Bloomsbury Publishing.

Taleb, N. N. (2007). **The black swan: The impact of the highly improbable**. Random House.

Tedlock, B. (1991). From participant observation to the observation of participation: The emergence of narrative ethnography. **Journal of Anthropological Research**, 47(1).

Tomlinson, C. A. (2014). **The differentiated classroom: Responding to the needs of all learners**. ASCD.

Touretzky, D., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for

K-12: What should every child know about AI? In **Proceedings of the AAAI Conference on Artificial Intelligence**, 33.

UNESCO. (2021). **Artificial intelligence in education: Challenges and opportunities for sustainable development**. United Nations Educational, Scientific and Cultural Organization.

UNESCO. (2021). **Equity, inclusion and learner diversity**. UNESCO Publishing.

Wendell, K. B., Koehler, C. M., Fanucchi, A. K., & Baral, K. (2021). Designing biomimetic robots: Iterative development of an integrated technology design curriculum. **Educational Technology Research and Development**, 69(6), 3141–3164.

Wobbrock, J. O., & Kientz, J. A. (2016). Research contributions in human-computer interaction. **Interactions**, 23(3).

Yin, R. (2014). **Case study research: Design and methods** (5th ed.). Sage.